Acta Psychologica 269 (2026) 107573

Contents lists available at ScienceDirect

Acta Psychologica

journal homepage: www.elsevier.com/locate/actpsy

Understanding task-specific AI adoption among academic professionals: AI literacy, professional role, and responsible use

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ARTICLE INFO

Keywords:
AI literacy
Task-specific AI adoption
Human-AI interaction
Professional technology-use
Higher education

ABSTRACT

Artificial intelligence (AI) tools are increasingly embedded in academic work; however, little is known about why academics adopt them for some tasks but not others. Drawing on technology adoption, professional identity, ethical decision-making, and professional technology-use perspectives, this study examines how demographic/professional characteristics and AI literacy dimensions are associated with academics' use of AI tools for general academic tasks, academic writing, literature reviews, and visual content creation. Survey data were collected from 368 academics working at 116 universities in Türkiye. Binary logistic regression was the main explanatory approach, and supplementary machine learning analyses were used for predictive validation. The findings show that academic AI adoption is task-specific rather than uniform. Usage competence significantly predicted general academic use and literature review, whereas awareness, evaluation, and ethics did not show consistent direct effects on these outcomes. Academic title differentiated adoption in general academic use, academic writing, and literature reviews. Gender was associated with the literature review, whereas the visual content creation model showed limited explanatory power. This study provides empirical evidence regarding task-specific human-AI interaction and professional technology-use research by showing that academic AI use is associated with practical competence, professional role expectations, perceived task value, and task legitimacy, rather than generalized technology acceptance alone.

1. Introduction

Artificial intelligence (AI) tools are increasingly embedded in academic work, reshaping how academics search for information, generate ideas, review literature, prepare teaching materials, and produce scholarly texts (Thomas, 2024; Vimos-Buenaño et al., 2024). Conversational AI tools such as ChatGPT, Gemini, and Claude are especially relevant because they provide accessible interfaces for text generation, summarization, translation, brainstorming, coding support, and literature-oriented tasks (González Ramírez et al., 2023; Ngo et al., 2025; Zahra & Rautela, 2024). Thus, AI use in academia has become a psychologically and professionally meaningful behavior rather than a purely technological choice.

Recent studies have shown that ChatGPT adoption in higher education is closely connected to academic integrity, teaching preparation, workplace stress, academic competence, staff performance, and the diffusion of generative AI in educational settings (Bin-Nashwan et al., 2023; Bin-Nashwan, Bouteraa, et al., 2025; Bin-Nashwan, Sadallah, et al., 2025; Bouteraa et al., 2024; Sadallah et al., 2025). AI tools may improve efficiency and reduce cognitive workload; however, they also raise concerns about academic integrity, authorship responsibility, transparency, epistemic reliability, and professional accountability (Bin-Nashwan et al., 2023; Carobene et al., 2024; Yitages & Kasai, 2024). These concerns are particularly salient because academic work is governed by originality, credibility, and ethical responsibility.

From a psychological and behavioral perspective, academics can be understood as expertise-driven and reputation-sensitive professional technology users whose AI adoption is shaped by both instrumental and normative considerations (Singh et al., 2024). Adoption may depend on perceived usefulness, ease of use, task compatibility, trust in AI-

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https://doi.org/10.1016/j.actpsy.2026.107573
Received 16 January 2026; Received in revised form 3 July 2026; Accepted 1 August 2026
Available online 8 August 2026

generated outputs, ethical risk, reputational consequences, and perceived task value (Hitsuwari & Takano, 2025; Pigola et al., 2023). This perspective aligns with technology adoption research, which emphasizes that users do not adopt technologies merely because they are available but because they perceive them as useful, trustworthy, legitimate, and contextually appropriate. Unlike many consumer or workplace technologies, AI tools in academia directly affect scholarly credibility, authorial responsibility, and institutional accountability. Therefore, academic AI adoption represents a distinctive form of human–AI interaction and professional technology adoption.

In this study, academics were conceptualized as professional technology users, rather than ordinary technology consumers. This distinction is important because academic AI adoption is embedded in professional norms, authorship responsibilities, institutional accountability, and reputational considerations. Accordingly, this study does not treat AI adoption as a purely individual preference or general technology-acceptance outcome. Instead, it frames task-specific AI use as a professional technology-use decision shaped by three interrelated considerations: perceived task utility, professional role expectations, and responsible-use boundaries. Technology adoption perspectives help explain why practical AI usage competence may facilitate adoption, professional role perspectives help explain why academic title and career stage may differentiate adoption, and ethical responsibility perspectives help explain why AI use may vary across tasks with different levels of authorship sensitivity and perceived legitimacy.

AI literacy is central to this issue. It is commonly understood as a multidimensional competence that includes awareness of AI systems, practical ability to use AI tools, critical evaluation of AI-generated outputs, and ethical sensitivity regarding responsible use (Asrifan et al., 2024; Ghani et al., 2024; Mansoor et al., 2024). In higher education, AI literacy is shaped by institutional culture, disciplinary norms, academic role expectations, and governance frameworks (Biagini, 2024; Chiu et al., 2024). However, AI literacy should not be treated merely as an operational skill; academics may know how to use AI tools but still avoid them in domains where authorship, originality, transparency, or ethical accountability are sensitive issues.

Despite growing attention to students' AI competencies and ethical concerns, academics remain relatively unexplored (Rachman et al., 2024; Sanusi et al., 2022). This gap is significant because academics are both users of AI technologies and normative gatekeepers who define acceptable scholarly practices, supervise students, evaluate academic work, and transmit standards of responsible AI use. Existing studies have often examined AI literacy, technology acceptance, and ethical concerns separately, offering limited insight into how these factors jointly shape academics' actual AI use in everyday academic work (Butson & Spronken-Smith, 2024; Martins & Faciola, 2025; Qadhi et al., 2024; Southworth et al., 2023; Tenório et al., 2023).

Another limitation is that AI adoption in academia is often treated as a general technology-use outcome. However, academic work comprises task domains with varying levels of cognitive demand, ethical exposure, authorship sensitivity, and professional legitimacy. AI use in literature reviews may be perceived as supportive because it helps academics identify, organize, summarize, and compare scholarly information. In contrast, AI use in academic writing may raise stronger concerns about authorship, originality, disclosure, and intellectual ownership (Khalifa & Albadawy, 2024; Kobrossy et al., 2025; Qaffas, 2024; Yitages & Kasai, 2024). Similarly, AI use for visual content creation may depend on disciplinary needs, exposure to creative tasks, familiarity with software, copyright risk, and the relevance of visual outputs to scholarly communication (González Ramírez et al., 2023; Herrmann et al., 2021; Qin & Zhang, 2025). This suggests that visual AI adoption in academia may be driven more by discipline-specific needs and domain expertise rather than general technological familiarity, as visual scientific communication often requires a distinct set of technical and aesthetic skills (Abbasnejad et al., 2026). Therefore, AI adoption in academia should be examined as a task-specific human–AI interaction rather than as a uniform behavioral outcome. This task-specific focus is not merely a technical distinction but reflects the core of academic autonomy and professional identity. For an academic, adopting a tool for administrative efficiency is a pragmatic choice, whereas using it for manuscript drafting involves navigating intellectual responsibility and reputational risks. Therefore, understanding the nuances of adoption requires a framework that considers how professional roles and ethical considerations intersect with technical literacy (Amini et al., 2025).

Professional positions and career stages may also influence academics' engagement with AI tools in their teaching. Academic rank, years of experience, and age may be associated with role expectations, publication pressure, concerns about reputation, and responsibility for maintaining scholarly standards. Early-career academics may adopt AI tools more actively to manage workload and publication demands, whereas senior academics may be more cautious when AI assistance could affect authorship, originality, or academic credibility (Doğan et al., 2025; Giray, 2024; McGrath et al., 2023; Osman et al., 2024; Segbenya et al., 2024; Wise et al., 2024). Accordingly, demographic and professional characteristics should be examined alongside AI literacy dimensions to understand the differentiated patterns of AI adoption across academic tasks.

From the perspective of a professional technology user, academics' AI adoption can be interpreted as a context-dependent evaluation of task value, trust, risk, and legitimacy. AI tools may be attractive when they provide clear functional benefits and fit naturally into academic workflows; however, they may be resisted when their use creates uncertainty regarding authorship, credibility, and ethical appropriateness. This is particularly important because academics do not evaluate AI tools only as individual users; they evaluate them as professionals whose technology use is embedded in institutional norms, academic standards, and reputational expectations. In this sense, academic AI use is governed as much by professional norms as by technical capability, highlighting a 'seniority-caution' paradox where institutional accountability may outweigh the perceived benefits of efficiency.

The present study addresses these gaps by examining academics' use of AI tools for general academic tasks, writing literature reviews, and creating visual content. This study adopts an integrative professional technology-use perspective, drawing on technology adoption, professional roles, and responsible-use considerations. This framing allows the study to examine whether academics' AI adoption differs across task domains and whether these differences are associated with AI literacy dimensions and demographic and professional characteristics of the respondents. Survey data were collected from 368 academics working at 116 universities in Türkiye. Binary logistic regression was used as the main explanatory approach, with demographic/professional variables and AI literacy dimensions as predictors of task-specific AI adoption in the workplace. Supplementary machine learning analyses were used solely as a predictive validation step and not as substitutes for explanatory modeling.

This study provides empirical evidence relevant to the existing literature in three ways. First, it shifts the focus from generalized AI acceptance to task-specific AI adoption. Second, it clarifies how the dimensions of AI literacy are associated with AI use, controlling for demographic and professional characteristics. Third, it highlights the importance of professional role expectations, authorship responsibility, reputational sensitivity, perceived task value, and task-related legitimacy in the academic AI use. Thus, this study offers a more context-sensitive account of how academic professionals integrate AI into scholarly work and why its adoption differs across different academic tasks.

2. Theoretical background and research questions

2.1. AI use in academia as task-specific human–AI interaction

Artificial intelligence (AI) tools are increasingly embedded in academic work, affecting information search, teaching preparation, idea generation, writing support, and scholarly communication (Thomas, 2024; Vimos-Buenaño et al., 2024). Conversational AI tools, such as ChatGPT, have intensified this transformation by supporting summarization, academic writing, instructional preparation, and content generation across scholarly tasks (González Ramírez et al., 2023; Ngo et al., 2025; Zahra & Rautela, 2024).

In this study, academic AI use was conceptualized as a task-specific form of human–AI interaction rather than a single, generalized behavioral adoption. This distinction is necessary because academic tasks differ in terms of cognitive demand, ethical exposure, authorship implications, and perceived professional legitimacy. A literature review may be viewed as supportive research assistance, whereas AI-supported academic writing may raise stronger concerns about originality, disclosure, authorship responsibility, and academic integrity (Khalifa & Albadawy, 2024; Kobrossy et al., 2025; Qaffas, 2024; Yitages & Kasai, 2024). Visual content creation may depend on disciplinary expectations, copyright concerns, design skills, and relevance to scholarly communication (Herrmann et al., 2021; Qin & Zhang, 2025).

Recent studies on ChatGPT also support this task- and norm-sensitive view of AI use in higher education. ChatGPT use involves a balance between practical assistance and academic integrity, as AI-generated content can blur the boundaries between legitimate support and inappropriate substitutions for human authorship (Bin-Nashwan et al., 2023). Technology acceptance and integrity-related considerations shape its diffusion in higher education (Bouteraa et al., 2024), while studies on academic staff link ChatGPT adoption to teaching preparation, performance, competence, personal goals, workplace stress, and institutional expectations (Bin-Nashwan, Bouteraa, et al., 2025; Bin-Nashwan, Sadallah, et al., 2025; Sadallah et al., 2025).

Accordingly, the central premise of this study is that academics do not simply accept or reject AI in general; rather, they evaluate AI tools differently for different academic tasks. From a professional technology-use perspective, the same academic may use AI for literature reviews, summarization, translation, or teaching preparation while remaining cautious about AI-supported academic writing and visual content creation. This task-level differentiation provides the basis for examining AI adoption in general academic use, writing literature reviews, and creating visual content.

2.2. AI Literacy as a multidimensional professional capability

AI literacy is a multidimensional competence that involves awareness of AI capabilities and limitations, practical ability to use AI tools, critical evaluation of AI-generated outputs, and ethical sensitivity regarding responsible use (Asrifan et al., 2024; Ghani et al., 2024; Mansoor et al., 2024; Ng et al., 2021). In academia, this competence is important because AI tools affect productivity, scholarly judgment, authorship responsibility, epistemic reliability, and professional accountability of researchers.

In this study, AI literacy is represented by four dimensions: awareness, usage, evaluation, and ethics. Awareness refers to understanding AI tools and their limitations; usage reflects the practical ability to use AI in academic work; evaluation refers to the critical assessment of AI-generated outputs; and ethics reflects sensitivity to responsible and transparent AI use in academia.

The theoretical role of AI literacy is directly aligned with the empirical model of this study. Awareness, usage, evaluation, and ethics were positioned as core explanatory predictors in the binary logistic regression models rather than as peripheral descriptive variables. This positioning allowed the study to examine whether different dimensions of AI literacy are associated with academics' adoption of AI tools across distinct task domains.

AI literacy should also be understood as a professional capability rather than merely technical familiarity. Academics may know that AI tools exist and may possess practical competence; however, their willingness to use AI can still depend on whether the task is perceived as useful, legitimate, risky, or ethically sensitive. For example, usage competence may support adoption when the task provides visible workflow benefits, such as summarization, translation, teaching support, or organizing literature reviews. In contrast, evaluation and ethics may be more relevant for setting boundaries around acceptable use, particularly for tasks connected to authorship, originality, transparency, and scholarly responsibility.

Therefore, this study examined whether the four AI literacy dimensions are associated with task-specific AI adoption while accounting for demographic and professional characteristics. This approach avoids treating AI literacy as a general adoption theory and instead positions it as a multidimensional predictor of AI use in academic tasks.

2.3. An integrative professional technology-use framework

To explain task-specific variations in academic AI adoption, this study adopts an integrative professional technology-use framework. This framework combines three complementary perspectives: technology adoption, professional role and identity, and responsible technology use (RTU). Together, these perspectives provide a coherent basis for understanding why academics may use AI tools for some academic tasks while remaining cautious in others.

First, technology adoption research emphasizes that technology use is shaped by users' beliefs about its usefulness, ease of use, performance benefits, facilitating conditions, and perceived behavioral control (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003). In the context of academic AI use, this logic is reflected in the role of practical AI competence in education. Academics who feel capable of using AI tools may be more willing to apply them to tasks that offer visible functional benefits, such as summarization, idea generation, translation, teaching preparation, and literature review. In this study, AI usage competence was positioned as a key predictor of task-specific AI adoption rather than merely a descriptive skill indicator.

Second, professional role and identity perspectives suggest that users evaluate technology not only as individuals but also as members of professional communities with shared expectations, role obligations, and reputational standards (Ashforth & Mael, 1989; Ibarra, 1999). For academics, professional identity is closely connected to scholarly credibility, authorship responsibility, supervision, publication pressure, and disciplinary expectations. Therefore, academic titles may reflect differences in career stages, professional autonomy, institutional responsibilities, and reputational exposure. This perspective helps explain why academics of different ranks may differ not only in their technical familiarity with AI tools but also in how they evaluate the professional consequences of AI use in scholarly work.

Third, responsible technology use emphasizes that ethical and normative boundaries constrain AI adoption in academia. Ethical decision-making research highlights that professional behavior is shaped by both individual judgment and situational conditions, particularly when decisions involve responsibility, accountability, and potential consequences for others (Treviño, 1986). In academic contexts, AI use may be perceived as more legitimate for preparatory or supportive tasks, such as organizing literature reviews, than for tasks closely tied to final scholarly authorship, such as academic writing itself. Thus, task-specific AI adoption can be understood as a professional decision shaped by the balance between perceived task utility and perceived ethical or reputational risks.

This integrative framework strengthens the theoretical grounding of this study by linking AI literacy, professional characteristics, and task-specific AI adoption within a single explanatory framework. Technology adoption perspectives clarify why practical AI-usage competence may facilitate AI adoption. Professional roles and identity perspectives clarify why academic titles and career stages may differ in their adoption. Responsible use perspectives clarify why AI adoption may vary across tasks with different levels of authorship sensitivity, ethical exposure, and perceived legitimacy.

The framework also clarifies the boundaries of this study's theoretical claims. Because the study relies on cross-sectional and self-reported data, this framework was used to guide the interpretation of associations rather than to establish causal psychological mechanisms. Accordingly, this study examined whether AI literacy dimensions and professional characteristics are associated with the probability of adopting AI tools for specific academic tasks in higher education. It does not claim that AI literacy causally regulates academic behavior; rather, it evaluates whether literacy-related capabilities and professional positioning correspond to different patterns of task-specific AI use in academia.

The integrative professional technology-use framework should not be interpreted as a new grand theory of technology adoption. Rather, its value lies in specifying how existing technology-adoption, professional-role, and responsible-use perspectives operate together in a high-accountability professional setting. Unlike TAM-based studies that primarily explain adoption through perceived usefulness, ease of use, or general acceptance, the present framework emphasizes a task-legitimacy mechanism. According to this mechanism, academics are more likely to adopt AI when three conditions converge: the task offers clear practical utility, AI use is compatible with professional role expectations, and the task does not violate responsible-use boundaries related to authorship, originality, disclosure, or reputational accountability.

This mechanism helps explain why the same academic may use AI for literature review, summarization, translation, or teaching preparation while remaining more cautious about academic writing or visual content creation. In this respect, the framework produces insights beyond conventional TAM-based explanations by showing that academic AI adoption is not only a function of usefulness or technical competence, but also a form of professional boundary-work. Academics selectively integrate AI tools when these tools support efficiency without threatening scholarly identity, intellectual responsibility, or institutional credibility. Because the present study is based on cross-sectional and self-reported data, this framework is used to guide the interpretation of associations rather than to establish causal psychological mechanisms.

2.4. Demographic and professional differences in academic AI use

Demographic and professional characteristics may influence AI adoption by shaping technology exposure, perceived usefulness, institutional expectations, and ethical sensitivity. Gender, age, education level, academic rank, and academic experience may affect academics' willingness or ability to use AI tools, although previous findings on age and gender are inconsistent (Mansoor et al., 2024; Oyetade & Zuva, 2025).

Academic rank is particularly important because it reflects the career stage, role expectations, publication pressure, supervisory responsibilities, and reputational exposure. Early-career academics may be more open to AI tools because they face demands for productivity, skill development, and methodological adaptation. Senior academics may adopt AI more selectively when its use is perceived to affect authorship responsibility, academic credibility, or institutional accountability.

From a professional technology-use perspective, these characteristics are not considered deterministic causes of AI adoption. Instead, they are interpreted as indicators of broader academic positions and role-based expectations. For example, academics at different career stages may differ not only in their technical familiarity with AI but also in how they evaluate the reputational and ethical consequences of AI use in scholarly work.

Therefore, this study included demographic and professional characteristics alongside AI literacy dimensions in the same regression models. This design allowed the study to examine whether AI literacy contributes to task-specific AI adoption while accounting for differences in academic position, experience, and professional background.

2.5. Task domains of AI use in academic work

This study focuses on four domains of academic AI use: general academic tasks, academic writing, literature review, and visual content creation. General academic use refers to the broad integration of AI tools into everyday academic work, including tasks such as idea generation, summarization, translation, planning, and teaching assistance.

Academic writing is more sensitive because it is tied to authorship, originality, scholarly responsibilities, and disclosure norms. Therefore, the use of AI in this domain may be constrained by concerns about academic integrity and reputational risk (Bin-Nashwan et al., 2023; Bin-Nashwan, Sadallah, et al., 2025).

A literature review refers to the use of AI tools to search, organize, summarize, compare, and synthesize academic information. This task may be perceived as a high-value, relatively legitimate domain for AI assistance because it supports the academic workflow without directly replacing the final act of authorship.

Visual content creation involves generating figures, diagrams, infographics, and visual research materials. This domain may depend more strongly on design needs, software familiarity, disciplinary communication norms, copyright concerns, image provenance, and journal policies.

Taken together, these four task domains enabled the study to examine whether AI adoption varied by task utility, authorship sensitivity, professional risk, and perceived legitimacy. This task-specific design addresses the limitation of treating AI adoption as a uniform technology-use outcome.

2.6. Research questions

Building on the task-specific view of academic AI adoption, this study examines how demographic characteristics, professional position, and AI literacy dimensions are associated with academics' use of AI tools across different academic tasks. In particular, this study focused on whether AI adoption varies across general academic use, academic writing, literature reviews, and visual content creation, and whether these adoption patterns can be explained more systematically in some task domains than in others. Accordingly, this study addresses the following research questions:

RQ1. To what extent do demographic and professional characteristics explain academics' task-specific adoption of AI tools?

RQ2. How are AI literacy dimensions associated with task-specific AI adoption when demographic and professional characteristics are considered simultaneously?

RQ3. Which AI literacy dimensions are most strongly associated with AI adoption in general academic use, academic writing, literature review, and visual content creation?

RQ4. Are AI adoption patterns among academics more strongly explained in text-based and research-oriented tasks than in visual content creation tasks?

RQ5. Do supplementary machine learning analyses indicate that academics' AI adoption patterns are predictively learnable beyond the baseline classification?

These research questions align with the two-stage analytical strategy of this study. Binary logistic regression was used to assess explanatory associations, while supplementary machine-learning analysis was used only to assess whether adoption patterns were predictively learnable beyond baseline classification. This distinction is important because the machine learning component is not intended to provide a theoretical explanation but to offer cautious predictive validation of the task-specific structure of AI adoption (Fig. 1).

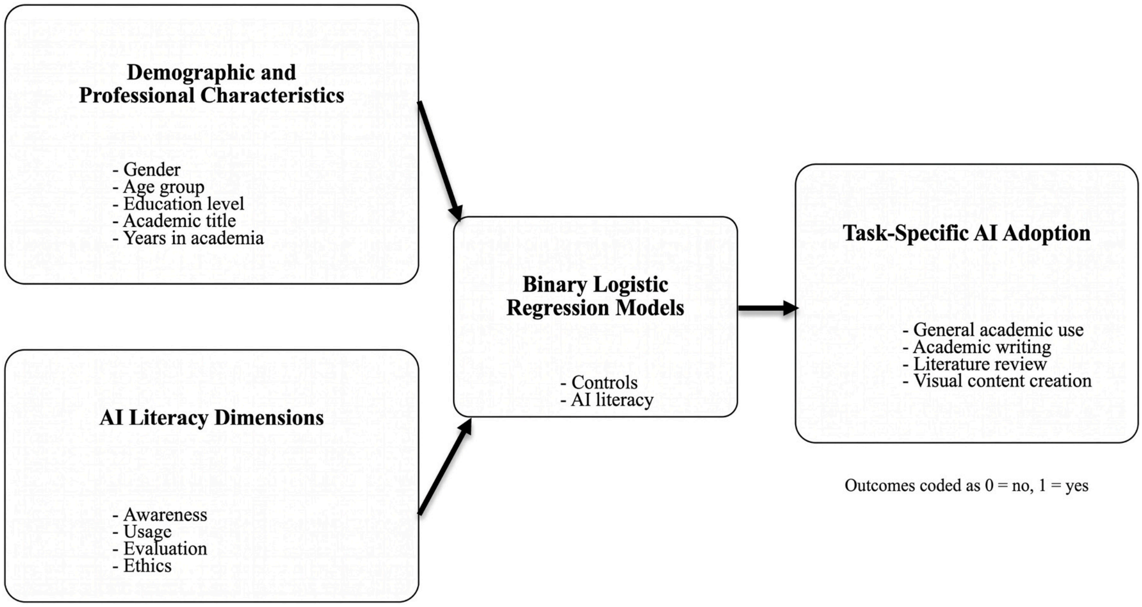

Fig. 1. Conceptual model.

3. Methodology

3.1. Research design

This study employed a quantitative cross-sectional research design to examine academics' adoption of task-specific AI. This study focused on whether academic professionals used AI tools for four distinct academic purposes: general academic tasks, academic writing, literature review, and visual content creation. Because these outcomes were measured as binary indicators, the study examined the adoption threshold, that is, whether academics used or did not use AI tools for each specific task domain.

This design is appropriate for identifying associations between AI literacy dimensions, demographic and professional characteristics, and task-specific AI adoption. However, because the data were cross-sectional and self-reported, the findings should be interpreted as associations rather than causal relationships. Therefore, this study does not claim that AI literacy directly causes AI adoption. Instead, it examines whether AI literacy dimensions and professional characteristics are statistically associated with the probability of using AI tools for various academic tasks.

The analytical strategy followed a two-stage approach. In the first stage, binary logistic regression was used as the main explanatory method because each dependent variable was coded as 0 = no and 1 = yes. The regression models examined whether demographic/professional variables and AI literacy dimensions were associated with the adoption of task-specific AI. In the second stage, machine learning-based classification and exploratory clustering were used as supplementary analysis.

The machine learning component was included only as a predictive validation step, rather than as a substitute for explanatory modeling. Its purpose was to assess whether the observed adoption patterns could be learned beyond the majority-class baseline classification. Therefore, the study's interpretation was primarily based on the logistic regression results, while the machine learning findings were used cautiously as complementary evidence.

3.2. Population and sample

The target population consisted of academic staff working at public and foundation universities in Türkiye. Data were collected through a voluntary online survey distributed to academics from various universities and disciplinary backgrounds. After data screening, the final analytical sample consisted of 368 academic staff from 116 universities.

The sample included academics of different academic ranks, age groups, educational levels, and fields of science. The participants had an average of 14.01 years of academic experience (SD = 7.93), indicating a meaningful variation in academic seniority. The sample also included a substantial proportion of social science and humanities academics, which is relevant because text-based generative AI tools are especially visible in research, writing, literature review, and teaching-related academic work.

Because this study used a non-probability sampling strategy, the sample should not be interpreted as statistically representative of all academics in Türkiye or other higher education systems. Nevertheless, the inclusion of academics from 116 universities increases institutional diversity and supports this study's exploratory purpose.

Accordingly, the findings should be interpreted as evidence from a diverse academic sample rather than as generalizable estimates. This limitation was explicitly considered when interpreting the results and discussing the study implications.

3.3. Data collection procedure and ethics

Data were collected via a voluntary, anonymous online questionnaire. The study was approved by the Balıkesir University Ethics Committee (Decision No. 2025.06/23, dated 26.06.2025). The approved protocol covered the target population, online survey procedure, measurement instruments, and data collection process used in the present study. Participants were informed about the purpose of the study, the voluntary nature of participation, confidentiality, and their right to withdraw from the survey at any time. Informed consent was obtained from all participants before they completed the questionnaire.

The questionnaire consisted of three sections. The first section measured whether the respondents used AI tools for specific academic purposes. The second section measured the AI literacy dimensions. The third section collected demographic and professional information, including gender, age group, education level, academic title, field of science, and years of academic experience.

An attention-check item was included to improve the data quality. Responses that failed the attention check were excluded from the final dataset. After screening, 368 valid responses were retained for the analysis.

The use of self-reported survey data is appropriate for examining academics' perceived AI literacy and task-specific AI use. However, self-reported data may be affected by recall bias, social desirability, and common method variance. Therefore, additional diagnostic checks were conducted before the main analyses.

3.4. Measures

3.4.1. Task-specific AI adoption

Task-specific AI adoption was measured using four binary indicators. Respondents were asked whether they used AI tools for the following academic purposes: general academic tasks, academic writing, literature reviews, and visual content creation. Each dependent variable was coded as 0 (no) or 1 (yes).

This binary coding strategy allowed us to examine whether academics crossed the adoption threshold for each task domain. However, it does not capture the frequency, intensity, duration, quality, or complexity of AI use. Therefore, the findings should be interpreted as evidence of whether academics use AI tools for specific purposes, not how often, intensively, or effectively they use them.

This measurement decision is consistent with the use of binary logistic regression, but also represents an important limitation. Future studies should measure the frequency of use, task complexity, perceived usefulness, perceived risk, disclosure behavior, and quality of AI-assisted outputs.

3.4.2. AI literacy dimensions

AI literacy was measured using the Artificial Intelligence Literacy Scale developed by Wang et al. (2023). The scale consists of 12 items organized across four dimensions: awareness, usage, evaluation, and ethics. Awareness refers to respondents' understanding of AI tools, their functions, and limitations. Usage reflects respondents' perceived practical ability to use AI tools in an academic context. Evaluation refers to respondents' ability to critically assess AI-generated outputs. Ethics reflects respondents' sensitivity to responsible, transparent, and appropriate AI use in academia.

All items were measured using a five-point Likert-type response format ranging from 1 = strongly disagree to 5 = strongly agree. Mean scores were calculated for each dimension using the items corresponding to that dimension. The four-dimensional scores were then used as observed composite indicators in the regression models.

Internal consistency was assessed using Cronbach's alpha. The Cronbach's alpha coefficients were $\alpha = 0.538$ for awareness, $\alpha = 0.621$ for usage, $\alpha = 0.864$ for evaluation, and $\alpha = 0.622$ for ethics. The overall AI literacy scale showed good internal consistency, $\alpha = 0.859$. Given the short three-item structure of each subdimension, these coefficients were considered in the interpretation of the findings, particularly for the awareness dimension. Therefore, the AI literacy dimensions were retained as observed composite indicators rather than modeled as reflective latent constructs. In research examining exploratory and emerging fields, it is an academic fact that the Cronbach's alpha coefficient for narrow sub-dimensions, such as three items, is mathematically dependent on the number of items, and that values between 0.50 and 0.60 are acceptable in early-stage psychometric measurements, as highlighted by Nunnally (1978). To compensate for potential measurement fluctuations that these relatively low coefficients might create, logistic regression analyses were supported by additional machine learning-based predictive validation, and the stability of the data structure was statistically proven.

3.4.3. Demographic and professional variables

The demographic and professional predictors included gender, age group, education level, academic title, and years of academic experience. The field of science was used to describe the sample composition. Categorical predictors were dummy-coded for binary logistic regression analysis, and academic experience was included as a continuous predictor.

For the binary logistic regression models, categorical predictors were retained in their original coding. Accordingly, the model degrees of freedom reflected gender, five age categories, four education categories, seven academic-title categories, years of academic experience, and the four AI literacy dimensions. This coding structure is consistent with the degrees of freedom reported in the regression models.

3.5. Data preparation and preliminary checks

Before the main analyses, the dataset was screened for missing values, sparse categories, common method bias, and multicollinearity. Cases with missing values for the dependent variables were excluded from the relevant models.

The four AI literacy dimensions were computed as the mean scores of their corresponding items and used as observed composite indicators. This study did not estimate a latent measurement model because the main objective was to examine whether dimension-level AI literacy scores were associated with task-specific binary adoption outcomes.

Because the study relied on self-reported cross-sectional data, potential common method bias was assessed before the main analysis. Harman's single-factor test was conducted using AI literacy items, and the first unrotated factor explained 42.65% of the total variance. This value was below the commonly used 50% threshold, suggesting that common-method bias was unlikely to be a dominant threat.

Multicollinearity was assessed using the variance inflation factor values for the four AI literacy dimensions. The VIF values ranged from 1.252 to 2.508, indicating no serious multicollinearity among the AI literacy predictors. These checks supported the suitability of including AI literacy dimensions in the same regression models.

3.6. Main analytical strategy: binary logistic regression

Binary logistic regression was used as the primary analytical technique because the dependent variables were binary. Four separate binary logistic regression models were estimated, one for each task-specific AI adoption outcome: general academic use, academic writing, literature reviews, and visual content creation.

In each model, demographic and professional variables, along with the four AI literacy dimensions, were entered as predictors. The demographic/professional predictors were gender, age group, education level, academic title, and years of experience. The AI literacy predictors were awareness, usage, evaluation, and ethics.

This analytical strategy directly aligns the theoretical positioning of AI literacy with an empirical model. AI literacy was not treated as a secondary or descriptive construct; rather, its four dimensions were included as core predictors of task-specific AI adoption. This directly addresses the need to connect AI literacy theories with empirical testing.

Model performance was evaluated using the model chi-square, Nagelkerke R^2, classification accuracy, odds ratios, and 95% confidence intervals. Odds ratios were used to interpret the direction and magnitude of the associations between the predictors and task-specific AI adoption.

The regression results were interpreted as associations with the probability of AI adoption, rather than causal effects. This interpretation is consistent with the cross-sectional design and self-reported nature of the data.

3.7. Supplementary predictive validation

In addition to binary logistic regression, machine learning-based classification was performed as a supplementary predictive validation step. This analysis aimed to examine whether academics' task-specific AI adoption patterns could be learned beyond the baseline classification.

Machine learning analysis was not intended to replace the explanatory role of binary logistic regression. Rather, it served as a robustness-oriented complement by comparing the predictive performance with that of a majority-class baseline classifier. This distinction is important because the primary aim of this study was explanatory rather than an algorithmic prediction.

The predictive performance of the machine learning models was compared with the baseline accuracy obtained by predicting the majority classes. Accuracy gain was used as a simple indicator of whether the observed predictors provided meaningful predictive improvement beyond the baseline.

Because the machine learning component was supplementary, the results were interpreted cautiously and not used as the basis for theoretical claims. The machine learning findings were used only to support broader conclusions regarding whether task-specific AI adoption patterns were structured sufficiently to be learned predictively.

3.8. Exploratory AI literacy profiling

Exploratory clustering was conducted using the four AI literacy dimension scores: awareness, usage, evaluation, and ethics. This analysis aimed to examine whether academics could be grouped into meaningful profiles based on their AI literacy characteristics.

Clustering analysis was conducted as a descriptive profiling procedure rather than a hypothesis-testing method. The resulting profiles provide additional insights into the heterogeneity among academics, particularly regarding practical AI engagement, evaluative capacity, and ethical sensitivity.

Therefore, the profiling results should be interpreted as exploratory and descriptive. They did not establish causal categories or confirm stable psychological types. Instead, they complement the regression results by illustrating that academics may differ not only in whether they adopt AI tools but also in how they combine their practical competence, evaluative capacity, and ethical sensitivity.

4. Results

4.1. Sample characteristics

The final sample comprised 368 academics from 116 universities in Türkiye. As shown in Table 1, 54.9% of the participants were female, and 45.1% were male. The largest age groups were 31–40 years (34.5%) and 41–50 years (38.6%), accounting for 73.1% of the sample. Most respondents held a doctoral degree (59.0%), followed by master's (22.0%), postdoctoral (14.9%), and bachelor's (4.1%) degrees.

Academic titles were distributed as follows: research assistants/research assistant doctors (16.3%), lecturers/lecturer doctors (27.2%), assistant professors (19.8%), associate professors (18.8%), and professors (17.9%). The sample also included participants from different broad fields of science, with the largest group coming from the social sciences and humanities (56.0%). The mean academic experience was 14.01 years (SD = 7.93, range = 1–40), indicating a meaningful variation in academic seniority.

Table 1
Demographic characteristics of the sample.

Variable	Category	n	%
Gender	Female	202	54.9
	Male	166	45.1
Age group	21–30	53	14.4
	31–40	127	34.5
	41–50	142	38.6
	51 and above	46	12.5
Education level	Bachelor's degree	15	4.1
	Master's degree	81	22.0
	Doctorate	217	59.0
	Postdoctoral	55	14.9
Academic title	Research assistant / research assistant doctor	60	16.3
	Lecturer / lecturer doctor	100	27.2
	Assistant professor	73	19.8
	Associate professor	69	18.8
	Professor	66	17.9
Broad field of science	Social sciences and humanities	206	56.0
	Engineering and technical sciences	68	18.5
	Health sciences	46	12.5
	Natural sciences	36	9.8
	Arts and design	12	3.3

Note: N = 368. Percentages may not total exactly 100 due to rounding. For descriptive presentation, the two oldest age categories are reported together as 51 and above, and some academic-title categories are presented in combined form. The regression models used the original categorical coding. Years in academia: M = 14.01, SD = 7.93, range = 1–40.

4.2. Preliminary analyses

Before the main analyses, descriptive statistics, correlations, common method bias, and multicollinearity were examined. The four AI literacy dimensions, awareness, usage, evaluation, and ethics, were calculated as mean scores of their corresponding items and used as observed composite indicators in the subsequent analyses. Internal consistency was also examined for the AI literacy scale and its four dimensions. The overall AI literacy scale demonstrated good internal consistency, $\alpha = 0.859$. At the subdimension level, Cronbach's alpha values were $\alpha = 0.538$ for awareness, $\alpha = 0.621$ for usage, $\alpha = 0.864$ for evaluation, and $\alpha = 0.622$ for ethics. Considering the short three-item structure of each subdimension, these coefficients were interpreted in line with the exploratory, dimension-level use of the AI literacy indicators in the present regression models.

As shown in Table 2, the dimensions of AI literacy were positively correlated. The strongest correlation was observed between usage and evaluation ($r = 0.740$), followed by awareness and usage ($r = 0.625$) and awareness and evaluation ($r = 0.619$). Ethics showed weaker correlations with the other AI literacy dimensions, including awareness ($r = 0.392$), usage ($r = 0.406$), and evaluation ($r = 0.381$). This pattern suggests that ethics is related to, but relatively more distinct from, the practical and evaluative dimensions of AI literacy.

Given the purpose of this study, the AI literacy dimensions were not modeled as reflective latent constructs. Instead, they were used as dimension-level, observed composite indicators to examine their associations with task-specific AI adoption.

4.3. Common method bias and multicollinearity

Because the study relied on self-reported cross-sectional survey data, potential common method bias was assessed before the main analysis. Harman's single-factor test indicated that the first unrotated factor accounted for 42.65% of the total variance. This value was below the commonly used 50% threshold, suggesting that common method bias was unlikely to be a dominant threat to the results of this study.

Multicollinearity was examined using the variance inflation factor values for the four AI literacy dimensions. As shown in Table 3, the VIF values ranged from 1.252 to 2.508. These values were below the conventional threshold levels and indicated no serious multicollinearity

Table 2
Descriptive statistics and correlations of AI literacy dimensions.

Variable	Mean	SD	1	2	3	4
1. Awareness	4.151	0.702	1			
2. Usage	4.038	0.721	0.625	1		
3. Evaluation	4.063	0.773	0.619	0.740	1	
4. Ethics	4.370	0.675	0.392	0.406	0.381	1

Note: AI literacy dimensions were calculated as mean scores of their corresponding items and used as observed composite indicators in subsequent analyses. Pearson correlation coefficients are reported.

Table 3
Common method bias and multicollinearity diagnostics.

Diagnostic test	Result	Interpretation
Harman's single-factor test	42.65%	Below 50%; common method bias is unlikely to be dominant
VIF: Awareness	1.849	Acceptable
VIF: Usage	2.508	Acceptable
VIF: Evaluation	2.442	Acceptable
VIF: Ethics	1.252	Acceptable

Note: Harman's single-factor test was conducted using the 12 AI literacy items. VIF values were calculated for the four AI literacy composite indicators. Internal consistency was assessed using Cronbach's alpha and reported in the Preliminary Analyses section.

problems among the AI literacy predictors. Therefore, the four AI literacy dimensions were retained in the regression models.

4.4. Binary logistic regression results

Four binary logistic regression models were estimated to examine academics' task-specific AI adoption. The dependent variables were general academic use, academic writing, literature reviews, and visual content creation. Each dependent variable was coded as 0 (no) or 1 (yes).

In each model, demographic/professional variables and the four AI literacy dimensions were entered as predictors. The demographic/professional predictors were gender, age group, education level, academic title, and years of academic experience. The AI literacy predictors were awareness, usage, evaluation, and ethics.

For the binary logistic regression models, categorical predictors were retained in their original coding. Thus, the model degrees of freedom reflected gender, five age categories, four education categories, seven academic-title categories, years of academic experience, and the four AI literacy dimensions. In the displayed coefficients, gender is interpreted as female relative to male, and academic title coefficients are interpreted relative to professors. The final binary logistic regression results are shown in Table 4.

4.4.1. General academic use of AI tools

For general academic use, the final model was statistically significant, $\chi^2(19) = 75.698$, $p < .001$, with a Nagelkerke R^2 of 0.256, and a classification accuracy of 72.6%. Usage competence emerged as a significant positive predictor of general academic AI use ($B = 0.739$, $p = .006$, $OR = 2.094$, 95% CI [1.241, 3.534]). This indicates that academics with a higher perceived AI usage competence had approximately twice the odds of using AI tools for general academic purposes.

Academic title also significantly differentiated general academic AI use ($p = .002$). Compared with professors, selected academic-title categories showed lower odds of general academic AI use: lecturers, $B = -1.891$, $p = .003$, $OR = 0.151$, 95% CI [0.043, 0.535]; lecturer doctors, $B = -1.273$, $p = .042$, $OR = 0.280$, 95% CI [0.082, 0.956]; and assistant professors, $B = -1.434$, $p = .004$, $OR = 0.238$, 95% CI [0.090, 0.635].

These findings suggest that general academic AI use is associated with both practical AI usage competence and one's professional position. General academic tasks may offer clear functional benefits and relatively lower authorship-related sensitivity, making them more compatible with routine AI use among academics who feel competent using such tools.

4.4.2. Use of AI tools for academic writing

For academic writing, the final model was statistically significant, $\chi^2(19) = 69.201$, $p < .001$, with a Nagelkerke R^2 of 0.234, and a classification accuracy of 69.0%. None of the AI literacy dimensions reached statistical significance in this study. However, academic title significantly differentiated AI use in academic writing ($p = .022$).

Compared with professors, the selected academic-title categories showed lower odds of AI use for academic writing: lecturers, $B = -1.410$, $p = .023$, $OR = 0.244$, 95% CI [0.072, 0.824], and assistant professors, $B = -1.288$, $p = .007$, $OR = 0.276$, 95% CI [0.108, 0.707]. Lecturer doctors showed a marginal negative association ($B = -1.140$, $p = .060$, $OR = 0.320$, 95% CI [0.098, 1.049]).

These results indicate that writing-related AI use was not directly explained by the AI literacy dimensions in the final model. Instead, it appeared more strongly differentiated by academic title. This pattern is theoretically meaningful because academic writing is closely tied to authorship, originality, disclosure norms, academic integrity, and reputational sensitivity.

4.4.3. Use of AI tools for literature review

The strongest model-level results emerged from the literature review. The final model was statistically significant, $\chi^2(19) = 103.771$, $p < .001$, with the highest Nagelkerke R^2 among the four models (0.334) and a classification accuracy of 74.5%.

Usage competence significantly predicted AI use for literature reviews ($B = 0.765$, $p = .005$, $OR = 2.150$, 95% CI [1.264, 3.657]). This indicates that academics with a higher perceived AI-usage competence were more than twice as likely to use AI tools for literature reviews. Awareness also showed a marginal positive association ($B = 0.448$, $p = .065$, $OR = 1.564$, 95% CI [0.973, 2.516]).

Table 4
Binary logistic regression results for task-specific AI adoption.

Outcome	Model χ^2	df	p	Nagelkerke R^2	Accuracy	Significant / marginal predictors	B	p	OR	95% CI for OR
General academic use	75.698	19	<.001	0.256	72.6%	Usage	0.739	.006	2.094	[1.241, 3.534]
						Academic title, overall		.002		
						Lecturer, vs. professor	−1.891	.003	0.151	[0.043, 0.535]
						Lecturer doctor, vs. professor	−1.273	.042	0.280	[0.082, 0.956]
						Assistant professor, vs. professor	−1.434	.004	0.238	[0.090, 0.635]
Academic writing	69.201	19	<.001	0.234	69.0%	Academic title, overall		.022		
						Lecturer, vs. professor	−1.410	.023	0.244	[0.072, 0.824]
						Lecturer doctor, vs. professor	−1.140	.060	0.320	[0.098, 1.049]
						Assistant professor, vs. professor	−1.288	.007	0.276	[0.108, 0.707]
Literature review	103.771	19	<.001	0.334	74.5%	Usage	0.765	.005	2.150	[1.264, 3.657]
						Awareness	0.448	.065	1.564	[0.973, 2.516]
						Female, vs. male	0.617	.022	1.853	[1.095, 3.135]
						Education, overall		.078		
						Academic title, overall		.034		
Visual content creation	21.337	19	.318	0.078	67.7%	Female, vs. male	−0.738	.003	0.478	[0.294, 0.777]

Note: OR = odds ratio; CI = confidence interval. Categorical predictors are interpreted relative to their reference categories. For displayed coefficients, gender is interpreted as female relative to male, and academic-title categories are interpreted relative to professor. Only statistically significant and theoretically relevant marginal predictors are displayed. The gender coefficient in the visual content creation model should be interpreted cautiously because the overall model was not statistically significant. AWA = awareness; USAG = usage; EVAL = evaluation; ETH = ethics.

Gender was significantly associated with AI use for literature review ($B = 0.617$, $p = .022$, $OR = 1.853$, 95% CI [1.095, 3.135]), indicating that female academics had higher odds of using AI tools for literature review than male academics. Education showed a marginal overall effect ($p = .078$), whereas academic title significantly differentiated AI use for literature reviews ($p = .034$).

These findings suggest that literature reviews were the task domain in which the included predictors most systematically explained AI adoption. A literature review involves searching, filtering, summarizing, comparing, and synthesizing academic information. Therefore, this domain may be especially compatible with AI assistance because it offers high task value while posing less direct authorship sensitivity than academic writing does.

4.4.4. Use of AI tools for visual content creation

For visual content creation, the final model was not statistically significant, $\chi^2(19) = 21.337$, $p = .318$, with a Nagelkerke R^2 of 0.078, and a classification accuracy of 67.7%. None of the AI literacy dimensions significantly predicted AI use for visual content creation.

Gender reached statistical significance within the visual content creation model ($B = -0.738$, $p = .003$, $OR = 0.478$, 95% CI [0.294, 0.777]). However, because the overall model was not statistically significant, this coefficient should not be interpreted as robust evidence of a systematic gender effect. Overall, the findings suggest that visual AI adoption was weakly explained by the demographic, professional, and AI literacy variables included in this study.

This result indicates that visual content creation may depend on more specialized and context-specific factors such as discipline-specific visual communication needs, design experience, software familiarity, familiarity with image-generation tools, copyright concerns, image provenance, and awareness of journal or institutional policies on AI-generated images. Therefore, the weak explanatory power of the visual content creation model should not be interpreted only as a statistical limitation, but also as an indication that visual AI adoption may follow a different logic from text-based AI adoption in academic work.

4.4.5. Comparison of AI literacy effects across task domains

Table 5 summarizes AI literacy and demographic and professional patterns across the four task domains. The results show that AI adoption among academics was task-specific, rather than uniform across tasks. Usage competence significantly predicted general academic use and literature reviews, but not academic writing or visual content creation. Awareness showed only a marginal association with the literature review, while evaluation and ethics did not show consistent direct effects across task domains.

A professional position also played an important role in the study. Academic title differentiated adoption in general academic use, academic writing, and literature review. Gender was associated with the literature review. Although gender also reached significance in the visual content creation model, this result should be interpreted cautiously, as the overall model was not statistically significant in this study.

Taken together, these findings suggest that academic AI adoption is associated with practical AI competence, task characteristics, and professional role expectations. However, because the data were cross-sectional and self-reported, these results should be interpreted as associative rather than causal.

4.5. Supplementary machine-learning validation

Supplementary machine learning-based classification was conducted to examine whether task-specific AI adoption patterns could be learned beyond the majority-class baseline classification. The purpose of this analysis was not to replace the explanatory interpretation provided by binary logistic regression but to provide complementary predictive checks.

As shown in Table 6, the predictive performance varied across the task domains. The clearest improvement over the baseline classification was observed in the literature review, with an accuracy gain of +10.3 pp. The predictive gains for academic writing were modest (+3.3 pp), whereas general academic use (+1.8 pp) and visual content creation (+1.3 pp) showed limited predictive gains.

These findings suggest that literature-review-related AI adoption was the most predictably learnable task domain in this study. In contrast, visual content creation was weakly predicted by the variables included in the analysis. However, the machine learning results should be interpreted cautiously because the observed gains were limited in most task domains, and the analysis was used only for supplementary predictive validation.

Table 5
Synthesis of AI literacy and professional predictors across task domains.

Outcome	AI literacy pattern	Demographic / professional pattern	Main interpretation
General academic use	Usage significantly and positively predicted adoption; awareness, evaluation, and ethics were not significant	Academic title significantly differentiated adoption; selected title categories showed lower odds	General academic AI use is shaped by practical usage competence and professional position
Academic writing	No AI literacy dimension reached statistical significance	Academic title significantly differentiated adoption; selected title categories showed lower odds	Academic writing is governed by a 'seniority-caution paradox' where reputational risks and professional role expectations outweigh technical AI literacy.
Literature review	Usage significantly predicted adoption; awareness showed a marginal positive association	Gender and academic title were significant; education was marginal	Literature-review AI use is the most systematically explained domain, with usage competence and professional/ demographic variables showing the clearest associations
Visual content creation	No AI literacy dimension significantly predicted adoption	Gender reached significance, but the overall model was not significant	Visual AI use appears specialized, context-dependent, and weakly explained by the included predictors

Note: This table summarizes the final binary logistic regression findings. AI literacy dimensions were used as observed composite indicators. The visual content creation gender result should be interpreted cautiously because the overall model was not statistically significant.

Table 6
Supplementary machine-learning classification performance.

Outcome	Baseline accuracy	ML accuracy	Accuracy gain	Interpretation
General academic use	65.3%	67.1%	+1.8%	Limited predictive gain
Academic writing	62.8%	66.1%	+3.3%	Modest predictive gain
Literature review	61.5%	71.8%	+10.3%	Strongest predictive gain
Visual content creation	66.1%	67.4%	+1.3%	Limited predictive gain

Note: Baseline accuracy refers to majority-class prediction. ML accuracy refers to supplementary classification performance. The ML analysis was used only as predictive validation and not as the main explanatory analysis.

4.6. Exploratory AI literacy profiles

To further explore the heterogeneity in academics' AI literacy patterns, exploratory clustering was conducted using the four AI literacy dimension scores: awareness, usage, evaluation, and ethics. The purpose of this analysis was not to test causal relationships but to examine whether academics could be grouped into meaningful descriptive profiles based on their AI literacy characteristics.

The clustering solution identified three profiles. The first profile consisted of academics with relatively high scores for awareness, usage, evaluation, and ethics. This group was labeled as holistic and principled integrators, reflecting both practical engagement with AI tools and strong ethical sensitivity. The second profile consisted of academics with lower scores across the AI literacy dimensions and was labeled reluctant adopters, reflecting limited AI engagement and lower perceived competence. The third profile showed relatively moderate-to-high awareness and usage but lower ethical scores, suggesting a more instrumentally oriented pattern of AI use. This group was labeled as utilitarian users.

These exploratory profiles support the broader interpretation that academic AI adoption should not be reduced to a simple user/non-user distinction. Academics may differ not only in whether they use AI tools but also in how they combine practical competence, evaluative capacity, and ethical sensitivity. Nevertheless, these profiles should be interpreted as descriptive and exploratory rather than stable psychological types (Table 7).

5. Discussion

This study examined academics' task-specific adoption of AI tools by integrating demographic and professional characteristics with four AI literacy dimensions: awareness, usage, evaluation, and ethics. The findings show that AI adoption in academia is not uniform across different task domains. The regression results indicate that AI literacy operates in a task-specific manner: usage competence significantly predicted general academic use and literature review, whereas awareness, evaluation, and ethics did not show consistent or direct effects across domains. This supports a more nuanced interpretation of academic AI adoption as a task-specific form of human–AI interaction associated with practical competence, professional position, and task characteristics, rather than as a uniform technology-acceptance behavior.

For general academic use, usage competence was a significant and positive predictor. Academics with a higher perceived ability to use AI tools had higher odds of using AI for broad academic purposes. Academic title also significantly differentiated general AI use, indicating that adoption is not only a matter of individual competence but also of professional position in the hierarchy. This finding is consistent with the view that AI adoption among academic professionals depends on both task utility and role-based expectation. General academic tasks, such as idea generation, summarization, translation, planning, and teaching-related support, may offer visible benefits while involving relatively lower authorship sensitivity. Therefore, academics who feel practically competent in using AI tools may be more willing to integrate AI into their everyday academic routines.

Table 7
Exploratory AI literacy profiles.

Profile	n	%	Main characteristics	Interpretation
Holistic and principled integrators	174	47.3	High awareness, usage, evaluation, and ethics	Active and ethically sensitive AI users
Reluctant adopters	83	22.6	Low scores across AI literacy dimensions	Limited AI engagement and lower perceived competence
Utilitarian users	111	30.2	Moderate-to-high awareness and usage, lower ethics	Instrumental and efficiency-oriented AI users

Note: Profiles were identified using exploratory clustering based on awareness, usage, evaluation, and ethics scores. Percentages may not total exactly 100 due to rounding. The analysis was used for descriptive profiling rather than hypothesis testing.

The clearest explanatory pattern emerged from the literature review. Usage competence significantly predicted AI use in this domain, awareness showed a marginal positive association, and gender and academic title were significant predictors of AI use. This result is theoretically meaningful because a literature review involves information search, summarization, comparison, synthesis, and cognitive workload management. These activities are highly compatible with AI assistance when the outputs are critically evaluated. From a professional technology-use perspective, literature reviews may represent a high-value and relatively legitimate task domain because they support academic workflow without directly replacing the final act of authorship. This interpretation suggests that AI use depends not only on technological availability but also on perceived task value, contextual fit, and acceptable use boundaries.

Academic writing shows a different pattern. None of the AI literacy dimensions reached statistical significance, whereas academic title significantly differentiated AI adoption. This suggests that writing-related AI use may be shaped less by direct self-perceived AI literacy and more by professional role expectations, authorship responsibility, disclosure norms, journal policies, academic integrity concerns, and reputational sensitivity. Compared with literature reviews, academic writing is closer to the final scholarly product and is therefore more sensitive to questions of originality and intellectual contribution. Our results, which show that academic title is a stronger predictor than self-perceived literacy in this domain, highlight a 'seniority-caution' paradox. As academics advance in rank, the decision to use AI for writing becomes less about technical ability and more about professional identity and reputation management. Higher-ranking academics may perceive greater risk to their established scholarly voice and authorial credibility, leading to a more conservative adoption pattern despite their potential competence. This interpretation is consistent with studies showing that ChatGPT adoption is closely linked to academic integrity, academic competence, workplace stress, and academic staff performance (Bin-Nashwan et al., 2023; Bin-Nashwan, Sadallah, et al., 2025; Sadallah et al., 2025). Thus, the use of AI in academic writing appears to be governed by a stronger normative filter than its use in preparatory or supportive research tasks.

The predictors in this study explained visual content creation only weakly. None of the AI literacy dimensions significantly predicted AI use in this domain, and the overall model showed limited explanatory power. Although gender reached statistical significance within the model, this coefficient should be interpreted cautiously because the overall visual content creation model was not statistically significant. Rather than treating this result merely as an underperforming model, it can be interpreted as evidence that visual AI adoption may differ fundamentally from text-based AI adoption in academic work. Text-based AI tools are closely aligned with common academic tasks such as summarization, translation, literature organization, idea generation, and writing support. These tasks are embedded in the linguistic and textual nature of academic labor and are therefore more directly connected to general AI usage competence.

By contrast, visual AI use often requires additional and more specialized conditions. Academics may use visual AI only when their discipline requires figures, diagrams, graphical abstracts, infographics, visual teaching materials, or other forms of visual scientific communication. In addition, visual AI adoption may depend on design experience, software familiarity, familiarity with image-generation tools, copyright concerns, image provenance, disclosure expectations, and awareness of journal or institutional policies on AI-generated visual materials. These requirements make visual AI more domain-specific and policy-sensitive than text-based AI use. Therefore, the weak explanatory power of the visual content creation model is theoretically meaningful: it suggests that general AI literacy and demographic/professional variables may be insufficient to explain visual AI adoption unless future models also include visual communication needs, design competence, software experience, copyright knowledge, and policy awareness.

The findings also highlight the importance of professional expectations. Academic title differentiated adoption in general academic use, academic writing, and literature review. This pattern is consistent with the view that academics' AI use is embedded in their career stage, publication pressure, supervisory responsibility, institutional accountability, and reputational exposure. The lower AI use among some academic-title categories may reflect heightened sensitivity to authorship responsibility, academic credibility, or institutional accountability. However, because professional identity, reputational risk, and perceived legitimacy were not directly measured, these interpretations should be treated as theoretically grounded explanations rather than as confirmed psychological mechanisms.

A further implication concerns the role of ethics and evaluation in AI literacy education. Although ethics and evaluation did not emerge as consistent direct predictors in the final models, this should not be interpreted as evidence of their irrelevance. Instead, they may function as boundary-shaping dimensions that influence where, how, and under what conditions AI use is considered acceptable in academic practice. Recent AI literacy research emphasizes that responsible AI use requires more than technical fluency; it also requires ethical awareness, critical evaluation, and the ability to judge whether AI outputs are appropriate for a given context (Biagini, 2025; Kong et al., 2024). Al-Abdullatif (2025) similarly shows that awareness, ethics, evaluation, and use are interrelated dimensions of AI literacy, with ethical reasoning and evaluation contributing to responsible human–machine cooperation. Accordingly, the present findings suggest that usage competence may be more directly associated with adoption in lower-risk or workflow-compatible tasks, whereas ethics and evaluation may shape the quality, boundaries, and legitimacy of adoption more indirectly.

Taken together, these findings provide empirical evidence for a task-specific understanding of AI adoption in academia. Academics appear to evaluate AI tools not merely as technologies but as professional resources, whose value depends on task fit, perceived usefulness, ethical acceptability, and professional accountability. Because several of these mechanisms were not directly measured, the study's contribution should be understood as an empirically grounded task-specific account of AI adoption rather than a causal test of psychological mechanisms. This interpretation connects the study to broader professional technology-use research by showing that academic AI adoption involves not only perceived usefulness or technical competence, but also role compatibility, authorship sensitivity, perceived task legitimacy, and responsible-use boundaries.

5.1. Theoretical contributions

This study provides empirical evidence regarding task-specific human-AI interaction and professional technology-use in academic settings in three ways. First, it shifts the focus from generalized AI acceptance to task-specific AI adoption. The findings show that academics differentiate between AI use for general academic tasks, academic writing, literature reviews, and visual content creation. This provides a more precise understanding of academic AI use than models that treat adoption as a single, uniform outcome.

Second, this study offers a cautious and empirically grounded account of AI literacy in the context of academic AI adoption in higher education. By including awareness, usage, evaluation, and ethics in the regression models, this study directly examined whether AI literacy dimensions are associated with task-specific AI use. The findings show that AI literacy is not a uniform, direct predictor across all tasks. Instead, its role is task-dependent: usage competence is most relevant for general academic use and literature reviews, whereas evaluation and ethics may shape responsible use more indirectly by influencing critical judgment, acceptable boundaries, and perceived legitimacy.

Third, this study situates AI adoption within the professional and ethical structures of academia. The findings suggest that academic AI use is associated not only with perceived competence or technological usefulness but also with professional role expectations, authorship sensitivity, reputational considerations, perceived task value, and task-related legitimacy. This responds to the need for a psychologically informed explanation of why academic professionals may adopt AI tools in some domains while remaining cautious in others.

Beyond higher education, the findings also speak to the professional contexts of technology adoption, where expert users must balance efficiency, trust, risk, task value, and ethical responsibility when integrating AI tools into their work environments. Furthermore, this study highlights the role of academic autonomy in technology adoption. By demonstrating that adoption varies across task domains, we show that academics do not passively accept AI tools; they actively negotiate their use based on the perceived impact on their professional agency. This provides empirical evidence for viewing AI adoption as a form of professional boundary-work, where users selectively integrate tools that enhance efficiency while remaining cautious toward uses that may threaten their core intellectual identity.

5.2. Practical implications

These findings have several implications for universities, academic leaders, policymakers, and organizations that seek to promote responsible AI use among professionals. First, AI training should be task sensitive rather than generic. Training programs should distinguish between AI use for literature reviews, academic writing, teaching preparation, data analysis, and visual content creation, as each domain involves distinct benefits, risks, and ethical considerations.

Second, universities should move beyond awareness-based AI training programs. The results show that practical use competence predicts AI adoption in general academic use and in literature reviews, but not uniformly across all domains. Therefore, training should include hands-on practice, prompt design, output evaluation, citation checking, disclosure norms, and discipline-specific use cases. From a professional technology-use perspective, such initiatives should emphasize task-specific value, user competence, trust, and responsible use boundaries rather than general awareness alone. To implement this, universities should move away from broad 'AI Awareness' workshops and instead offer modular, task-specific training such as 'AI for Systematic Literature Mapping' or 'Ethical Prompting for Manuscript Drafting.' By aligning training with specific academic workflows, institutions can directly address the unique professional anxieties, such as authorship sensitivity and disclosure norms, that arise at different stages of research.

Third, academic writing requires clear institutional and journal-level guidance. Universities and journals should clarify which forms of AI assistance are acceptable and which are not, including grammar correction, translation, editing, idea generation, drafting, and content generation. Clear policies can reduce uncertainty and support responsible use, especially because writing-related AI adoption appears to be strongly shaped by professional role expectations and reputation concerns.

Fourth, visual AI requires specific ethical, technical, and policy-oriented guidance. Universities and journals should address copyright, image provenance, disclosure, data protection, originality, image manipulation, and journal compliance issues related to AI-generated visual materials. Because visual content creation was weakly predicted by general AI literacy indicators and demographic/professional variables, institutions should not assume that general AI training is sufficient for this domain. Instead, visual AI training should include discipline-specific examples, guidance on acceptable image generation and editing practices, and clear rules regarding the use, disclosure, verification, and attribution of AI-generated visual outputs.

Finally, support should be tailored to the academic career stage. Early-career academics may require guidance on responsible use and disclosures. In contrast, senior academics may benefit from evidence-based examples of how AI can support scholarly work without compromising its integrity, authorship standards, or institutional credibility.

5.3. Limitations and future research

This study had several limitations. First, the dependent variables were binary indicators of whether the academics used AI tools for specific purposes. Therefore, the findings reflect task-specific adoption or non-adoption, rather than the frequency, intensity, duration, quality, or complexity of AI use. Future studies should use more refined measures to address these limitations. Specifically, replacing binary indicators with Likert-type scales would allow researchers to distinguish between exploratory experimentation and systematic integration. Measuring the frequency, intensity, and perceived quality of AI-assisted outputs would provide a more granular view of how AI literacy dimensions influence the depth of technology adoption in the academic workplace.

Second, the study relied on cross-sectional and self-reported data; therefore, causal conclusions cannot be drawn. Longitudinal, experimental, or behavioral-log-based studies are needed to examine whether AI literacy leads to adoption, whether adoption improves AI literacy over time, and whether institutional and professional factors shape both.

Third, the sample was limited to academics working at universities in Türkiye. Although the participants came from 116 universities, the findings should not be generalized to other national higher education systems. Future research should adopt a cross-national and comparative design.

Fourth, AI literacy dimensions were used as observed composite indicators rather than as reflective latent constructs. This approach was suitable for examining dimension-level associations with binary adoption outcomes. Although the overall AI literacy scale showed good internal consistency, the internal consistency coefficients differed across the subdimensions. Considering the short three-item structure of each subdimension, the reliability coefficients were interpreted in line with the exploratory, dimension-level use of the scale in the present regression models. Future research should further validate the AI literacy measurement structure among academic staff and may consider using longer or context-specific AI literacy measures.

Fifth, A significant methodological limitation of the study is the relatively low internal consistency coefficients calculated for the awareness ($\alpha = 0.538$) and usage ($\alpha = 0.621$) sub-dimensions of the AI literacy scale. This is due to the short-form structure of each sub-dimension, consisting of only three questions; indeed, the mathematical dependence of the Cronbach's alpha coefficient on the number of items in the scale, and as highlighted by Nunnally (1978), values between 0.50 and 0.60 are known to be acceptable in exploratory research in emerging fields. Due to this psychometric limitation, the AI literacy dimensions were preserved as observed composite indicators and included in the analyses, rather than being modeled as reflective latent constructs. To compensate for potential measurement fluctuations that these relatively low coefficients might create and to increase the reliability of the findings, the main logistic regression models were supported with additional machine learning-based predictive validations, and the stability of the data structure was statistically verified. Future research is recommended to incorporate broader item structures or context-specific scale variations, particularly in the awareness and usage dimensions, to further optimize measurement sensitivity.

Finally, future studies should include additional predictors, such as academic discipline, institutional AI policy, prior AI training, perceived usefulness, perceived risk, perceived task value, trust in AI outputs, journal policy awareness, and direct measures of academic integrity concern. These variables may be particularly important for explaining academic writing and visual content creation.

6. Conclusion

This study examined task-specific AI adoption among academics by integrating demographic and professional characteristics with AI literacy dimensions. The findings show that AI adoption in academia is not uniform across task domains. Instead, academics appear to evaluate and use AI tools differently across general academic tasks, academic writing, literature reviews, and visual content creation.

The final regression results indicate that the AI literacy dimensions do not operate as uniform direct predictors across all task domains. Usage competence significantly predicted general academic use and literature review, suggesting that practical ability with AI tools is especially important when the task is perceived as useful, workflow-compatible, and relatively legitimate. In contrast, awareness, evaluation, and ethics did not show consistent, direct effects across the models. This does not imply that these dimensions are unimportant; rather, they may indirectly shape the boundaries, quality, and perceived legitimacy of AI use.

Professional and demographic factors also play important roles. Academic title differentiated AI adoption in general academic use, academic writing, and literature reviews, indicating that AI use is embedded in professional role expectations, authorship sensitivity, reputational concerns, and academic accountability. Gender was associated with the literature review. Although gender also reached significance in the visual content creation model, this finding should be interpreted cautiously, as the overall model was not statistically significant in this study.

Overall, this study provides empirical evidence regarding task-specific human-AI interaction and professional technology-use in academic settings. The findings show that responsible AI integration requires more than general acceptance, awareness, and technical familiarity. Therefore, universities should develop task-specific, ethically grounded, and career-stage-sensitive approaches to AI training and governance, with particular attention to practical usage competence, critical evaluation, disclosure norms, and professional risks associated with different forms of academic AI use.

CRediT authorship contribution statement

Alaaddin Selcuk Koyluoglu: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Resources, Methodology, Investigation, Formal analysis, Data curation. **İbrahim Halil EFENDİOĞLU:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Bilge Villi:** Writing – review & editing, Writing – original draft, Resources, Investigation. **Fatih Koc:** Visualization, Supervision, Methodology, Investigation, Formal analysis.

Ethics approval and informed consent

Ethics approval for this study was obtained from the Balıkesir University Ethics Committee (Decision No. 2025.06/23, dated 26.06.2025). The approved protocol covered the target population, online survey procedure, measurement instruments, and data collection process used in the present study. All participants were informed about the study purpose, voluntary participation, confidentiality, and their right to withdraw, and informed consent was obtained prior to participation.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the revision of this manuscript, the authors used AI-assisted tools only for language refinement, organization, consistency checks, and clarity of expression. The authors reviewed and edited all AI-assisted outputs and took full responsibility for the content, analyses, interpretations, and conclusions of the manuscript.

Funding

The authors did not receive any funding for this study.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Abbreviations

AHC: agglomerative hierarchical clustering
AI: artificial intelligence
BLR: binary logistic regression
ML: machine learning
MLP: multi-layer perceptron