Exploring the Effects of Generative Artificial Intelligence Adoption on Academic Productivity and Pedagogical Innovation: A Mixed-Methods Analysis

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***Abstract*—The aim of this research is to examine how the adoption level of Generative Artificial Intelligence (GAI) influences not only the number of academic outputs produced by academicians but also their instructional innovation, assessment practices, and pedagogical processes. This relationship is evaluated through a mixed-method approach combining quantitative and qualitative analyses. The population of the research consists of 515 academicians working in state and private/foundation universities in Türkiye as of the 2024–2025 academic year. In the study, a mixed method research design was used: Generative Artificial Intelligence Acceptance Scale (GAIAS) and academic output indicators were used for quantitative data, and qualitative data were collected with open-ended questions. Quantitative findings revealed that GAI acceptance level showed significant differences according to academic title, institution type, and partially gender variables. Academicians working in foundation universities had higher scores for performance and expectation of GAI. Weak and often insignificant relationships were determined between GAI acceptance and Google Scholar and Web of Science h-index/number of publications in the short term. Qualitative findings show that academicians use GAI most frequently in article writing, data analysis, and literature review; their usage motivations are concentrated around increasing productivity, ease of access to information, and saving time. In addition, participants drew attention to ethical problems, accuracy risk, and the danger of over-reliance, despite the potential of GAI to increase academic productivity. The research results show that the effect of GAI on the number of academic outputs depends on contextual factors and may become more evident in the long term.**

***Keywords*—generative artificial intelligence, acceptance level, academic output, higher education**

I. Introduction

Generative Artificial Intelligence (GAI) is a sub-branch of artificial intelligence technologies and refers to systems that have the ability to generate new and original content (text, images, audio, video, etc.). These systems can create similar but new examples by learning from existing data. For example, GPT models for text generation, DALL-E or Stable Diffusion models for visual generation are among the successful applications of GAI [1, 2]. GAI is defined as systems that can produce content according to the needs of users, and the use of these systems increases the number and diversity of academic research. GAI is used in many fields such as art, education, health, marketing and academic research. With its ability to quickly process complex data sets, automatically generate text, and even create visual content, these models accelerate research processes and allow researchers to produce more academic outputs [3]. For example, Bozkurt [4] discusses the reflections and potential role of GAI in the field of education and emphasizes that the applications of this technology in education are increasing. The impact of GAI systems on the number of academic outputs may differ between disciplines. For example, in the fields of natural sciences and engineering, the use of these technologies in data analysis and modelling processes helps researchers obtain faster results [5], while in social sciences, it can have a similar effect in areas such as text production and literature review. However, ethical use of these technologies, academic integrity, and the quality of outputs are important factors that should be considered when evaluating the impact of GAI adoption on the number of academic outputs [6]. GAI has created a significant transformation in academic writing and education processes in recent years. This transformation leads to significant changes both in academic outputs and in education methods. The effects of GAI on academic writing have become even more evident with the use of advanced language models such as ChatGPT. Dergaa *et al.* [7] examined the opportunities and potential threats that ChatGPT provides in academic writing and emphasized the potential of such tools to increase academic outputs. In this context, important findings are presented on how GAI transforms academic writing processes. Nazari *et al.* [8] examined the applications of artificial intelligence-supported writing assistants in higher education and revealed the potential of such tools to reduce students' cognitive load. While such applications help students improve their writing skills, they also increase academic outputs. The integration of GAI not only increases the quality of academic writing but also transforms research processes. Maphoto *et al.* [9] investigated the potential of GAI to improve academic writing skills in the context of distance education and emphasized the role of such technologies in education. In this context, it was concluded that GAI can be an important tool in improving students' writing skills and increasing their academic success.

Among the factors determining the importance of the research are the increasing role of GAI in the academic world and the fact that the effects of these technologies on scientific production processes have not yet been sufficiently investigated. In this context, the research focuses on three

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basic questions:

1) To what extent are academicians adopting GAI technologies in their research and teaching practices?
2) How does the use of these technologies influence not only the number and quality of academic outputs (e.g., articles, papers, projects) but also innovation in instructional design, assessment, and learning processes?
3) What opportunities and challenges do the adoption of GAI create for enhancing academic productivity, pedagogical effectiveness, and ethical research practices?

This study aims to understand how GAI technologies transform academic productivity and educational practices by examining their adoption among academicians through a mixed-method approach that combines quantitative and qualitative analyses. The research further seeks to reveal the potential benefits, risks, and discipline-specific differences associated with GAI use in higher education.

The remainder of this article is structured as follows. The Method section explains the mixed-methods design, including the quantitative (survey-based) and qualitative (open-ended) components of the study, and details the sampling, data collection, and analysis procedures. The Results section presents the quantitative findings obtained from the Generative Artificial Intelligence Acceptance Scale (GAIAS) and bibliometric indicators (Google Scholar and Web of Science), followed by qualitative themes derived from participants' responses regarding GAI use, motivations, and challenges. The Discussion section integrates these findings, interprets them in the context of existing literature, and highlights theoretical and practical implications. Finally, the Conclusion section summarizes key findings, acknowledges limitations, and offers recommendations for future research and institutional policy.

II. Literature Review

The emergence of Generative Artificial Intelligence (GAI) has triggered a rapid transformation in academic research and productivity. Recent studies show that GAI technologies, such as ChatGPT and similar large language models, are increasingly being integrated into academic workflows, influencing research design, writing, and data analysis practices [10]. By automating time-intensive processes like literature synthesis and coding, GAI tools have been found to enhance efficiency and expand accessibility to complex analytical methods. However, Kldiashvili *et al.* [11], Delgado *et al.* [12] emphasize that this productivity gain must be balanced with attention to research integrity and the ethical use of AI-assisted tools.

Quantitative evidence regarding GAI's impact on academic productivity is still emerging. Kamau [13] demonstrated that GAI has a positive and significant effect on academic performance and efficiency within smart learning environments, suggesting that the adoption of AI technologies can foster both individual and institutional productivity. Similarly, a bibliometric analysis by Omeneke [14] revealed an exponential rise in publications related to GAI and academic research, indicating that AI has become a pivotal tool in enhancing interdisciplinary collaboration and research output. Nonetheless, Tang *et al.* [15] highlighted that GAI's benefits may not be equally distributed-finding gender disparities in adoption rates and productivity gains among academics. This implies that contextual factors such as gender, discipline, and institutional support can mediate GAI's effectiveness.

Beyond quantitative impacts, researchers have also examined the broader pedagogical and ethical implications of GAI. Mesquita [16] reported that GAI improves engagement and personalization in higher education but raises concerns regarding over-reliance and academic integrity. Similarly, Benbya *et al.* [17] and Naqbi *et al*. [18] noted that while GAI enhances productivity across sectors, it simultaneously challenges traditional notions of authorship, creativity, and accountability in knowledge production. Collectively, the literature suggests that while GAI presents clear opportunities for improving efficiency and innovation in academic work, it also necessitates new frameworks to ensure responsible, equitable, and ethical integration within scholarly environments.

Despite the growing body of research on generative artificial intelligence in higher education, existing studies have generally examined academic output and teaching innovation as separate domains. While some research focuses on bibliometric indicators and productivity outcomes, others emphasize instructional innovation, pedagogical transformation, or ethical concerns related to AI use. Moreover, although several studies report weak or insignificant short-term effects of GAI adoption on academic output, they rarely explain the underlying reasons for this pattern. As a result, the mechanisms through which GAI influences research productivity and teaching practices remain insufficiently understood. Addressing this gap, the present study simultaneously considers academic output and pedagogical dimensions and integrates quantitative and qualitative evidence to explain the lack of significant short-term effects.

III. Materials and Methods

A. Research Design

This research was designed as a convergent mixed-methods study within the framework of the descriptive survey model. Using both qualitative and quantitative methods allows for a more comprehensive understanding than employing a single approach alone [19]. Through the integration of quantitative and qualitative data collection, the study aimed to examine in depth the level of adoption of Generative Artificial Intelligence (GAI) technologies by academics and their potential effects on academic outputs.

The Convergent Parallel Design approach was adopted as the research model. In this design, both quantitative and qualitative data were collected simultaneously, analysed independently and then merged during the interpretation phase to ensure methodological triangulation and enhance the validity of the findings. This integration provided a holistic view of the research problem and increased the robustness of the conclusions.

In terms of research type, this study employed a relational survey model, as it sought to determine the association between the level of GAI adoption and the number of academic outputs. Relationships between academics' Google Scholar and Web of Science h-indices and survey results were analysed quantitatively, while qualitative data were used to contextualize and explain these relationships. This integrated approach strengthened the credibility and reliability of the study by combining numerical patterns with contextual insights.

B. Research Study Group

The population of the study consisted of 515 academicians from various universities (Table 1). Participation in the study was voluntary, and no incentives were provided. Invitations were distributed via institutional email lists and academic networks, allowing academics from different disciplines and institutions to participate online. Therefore, the study followed a convenience sampling approach rather than a full census or simple random sampling. This method enabled broad participation but may limit the representativeness of the entire academic population.

Table 1. Demographic data of participants

Variable	Demographic characteristics	Frequency (*n*)	Percentage (%)
Gender	Female	250	48.5
	Male	265	51.5
	Total	515	100.0
Academic title	Prof. Dr.	70	13.6
	Assoc. Prof. Dr.	140	27.2
	Assist. Prof. Dr.	175	34.0
	Lecturer. Dr.	15	2.9
	Lecturer	65	12.6
	Res. Assist. Dr.	15	2.9
	Res. Assist.	35	6.8
	Total	515	100.0
University type	State	480	93.2
	Private/Foundation	35	6.8
	Total	515	100.0

A total of 515 academics participated in the research. When the gender distribution of the participants is examined, 48.5% are women ($n = 250$) and 51.5% are men ($n = 265$). When the distribution of the participants according to their academic titles is examined, 13.6% are Professors ($n = 70$), 27.2% are Associate Professors ($n = 140$), 34.0% are Assistant Professors ($n = 175$), 2.9% are Lecturers Doctor ($n = 15$), 12.6% are Lecturers ($n = 65$), 2.9% are Research Assistants Doctor ($n = 15$) and 6.8% have the title of Research Assistant ($n = 35$). When the distribution of the participants according to the types of universities they work for is evaluated, it was determined that 93.2% work in state universities ($n = 480$) and 6.8% work in private/foundation universities ($n = 35$).

C. Data Collection Tools

A three-part form was prepared as a data collection tool. The first part includes items regarding the demographic characteristics of the participants, the second part includes items from the "Generative Artificial Intelligence Acceptance Scale", and the third part includes 4 open-ended questions.

In the quantitative part of the research, the attitudes and acceptance levels of academics towards these technologies were measured using the "Generative Artificial Intelligence Acceptance Scale (GAIAS)" developed by Karaoglan *et al*. [20]. The scale consists of 20 items and four sub-factors (performance expectancy, effort expectancy, facilitating conditions, and social influence) on a 5-point Likert type scale (5-Strongly Agree, 1-Strongly Disagree). The reliability analysis of the scale found that Cronbach's alpha coefficient was 0.97. The academic output data were collected from Google Scholar and Web of Science (WoS) databases between April 10–15, 2025. For each participant, author profiles were manually verified to prevent homonym errors (i.e., confusion with other researchers with the same name). Only verified profiles that matched the participant's institutional affiliation and research field were included. Self-citations were excluded from citation counts, and the data reflected each participant's all-time metrics as of April 2025. All data were independently collected by the researchers rather than self-reported by participants. Details of the data extraction and verification steps are provided in Appendix A to ensure transparency and reproducibility.

In the qualitative section, detailed information was collected on the opportunities and challenges faced by academics in the process of using GAI and the effects of these technologies on academic productivity, using a Structured Interview Form consisting of 4 open-ended questions. This method provides the opportunity to understand the views and experiences of the participants in depth.

D. Data Analysis

Confirmatory Factor Analysis (CFA) was conducted to validate the factor structure of the Generative Artificial Intelligence Acceptance Scale (GAIAS). The CFA supported a three-factor solution—Performance–Effort Expectancy, Social Influence, and Facilitating Conditions—with acceptable fit indices (CFI = 0.94, RMSEA = 0.052, SRMR = 0.047). Reliability and validity indicators were satisfactory ($\alpha = 0.92$–0.95; CR = 0.88–0.93; AVE > 0.50). Consequently, subsequent analyses were conducted using these three validated subscales. The research data were then evaluated for normality using the Kolmogorov–Smirnov and Shapiro–Wilk tests. Both tests yielded significant results ($p < 0.001$), which is common in large samples ($n = 515$) and indicates deviations from perfect normality. Visual inspections of histograms and Q–Q plots also suggested non-normal distributions. Considering these findings and the ordinal nature of the Likert-type items, the assumptions of parametric tests were deemed not fully met. Therefore, non-parametric tests (Mann–Whitney U and Kruskal–Wallis) were applied in subsequent analyses to ensure robust and reliable interpretations [21]. This approach is consistent with prior recommendations, as Likert-type data in large social science samples often deviate from normality [22, 23].

IV. FINDING

A. Quantitative Findings Regarding the Research

Reliability tests for GAIAS were conducted to determine the suitability of the data set for factor analysis and are given in Table 2.

Table 2. Reliability analyses

Test	Statistics	*p*-value
KMO Measure	0.901	-
Bartlett's Sphericity Test (Chi-square)	11323.902	**0.000**

By performing GAIAS factor analysis, the Kaiser-Meyer-Olkin (KMO) value was found to be 0.901. This value is considered excellent as it is above 0.80. The Bartlett Sphericity Test yielded $\chi^2(190) = 11323.90, p < 0.001$.

This result indicates that the data is suitable for factor analysis. The explained variance analysis of the data set is given in Table 3.

Table 3. Explained variance

Component	Variance (%)	Cumulative (%)
1	51.70	51.70
2	16.11	67.80
3	8.73	76.53

According to the data in Table 3, the scale explains a large part of the scale data with its three-factor structure, and the items in the scale statistically strongly represent the targeted structures. The total variance explained is 76.53%, which is a very high value for social sciences.

The factor loadings for the scale were calculated and are given in Table 4.

As a result of factor analysis, the scale is divided into three main components:

1) Performance and Effort Expectancy (high loads between M1–M15)
2) Social Impact (M16–M20 high loads)
3) Facilitating Conditions (M13–M15 lower but significant loads)

Table 4. Factor loadings

Article	Factor 1 (Performance/Effort)	Factor 2 (Social Impact)	Factor 3 (Facilitating Conditions)
M1–M7	0.77–0.83	-	-
M8–M12	0.62–0.73	Negative loads (around –0.55)	-
M13–M15	0.62–0.79	-	0.19–0.24
M16–M20	0.58–0.67	0.51–0.59	0.15–0.38

Whether there is a significant difference between the total score of GAIAS and the four sub-dimensions of the scale according to the gender of the academics was examined by using the Mann-Whitney U test because the parametric test assumptions were not met, and the results are given in Table 5.

Table 5. Mann-Whitney U test results by gender

Test Variable	Sample Size (Group 1)	Rank Mean (Group 1)	Sample Size (Group 2)	Rank Mean (Group 2)	*U* Statistic	*p*-value	*Z* Statistic	Effect Size (*r*)
Scale Total Score	250	243.650	265	271.540	29,537.500	**0.033**	–2.127	0.094
Performance Expectancy	250	249.150	265	266.350	30,912.500	0.188	–1.317	0.058
Effort Expectancy	250	234.100	265	280.550	27,150.000	**0.000**	–3.589	0.158
Facilitating Conditions	250	255.950	265	259.930	32,612.500	0.759	–0.306	0.013
Social Influence	250	266.250	265	250.220	31,062.500	0.219	–1.228	0.054

According to the gender variable Mann-Whitney U test results in Table 5, statistically significant differences were found in the scale total score ($U = 29537.500$, $p = 0.033$, $r = 0.094$) and effort expectation ($U = 27150.000$, $p < 0.001$, $r = 0.158$) sub-dimensions. However, the effect size of both differences is small. There is no significant difference in performance expectation, facilitating conditions and social impact sub-dimensions, $p > 0.05$. These results indicate that the gender factor has a small effect only on the total score and effort expectation.

Whether there is a significant difference in the GAIAS total score and its four sub-dimensions according to the academic titles of the academicians was examined using the Kruskal-Wallis test because the parametric test assumptions were not met, and the results are given in Table 6.

Table 6. Kruskal-Wallis test results of the scale total score and sub-factors according to the academic title variable

Test Variable	Chi-Square (χ^2)	*df*	*p*-value	Effect Size (η^2)
Scale Total Score	60.037	6	0.000	0.106
Performance Expectancy	53.221	6	0.000	0.093
Effort Expectancy	46.071	6	0.000	0.079
Facilitating Conditions	52.100	6	0.000	0.091
Social Influence	43.705	6	0.000	0.074

According to the Kruskal-Wallis test results in Table 6, statistically significant differences were found between academic title groups in the scale total score and all sub-dimensions ($p < 0.001$ for all variables). The effect size was moderate in the scale total score ($\chi^2 = 60.037$, $\eta^2 = 0.106$) and performance expectancy ($\chi^2 = 53.221$, $\eta^2 = 0.093$) sub-dimensions, and it is seen that academic title has a significant effect in these areas. Although significant differences were also found in the effort expectancy ($\chi^2 = 46.071$, $\eta^2 = 0.079$), facilitating conditions ($\chi^2 = 52.100$, $\eta^2 = 0.091$) and social influence ($\chi^2 = 43.705$, $\eta^2 = 0.074$) dimensions, the effect sizes are at the lower limit of the moderate level. In general, it can be said that academic title creates significant and remarkable effects on both the scale total score and all sub-factors.

Whether there is a significant difference in the GAIAS total score and its four sub-dimensions according to the type of institution (state or foundation/private) where the academicians work was examined using the Mann-Whitney U test because the parametric test assumptions were not met, and the results are given in Table 7.

Table 7. Mann-Whitney U test results by institution type

Test Variable	Sample Size (Group 1)	Rank Mean (Group 1)	Sample Size (Group 2)	Rank Mean (Group 2)	*U* Statistic	*Z* Statistic	*p*-value	Effect Size (*r*)
Scale Total Score	480	268.490	35	114.070	3362.500	–5.932	**0.000**	0.261
Performance Expectancy	480	269.150	35	105.140	3050.000	–6.323	**0.000**	0.279
Effort Expectancy	480	267.970	35	121.210	3612.500	–5.710	**0.000**	0.252
Facilitating Conditions	480	264.980	35	162.290	5050.000	–3.978	**0.000**	0.175
Social Influence	480	262.270	35	199.430	6350.000	–2.424	**0.015**	0.107

According to the Mann-Whitney U test results in Table 7, statistically significant differences were found in the scale total score ($U = 3362.500$, $p < 0.001$, $r = 0.261$), performance expectancy ($U = 3050.000$, $p < 0.001$, $r = 0.279$) and effort expectancy ($U = 3612.500$, $p < 0.001$, $r = 0.252$) sub-dimensions according to the institution type variable, and the effect sizes of these differences were found to be moderate. Significant differences were also found in the facilitating conditions ($U = 5050.000$, $p < 0.001$, $r = 0.175$) and social influence ($U = 6350.000$, $p = 0.015$, $r = 0.107$) sub-dimensions, but the effect sizes of these differences are small. In general, it can be said that the type of institution where they work has significant effects on the academicians' total score on the Acceptance Scale for Generative Artificial Intelligence and all sub-factors, and this effect is more evident especially in performance expectancy, effort expectancy and total score.

As presented in Table 8 the relationships between the academicians' Google Scholar (GS) h-index and GS publication count and the total score and four sub-dimensions of the Acceptance Scale for GAI were examined using the nonparametric Spearman rank correlation method because the variables did not meet the normal distribution assumption.

Table 8. Google academic h-index and publication count Spearman correlation results

Independent Variable	Dependent Variable	Spearman rho	*p*-value
GS h-Index	Scale Total Score	0.041	0.350
	Performance Expectancy	0.050	0.256
	Effort Expectancy	–0.070	0.114
	Facilitating Conditions	0.058	0.186
	Social Influence	0.031	0.479
GS Publication Count	Scale Total Score	–0.035	0.434
	Performance Expectancy	–0.003	0.942
	Effort Expectancy	–0.091	**0.038**
	Facilitating Conditions	–0.027	0.540
	Social Influence	–0.060	0.175

A very weak and positive relationship was found between the GS h-Index and the Scale Total Score, and this relationship is not significant (*rho* = 0.041, *p* = 0.350). A very weak and positive relationship was found between the GS h-Index and Performance Expectancy, and this relationship is not significant (*rho* = 0.050, *p* = 0.256). A very weak and negative relationship was found between the GS h-Index and Effort Expectancy, and this relationship is not significant (*rho* = –0.070, *p* = 0.114). A very weak and positive relationship was found between the GS h-Index and Facilitating Conditions, and this relationship is not significant (*rho* = 0.058, *p* = 0.186). A very weak and positive relationship was found between the GS h-Index and Social Influence, and this relationship is not significant (*rho* = 0.031, *p* = 0.479). A very weak and negative relationship was found between the GS Publication Count and the Scale Total Score, and this relationship is not significant (*rho* = –0.035, *p* = 0.434). A very weak and negative relationship was found between the GS Publication Count and Performance Expectancy, and this relationship is not significant (*rho* = –0.003, *p* = 0.942). A very weak and negative relationship was found between the GS Publication Count and Effort Expectancy, and this relationship is significant (*rho* = –0.091, *p* = 0.038). A very weak and negative relationship was found between the GS Publication Count and Facilitating Conditions, and this relationship is not significant (*rho* = –0.027, *p* = 0.540). A very weak and negative relationship was found between the GS Publication Count and Social Influence, and this relationship is not significant (*rho* = –0.060, *p* = 0.175).

The relationships between the Web of Science (WoS) h-index and WoS publication count of academics and the GAIAS total score and its four sub-dimensions were examined using the non-parametric Spearman rank correlation method because the variables did not meet the normal distribution assumption, and the results are given in Table 9.

Table 9. Spearman correlation results of Web of Science h-index and publication count

Independent Variable	Dependent Variable	Spearman rho	*p*-value
WoS h-Index	Scale Total Score	0.078	0.075
	Performance Expectancy	0.123	**0.005**
	Effort Expectancy	–0.001	0.983
	Facilitating Conditions	0.037	0.405
	Social Influence	0.037	0.404
WoS Publication Count	Scale Total Score	0.004	0.920
	Performance Expectancy	0.053	0.230
	Effort Expectancy	–0.005	0.904
	Facilitating Conditions	–0.004	0.927
	Social Influence	–0.088	**0.047**

A very weak and positive correlation was found between the WoS h-Index and the Scale Total Score, and this relationship is not significant (*rho* = 0.078, *p* = 0.075). A small and positive correlation was found between the WoS h-Index and Performance Expectancy, and this relationship is significant (*rho* = 0.123, *p* = 0.005). A very weak and negative correlation was found between the WoS h-Index and Effort Expectancy, and this relationship is not significant (*rho* = –0.001, *p* = 0.983). A very weak and positive correlation was found between the WoS h-Index and Facilitating Conditions, and this relationship is not significant (*rho* = 0.037, *p* = 0.405). A very weak and positive correlation was found between the WoS h-Index and Social Influence, and this relationship is not significant (*rho* = 0.037, *p* = 0.404). A very weak and positive correlation was found between the WoS Publication Count and the Scale Total Score, and this relationship is not significant (*rho* = 0.004, *p* = 0.920). A very weak and positive correlation was found between the WoS Publication Count and Performance Expectancy, and this relationship is not significant (*rho* = 0.053, *p* = 0.230). A very weak and negative correlation was found between the WoS Publication Count and Effort Expectancy, and this relationship is not significant (*rho* = –0.005, *p* = 0.904). A very weak and negative correlation was found between the WoS Publication Count and Facilitating Conditions, and this relationship is not significant (*rho* = –0.004, *p* = 0.927). A very weak and negative correlation was found between the WoS Publication Count and Social Influence, and this relationship is significant (*rho* = –0.088, *p* = 0.047).

B. *Qualitative Data Regarding the Research*

In the qualitative part of the research, the analysis of 4 open-ended questions directed to the participants was carried out. In the analysis process, the answers were coded, appropriate themes were created, and the participants were coded according to their gender (M.., F…) and transferred to the table. The qualitative data were analysed through thematic analysis. Two researchers independently coded the responses and compared their results to ensure consistency, achieving high intercoder agreement (Cohen's $\kappa = 0.86$). Coding was conducted in two rounds—first to identify initial codes and then to refine them into broader themes. Thematic saturation was reached when no new insights emerged. Analytic memos were used throughout the process to maintain transparency. For each main theme, representative verbatim quotations were included to illustrate the findings while preserving participant anonymity. To improve readability, extensive participant ID lists were replaced with concise summaries that include frequency counts and exemplar quotes in Tables 10–13.

The first question of the research aims to reveal how often and for what purposes academics use GAI tools in their academic studies. The answers obtained are given in Table 10.

Table 10. Distribution of answers given to the question "how often and for what purposes do you use generative artificial intelligence tools in your academic studies?" according to themes

Row	Theme	Frequency (*n*)	Percentage (%)
1	Versatile and Purpose-Varying Usage	275	53.4
2	Article Writing	70	13.59
3	Frequent Usage	60	11.65
4	Resource Investigation	55	10.68
5	Data analysis	50	9.71
6	Difficulty / Low Usage	5	0.97

When the findings in the table are evaluated in terms of gender, academic title, type of university served, and academic performance indicators (Google Scholar and Web of Science h-index and publication counts), some remarkable points emerge. In terms of gender, the theme of Versatile and Purpose-Dependent Use is dominant among both female and male participants, but male participants are observed to be relatively more involved in the themes of "Article Writing" and "Data Analysis". Female participants, on the other hand, show a more balanced distribution in the themes of "Resource Research" and "Frequent Use". In terms of academic title, participants with the title of Prof. Dr. and Assoc. Prof. Dr. are concentrated in the themes of "Article Writing" and "Data Analysis", while Lecturers and Research Assistants are mostly found in the themes of "Resource Research" and "Frequent Use". According to the data on the type of university served, participants working in state universities are mostly in the themes of "Article Writing" and "Data Analysis", while participants in foundation universities are concentrated in the themes of "Resource Research" and "Versatile Use". When academic performance indicators are examined, it is noteworthy that participants with high Google Scholar (GS) h-index and publication count averages are particularly involved in the themes of "Article Writing" and "Data Analysis", while participants with low Web of Science (WoS) h-index and publication count averages are mostly in the themes of "Resource Research" and "Frequent Use". This situation reveals that the usage patterns of GAI are closely related to the level of academic experience and productivity indicators. Participants described using GAI for different stages of research, particularly writing and analysis. For example: "GAI tools save me time in literature review and help me write more efficiently" (F13); "I mostly use ChatGPT to analyse data and summarize sources" (M8).

The second question of the research aims to reveal the effects of GAI tools on the quality and process of academic studies. In this context, participants were asked to share their experiences regarding how these tools contribute to research, writing, data analysis, and general academic productivity processes, or what limitations they encounter. The obtained responses are given in Table 11.

Table 11. Distribution of answers to the question "how do you think generative artificial intelligence tools have affected your number of academic outputs?" according to themes

Row	Theme	Frequency (*n*)	Percentage (%)
1	Diversified and Context-Dependent Perspectives	365	70.87
2	Productivity Increase	90	17.48
3	Difficulty / Limited Impact	35	6.8
4	Research Convenience	10	1.94
5	Spelling Support	10	1.94
6	Data Analysis	5	0.97

When the answers in Table 11 are evaluated in terms of gender, academic title, institution type, and academic performance indicators, the following findings stand out: The gender distribution of the participants is quite balanced; 51.5% are male (n = 265) and 48.5% are female (n = 250), and it is observed that the theme of "Diversified and Context-Dependent Views" is dominant in both groups. In terms of academic title, the highest participation comes from the Dr. Instructor Member (n = 175) group, while Assoc. Prof. Dr. (n = 140) and Prof. Dr. (n = 70) titled participants are particularly concentrated in the "Productivity Increase" theme. Lecturers and Research Assistants are relatively more represented in the "Difficulty / Limited Impact" theme. In the distribution of institution type, the majority of the participants work in state universities (n = 480), where the "General/Other" theme is dominant; private/foundation universities (n = 35) have a more significant rate in the "Productivity Increase" theme. When academic performance indicators are examined, the average GS h-index is 7.64, the average number of GS publications is 39.25; the average WoS h-index is 3.83, and the average number of WoS publications is 11.53. The fact that participants with high h-index and number of publications are more likely to be in the "Productivity Increase" and "Research Convenience" themes indicates that this group benefits from GAI in a way that increases the number of outputs; on the other hand, the fact that participants with lower h-index values tend to the "Difficulty/Limited Impact" theme may be related to the level of technology use and experience. Participants expressed mixed views on the productivity impact of GAI. "It depends on the task—GAI helps with drafting, but not with creative analysis" (M22).

The third question of the research aims to reveal the opportunities and risks regarding the use of GAI tools in academic studies from the perspective of the participants. In this context, participants were asked to evaluate the potential advantages of these technologies for academic processes, together with the possible ethical, methodological, or quality-related problems they may create. The obtained responses are given in Table 12.

Table 12. Distribution of answers to the question "opportunities and risks regarding the use of generative artificial intelligence tools in academic studies" according to themes

Queue	Theme	Frequency (*n*)	Percentage (%)
1	Opportunities—Productivity and Speed	270	52.43
2	Complex and Multi-Dimensional Assessments	185	35.92
3	Opportunities—Research and Information Access	30	5.83
4	Opportunities—Writing and Editing	15	2.91
5	Risks—Ethics and Academic Integrity	10	1.94
6	Risks—Information Accuracy and Reliability	5	0.97

When the answers in Table 12 are evaluated in terms of gender, academic title, institution type, and academic performance indicators, the following results stand out: 51.5% of the participants are male (*n* = 265), 48.5% are female (*n* = 250), with men focusing more on the "Opportunities—Productivity and Speed" theme, and women focusing on the "Opportunities—Research and Information Access" and "Risks—Ethics and Academic Integrity" themes. In terms of academic title, the largest group is Dr. Instructor Member (*n* = 175), and this group reveals a balanced distribution in opportunity and risk themes. Assoc. Prof. Dr. (*n* = 140) and Prof. Dr. (*n* = 70) titled participants are more inclined towards opportunity themes, while academics in lower positions such as Lecturers (*n* = 65) and Research Assistants (*n* = 35) emphasize risk themes more. In the context of institution type, the majority of the participants work in state universities (*n* = 480), where ethical and reliability issues stand out; participants working in private/foundation universities (*n* = 35) mentioned positive contributions such as speed, productivity, and research convenience more. When academic performance indicators are examined, the average GS h-index is 7.64, the average number of publications is 39.25; the average WoS h-index is 3.83, and the average number of publications is 11.53. It is observed that participants with high h-index and number of publications emphasize the speed and productivity advantages that GAI provides to research processes more; those with lower values highlight negative effects such as ethical problems, risk of inaccuracy, and dependence. Although this study did not directly measure constructs such as university support and self-efficacy, these factors implicitly emerged in the qualitative themes related to training needs and infrastructure disparities. Prior research has demonstrated that institutional support and self-efficacy are pivotal determinants of individuals' acceptance and engagement with AI-driven systems in higher education [5]. In this regard, the qualitative findings of this study suggest that the perceived adequacy of university infrastructure and the confidence of academics in using GAI tools may influence adoption levels and sustained engagement. Future research should explicitly model these constructs to provide a more comprehensive understanding of the mechanisms shaping GAI acceptance in academic settings. Participants' remarks reflected a balance between recognizing the advantages of GAI and expressing concerns about its reliability and accuracy. "These tools make the research process faster, but I worry about accuracy" (F7); "I use GAI for quick edits, but I double-check everything" (M5).

The fourth question of the study aims to reveal the participants' views on the possible effects of GAI on future academic research. In this context, participants were asked to evaluate the technology's potential contributions and risks to academic productivity, research methods, access to information, ethical standards, and academic culture. The obtained responses are given in Table 13.

Table 13. Distribution of answers to the question "the impact of generative artificial intelligence on future academic research" according to themes

Rank	Theme	Frequency (*n*)	Percentage (%)
1	Comprehensive and Diverse Assessments	290	56.31
2	Positive Impact—Information Access and Research	105	20.39
3	Positive Impact—Efficiency and Speed	85	16.5
4	Risk—Ethics and Reliability	30	5.83
5	Positive Impact—Academic Development	5	0.97

When the answers in Table 13 are examined in terms of gender, academic title, institution type, and academic performance indicators, it is seen that 51.5% of the participants are male (*n* = 265) and 48.5% are female (*n* = 250). While male participants mostly focused on the themes of "Positive Impact—Efficiency and Speed" and "Positive Impact—Information Access and Research", female participants were more likely to be in the themes of "Risk—Ethics and Reliability" and "Positive Impact—Academic Development". In terms of academic title, the highest participation came from the Dr. Instructor Member (*n* = 175) group, and the participants in this group showed a balanced distribution between positive and risk themes. Assoc. Prof. Dr. (*n* = 140) and Prof. Those with the title of Dr. (*n* = 70) focused more on opportunity themes. In the Instructor (*n* = 65) and Research Assistant (*n* = 35) groups, risk themes stood out more. In the distribution of institution type, the majority of participants work in state universities (*n* = 480), where the emphasis on ethics, reliability, and academic integrity is more pronounced; In private/foundation universities (*n* = 35), the advantages of speed, efficiency, and access to information are mentioned more. When looking at academic performance indicators, the average GS h-index was found to be 7.64, the average number of publications was 39.25; The average WoS h-index was found to be 3.83 and the average number of publications was 11.53. Participants with high h-index and number of publications stated that GAI will make positive contributions to future academic research, while participants with lower values focused more on risks and possible negative effects. Participants' statements further illustrated these expectations, emphasizing both optimism about the transformative potential of GAI and caution regarding its ethical implications. “In the future, I expect GAI will reshape how we conduct research” (F10); “It will increase speed, but ethical problems must be controlled” (M14).

V. Result and Discussion

A. Quantitative Results

The quantitative findings of the study revealed that the acceptance level of GAI shows significant differences according to demographic variables, academic title, and institution type. As shown in Table 5, gender creates a statistically significant difference only in the total score and effort expectancy dimensions; however, the effect size remains small. This finding suggests that gender is not a primary determinant of GAI acceptance, although minor differences in usage motivations may exist. Qualitative findings support this interpretation, as both female and male participants primarily described using GAI for efficiency-oriented tasks rather than fundamentally different academic purposes. Similarly, Kasneci *et al.* [24] reported that gender has a limited effect on the adoption of AI-based tools, while prior technological experience and self-efficacy play a more decisive role. This limited effect may be explained by the task-oriented nature of GAI use in academic contexts, where functional benefits such as efficiency and accuracy outweigh gender-based differences in technology attitudes. Additionally, the widespread availability of GAI tools may reduce traditional access-related disparities, resulting in more homogeneous usage patterns across gender groups.

The findings presented in Table 6 indicate that academic title has a significant and moderately strong effect on GAI acceptance ($\eta^2 = 0.106$). Academics holding the titles of professor and associate professor reported higher performance and effort expectancy scores, suggesting that senior academics perceive GAI as a tool that enhances research efficiency. Qualitative results help explain this pattern, as participants with higher academic ranks more frequently emphasized using GAI for article writing, data analysis, and workflow optimization. These academics often described GAI as a supportive instrument that accelerates routine research processes without replacing intellectual judgment. This interpretation is consistent with previous research showing that senior academics tend to approach GAI more positively due to its perceived contribution to research efficiency [25, 26]. This absence of significant short-term effects can be interpreted through several interrelated mechanisms. First, gains from GAI adoption may initially emerge in efficiency and process quality rather than in publication quantity, which was not directly measured in this study. Second, qualitative evidence indicates that GAI is predominantly used for peripheral research activities rather than core knowledge production, limiting its immediate impact on output indicators. Finally, an adaptation period is required for academics to integrate GAI effectively into their research routines, including learning how to evaluate, verify, and refine AI-generated content.

Regarding institution type, the results in Table 7 show that academics working in foundation universities have significantly higher GAI acceptance scores than those in state universities ($r = 0.261$). This difference is likely related to broader access to technological infrastructure and institutional support. Qualitative findings reinforce this explanation, as participants from foundation universities more frequently reported ease of access to GAI tools and organizational encouragement for experimentation, whereas participants from state universities more often mentioned infrastructure-related constraints. Consistent with these findings, Shen *et al.* [27] emphasized that institutional technology infrastructure is a critical determinant of AI adoption in academic contexts. Beyond infrastructure, institutional policies and incentive structures may also shape these differences. Foundation universities often adopt innovation-oriented strategies and performance frameworks that encourage experimentation with emerging technologies. At the process level, sustained institutional support may facilitate continuous and deeper integration of GAI into academic workflows, whereas fragmented or short-term support can limit adoption to surface-level use. These institutional dynamics provide a multi-dimensional explanation for the observed differences in GAI acceptance.

Correlation analyses (Tables 8 and 9) revealed weak and mostly insignificant relationships between GAI adoption and bibliometric indicators such as Google Scholar and Web of Science h-index values and publication counts. This suggests that GAI adoption does not immediately translate into measurable increases in academic output. Qualitative insights provide an important explanation for this pattern, showing that academics primarily use GAI to improve efficiency, organization, and writing quality rather than to directly increase publication volume. As one participant noted, GAI tools save time but do not replace core analytical work. These findings align with Noy and Zhang’s [28] conclusion that improvements in workflow efficiency often precede observable productivity gains in technology adoption processes. This lack of significant short-term effects can be explained through several interrelated dimensions. First, gains associated with GAI adoption may initially manifest in process-oriented outcomes such as efficiency, time savings, and workflow quality rather than in quantitative publication indicators. As this study focused on bibliometric outcomes, such intermediate efficiency-related indicators were not directly measured, which may partially explain the absence of observable short-term effects. Second, qualitative findings indicate that academics primarily use GAI for basic research processes, including drafting, editing, and information retrieval, rather than for core research activities such as theory development, methodological design, or original data interpretation. This limited depth of use constrains the potential of GAI to translate into immediate growth in academic output. Finally, integrating GAI into the research process requires an adaptation period during which academics learn how to critically evaluate AI-generated content, filter generated literature, and verify analytical outputs. During this learning and adjustment phase, the benefits of GAI are more likely to be reflected in improved research practices than in short-term increases in publication quantity. An additional explanation for this weak relationship is the absence of key moderating variables in the present study. Specifically, institutional support and individual self-efficacy were not directly measured, although prior research consistently identifies these factors as critical moderators shaping the effects of GAI use. Variations in university-level support mechanisms and academics' confidence in using AI tools may influence how acceptance translates into actual usage behavior and, ultimately, academic output. The omission of these moderators may therefore have limited the ability of the current analysis to capture the complete impact pathway between GAI acceptance and bibliometric outcomes.

A. Qualitative Results (Integrated Interpretation)

The qualitative findings further reveal that academics use GAI tools for diverse purposes and at varying intensities (Table 10). More than half of the participants (53.4%) reported using GAI in a versatile and purpose-dependent manner, integrating it into multiple stages of the research process. This flexible usage pattern complements the quantitative finding that acceptance levels vary by experience and institutional context. Similar patterns have been reported by Jahnke *et al.* [29], who found that academics integrate AI tools in an interdisciplinary and task-specific manner, particularly during literature review, data cleaning, and drafting stages.

Article writing (13.6%) emerged as one of the most frequently reported purposes of GAI use, especially among participants with higher academic titles. This finding supports Dergaa *et al.*'s [7] conclusion that language models such as ChatGPT enhance efficiency and quality in academic writing. Data analysis (9.71%) and source investigation (10.68%) were also prominent usage areas, indicating that GAI contributes not only to text production but also to analytical and exploratory research tasks [8, 30].

As shown in Table 11, the perceived impact of GAI on academic output is highly context-dependent. While a subset of participants reported increased productivity, others emphasized limited or task-specific benefits. This diversity of perceptions aligns with Floridi's [6] argument that the benefits of artificial intelligence are strongly shaped by contextual and ethical conditions.

The analysis of opportunities and risks (Table 12) indicates that productivity, speed, and access to information are the most frequently cited advantages of GAI, whereas ethical and accuracy-related concerns remain salient [6, 7]. Although familiarity and system quality were not directly measured in this study, qualitative findings suggest that ease of use and perceived efficiency influence adoption behaviours. Prior research similarly demonstrates that familiarity and convenience shape engagement with AI-enabled tools [5].

Participants' expectations regarding the future impact of GAI (Table 13) further reflect this dual perspective. While many anticipate that GAI will enhance efficiency and access to information in academic research, others emphasize the growing importance of ethical oversight. This balance between opportunity and caution is consistent with previous predictions that the widespread adoption of GAI will simultaneously accelerate academic innovation and intensify ethical challenges [8, 31].

VI. CONCLUSION

The findings indicate that GAI adoption levels vary according to academic title, institution type, and, to a lesser extent, gender. While higher-ranked academics tend to perceive GAI as a tool that enhances research efficiency and reduces workload, no significant short-term relationship was found between GAI adoption and bibliometric indicators such as publication counts and h-index values. Rather than indicating ineffectiveness, these results suggest that GAI currently contributes more to improving academic workflows and research processes than to immediately increasing measurable output.

This study has several limitations that should be acknowledged when interpreting the findings. First, the voluntary participation and convenience sampling approach may limit the generalizability of the results. In addition, the number of participants from foundation universities was considerably smaller than that from state universities, which may have influenced the observed institutional differences. Moreover, key variables such as institutional support and individual self-efficacy were not directly measured, potentially limiting the ability to fully explain the mechanisms underlying GAI adoption and its effects.

Based on these findings, higher education institutions are encouraged to develop clear ethical guidelines, strengthen institutional support mechanisms, and provide targeted training to enhance responsible and effective GAI use. Future research should adopt longitudinal designs to examine whether sustained GAI use leads to measurable gains in academic productivity over time. In addition, comparative studies across academic disciplines and research focusing on quality-oriented indicators, such as citation impact, would further clarify the long-term role of GAI in academic work.

APPENDIX

A. Academic Output Data Collection Procedure

The following steps were followed to collect and verify academic output metrics:

1) Searched each participant's name in Google Scholar and Web of Science databases using institutional affiliation and research area as filters.
2) Selected and verified the correct author profile manually, excluding duplicate or homonymous records.
3) Recorded four key variables:
- Google Scholar h-index
- Google Scholar total publications
- Web of Science h-index
- Web of Science total publications
4) Excluded self-citations from citation counts.
5) Confirmed all data reflect values as of April 2025.
6) Exported data into an Excel spreadsheet for analysis.

This procedure ensures consistent and reproducible collection of academic performance metrics across participants.

ETHICAL ISSUE

Ethical approval was received from the Sinop University Ethics Review Committee (SN-14.02.2025-1/42). All participants were informed about the purpose, procedures, and voluntary nature of the research before participation. Informed consent was obtained from all participants through a digital consent form at the beginning of the survey.

Participants also consented to use their publicly available

Google Scholar and Web of Science author metrics, which were linked with their survey responses for analytical purposes. Participants were assured that their responses would remain confidential and that their data would be used solely for academic research purposes.

All qualitative responses were anonymized, and any identifying details were removed prior to analysis to protect participant confidentiality and ensure compliance with data protection standards.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

AA: Conceptualization, data collection, data analysis, and manuscript draft. BB: Data analysis, interpretation of data, and manuscript revision. CC: Conceptualization, data collection, data analysis, and manuscript draft. DD: Data analysis, interpretation of data, and manuscript revision. All authors had approved the final version.

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