

# Generational Divide in AI Adoption for Academic Writing: Evidence from Serbian Social Scientists

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## Abstract

This cross-sectional study examines a generational divide in the adoption of AI for academic writing among academic researchers in Serbia. A survey of 823 social scientists analyzed usage patterns and measured age-related adoption rates through logistic regression analysis. The findings indicate that 27.2% of researchers employ AI for academic writing, with adoption rates varying significantly by age: 42.9% of researchers in their twenties use these tools, compared to 14.3% of those in their sixties. Researchers aged 23-34 were twice as likely to adopt AI writing tools as those aged 49-80. Each additional year of age reduced the odds of AI adoption by 3.8%, even when controlled for academic title, sex and workplace type. This age effect persisted while gender and institutional context showed no significant association with adoption. The significant variation in AI adoption across age groups suggests potential shifts in academia. Senior faculty who avoid AI writing tools cannot effectively mentor graduate students who rely on them. Manuscripts now face inconsistent peer review standards; reviewers familiar with AI-assisted writing apply different criteria than those who reject it entirely. Universities face competing demands: junior researchers insist AI tools help them publish enough to secure tenure, yet senior faculty argue that students who depend on these tools never learn to construct arguments or evaluate evidence independently.

**Keywords:** ChatGPT, diffusion of innovations, knowledge transfer, peer review, digital divide, technology acceptance, publish or perish

## 1 Introduction

The rapid emergence of generative artificial intelligence (AI) tools in late 2022 altered academic writing practices, but we lack systematic evidence about who adopts these technologies and why. While institutional discussions have centered on ethical guidelines, potential misuse, and pedagogical applications (Dabis and Csáki, 2024; Thompson et al., 2023), there is a more basic unanswered question: which researchers actually use AI writing tools, and what explains variation in adoption patterns? Without empirical data on usage patterns and their determinants, institutions cannot develop evidence-based policies to govern AI integration in research practices. Understanding adoption patterns is important for developing evidence-based institutional policies, anticipating shifts in knowledge

production and transfer, and addressing emerging challenges in peer review and scholarly mentorship. This study provides the first systematic quantification of age-related differences in AI adoption among academic researchers, documenting a generational divide with implications for the future of scholarly practice.

Early observations suggest heterogeneity in AI adoption across academic communities. Research shows signs of AI assistance (Glynn, 2024; Tang and Eaton, 2024), reviewer comments reference suspected AI use (Hadan et al., 2024), and author responses to reviews occasionally acknowledge AI tools (Mollaki, 2024). Current debates on AI in academia highlight both enthusiasm and anxiety: some scholars view AI as a tool to enhance efficiency and productivity, while others see it as a threat to creativity and ethical authorship (Thompson et al., 2023; Herman et al., 2024). This tension reflects a broader question of technological adoption, why some groups integrate innovations quickly while others resist them. According to Rogers' (2003) Diffusion of Innovations theory, adoption depends on perceived advantages, compatibility with existing practices, and user characteristics, including age and professional culture. Generational differences may therefore be central to understanding the diffusion of AI tools within academic settings.

Everett Rogers' Diffusion of Innovations Theory (2003), guides this study; it covers idea and technology spread in social systems via adopter traits, innovation features, and context. Dodala sam - Technology adoption research consistently documents age-related patterns: younger individuals adopt innovations earlier due to greater risk tolerance, fewer sunk costs in existing practices, and stronger future orientation (Rogers, 2003; Venkatesh et al., 2003). Rogers' Diffusion of Innovations theory identifies five adopter categories (innovators, early adopters, early majority, late majority, laggards) distributed along a temporal adoption curve. Individual adoption decisions result from the interplay between perceived innovation characteristics—relative advantage, compatibility, complexity, trainability, observability—and adopter characteristics including age, education, and social status. The theory predicts that younger individuals adopt innovations earlier due to greater risk tolerance, fewer sunk costs in existing practices, and stronger future orientation. Applied to academic AI adoption, this framework suggests that younger researchers should perceive greater relative advantage (productivity gains under publish-or-perish pressure), higher compatibility (alignment with digital-native practices), and face lower psychological costs of abandoning traditional writing methods. Our empirical analysis tests whether these predicted patterns manifest as a quantifiable age gradient.

Younger academics see benefits in generative AI for writing, like faster manuscript work, fitting their digital habits and speeding spread. Older groups prioritize fit with ethics and knowledge habits, slowing adoption. Venkatesh et al. (2003) similarly report demographic patterns in technology uptake. Ball and Huang (2023) discuss a “generative AI divide” from gaps in access, skills, and results. Verma et al. (2025) use the theory for AI in academia, noting benefits and ethics in adoption choices. The paper investigates a generational split in AI writing use through early data on adoption.

Despite extensive commentary on AI's potential impacts on academia, empirical research on actual adoption patterns remains scarce. Ball and Huang (2023) theorize a 'generative AI divide' based on gaps in access, skills, and outcomes, but provide limited quantitative evidence. Verma et al. (2025) apply diffusion theory to predict AI adoption in academic research, emphasizing perceived benefits and ethical concerns, but focus on behavioral intentions rather than documented usage. Herman et al. (2024) review literature on AI's impact on early-career researchers, finding abundant speculation but minimal concrete data on tool use. Kim et al. (2025) document faculty and student perceptions of generative AI, revealing disciplinary and gender variation in attitudes, but do not quantify actual adoption rates or test age effects while controlling for career stage.

The literature thus offers theoretical frameworks and attitudinal data, but lacks large-sample empirical studies that: (1) quantify population-level AI adoption rates for academic writing; (2) test for age-related gradients using appropriate statistical controls; and (3) disentangle age effects from career-stage effects (academic rank, institutional position).

Previous studies have described general ethical concerns, plagiarism risks, and the need for new assessment policies (Cuschieri, 2022), while others have documented broad acceptance of AI among

students and early-career researchers (Lund et al., 2023). However, most of this research is either anecdotal or focused on pedagogical contexts rather than scholarly writing practices among academics themselves. Existing literature tends to treat “academics” as a homogeneous group, overlooking how digital competence, workload pressures, and generational attitudes might produce uneven adoption. As a result, there is little quantitative evidence showing how age and professional status influence AI use in academic writing—a gap that limits evidence-based policymaking in higher education.

This study addresses the empirical gap by quantifying AI adoption rates for academic writing among social scientists in Serbia and testing whether age predicts adoption after controlling for career stage and sex. Our specific research questions are: What proportion of academic researchers use AI tools for academic writing? Does researcher age predict AI adoption, and if so, what is the magnitude of this relationship? Does the relationship between age and AI adoption persist after controlling for academic title (career stage) and sex, or is it explained by these factors?

We surveyed 823 social science researchers in Serbia, measuring self-reported AI use for academic writing and fitting logistic regression models to quantify age effects with and without demographic controls.

This study addresses this gap by examining age-related patterns in AI writing tool adoption among social science researchers in Serbia. We pursue three specific objectives: (1) estimate the population-level prevalence of AI writing tool use among academic researchers, (2) quantify the relationship between researcher age and AI adoption, and (3) determine whether this relationship persists after controlling for career stage (academic title) and gender.

The generational divide in AI adoption creates practical problems for academic work. Supervisors who lack AI experience cannot guide students who rely on these tools. Peer reviewers judge manuscripts based on personal views about AI rather than consistent standards. Universities face competing demands: supporting junior researchers who need AI for publication requirements while addressing senior faculty concerns about degraded critical thinking skills. These unresolved conflicts worsen existing structural problems in academia.

The Serbian social science context offers a useful setting to analyze how different generations use AI. In the natural sciences, physical experiments and equipment limits often determine the pace of work. Comparatively, social science output depends more on how fast a scholar can read, process, and write text. Generative AI speeds up these specific tasks. Serbia's social science research community provides a salient context for examining age-related AI adoption. The official statistics show that 75.9% of Serbian social science researchers hold a PhD, whereas only 49.2% of researchers in engineering and technology do so (Statistical Office of the Republic of Serbia, 2025a). In Serbian social sciences, there is little room for those without a PhD, and career survival depends on publishing. Junior researchers face these demands inside a system dominated by older, higher-ranking faculty.

Government data list the median age of social science researchers at 42.4 years (Statistical Office of the Republic of Serbia, 2025a). The rank structure also reflects this as the data from the national database, eNauka (Ministry of Science, Technological Development, and Innovation 2025), records that 50.9% of social science researchers hold senior ranks, such as Senior Research Associate or Associate Professor. Once promoted, lenient re-election criteria reduce publication pressure, reinforcing age-rank correlation. A digital gap worsens this situation. National statistics on the general population from 2025 show a clear generational split in Generative AI usage: 33.4% of individuals aged 25–34 use these tools, compared to only 8.7% of those aged 55–64, dropping to 1.7% in the 65–74 group (Statistical Office of the Republic of Serbia, 2025b, p. 36). While these figures represent the broader population rather than academics specifically, they suggest a national pattern of age-stratified technology adoption that likely extends to academic settings (see also Mitrović, 2025).

Academic rules in Serbia increase this generational strain by combining strict metric requirements with a rigid hierarchy. Since the early 2000s, promotion guidelines have forced academics to prove their international reach. They must meet specific citation counts and publish in journals with impact

factors listed in WoS or Scopus (Rębisz & Lungulov, 2022). Ivanović et al. (2025) describe this as a harsh "publish-or-perish" setting where quantity determines career longevity. Since generative AI directly accelerates text production, it offers junior researchers a way to meet numerical thresholds faster. For early-career staff trying to meet these numbers, AI writing software becomes a necessary tool to stay employed (Ivanović et al., 2025).

This difference causes friction in the institution and affects consistency in peer review and knowledge transfer. While Serbia has adopted a national AI Strategy (Government of the Republic of Serbia, 2020) and Ethical Guidelines (Government of the Republic of Serbia, 2023), these documents address AI governance broadly and do not specifically address AI use in academic research or publishing. No empirical data on AI adoption among Serbian academics exist. This study provides the first evidence.

Serbia's national research database (eNauka) (Ministry of Science, Technological Development, and Innovation, 2025) enabled systematic sampling of the entire population of social scientists, not just a convenience sample. Serbia's academic system faces resource constraints and pressure to publish internationally, which may intensify generational disagreements. Younger researchers may depend on AI for international publication, while senior academics maintain earlier scholarly practices. The evidence provides data for Serbian academic policy and suggests how institutional pressures shape technology adoption in other contexts. Using a large sample of 823 social scientists in Serbia, we estimate population-level use of AI writing tools and examine multiple potential predictors, including age, gender, academic rank, and institutional context.

University leaders face hurdles in developing coherent strategies for responsible AI adoption, since uniform policies overlook divergent generational needs and practices (Tarisayi, 2024). Scholarly discourse has so far focused intensely on ethical guidelines, the potential for misuse, and pedagogical applications. Yet these discussions rarely address a basic question: Who actually uses these tools? Answering this question would help institutions develop appropriate policies. This paper addresses the question: to what extent does a generational divide exist in the adoption of generative AI for academic writing among social scientists in Serbia? By quantifying adoption rates and modeling age effects, we provide early empirical evidence for policy and mentorship challenges in AI-augmented scholarship.

Understanding who adopts AI writing tools has practical importance: university leaders face pressure to develop AI policies, but uniform approaches risk either stifling innovation among early adopters or failing to support faculty uncomfortable with these technologies (Tarisayi, 2024). Evidence on actual usage patterns enables differentiated policy approaches. Second, it addresses a theoretical question in technology diffusion research: while Rogers' (2003) diffusion of innovations theory predicts age-related adoption patterns, the magnitude and persistence of such patterns in academic settings—where institutional structures, reward systems, and professional norms theoretically equalize access and incentives—remains unquantified. Third, age-related adoption differences have structural implications for academic knowledge production. Academia has traditionally relied on apprenticeship models where senior scholars mentor junior colleagues in both explicit techniques and tacit practices (Alavi et al., 2024). When different generational cohorts adopt fundamentally different writing technologies, these knowledge transfer mechanisms face potential disruption, with consequences for scholarly development, peer review consistency, and the reproduction of academic norms.

## **2 Methods and data**

### **2.1 Sampling and recruitment**

We set out to recruit a representative sample of social scientists from Serbia through systematic identification and direct outreach. The recruitment target stemmed from an a priori power analysis for the larger study. This analysis indicated a required minimum of 320 participants to detect a small-to-medium effect size ( $r \approx 0.2$ ) with 80% power at a .05 significance level.

The sampling procedure consisted of three primary sources (Figure 1). First, we extracted publicly available email addresses of 656 active social science researchers listed in the Serbian national research database (eNauka) (Ministry of Science, Technological Development, and Innovation, 2025), which documented 3,454 active social science researchers. Second, we collected publicly available email addresses from institutional websites of social science research organizations in Serbia. Third, we identified Serbian social science researchers who published in Scopus-indexed journals between 2015 and 2024 and extracted their corresponding author email addresses.

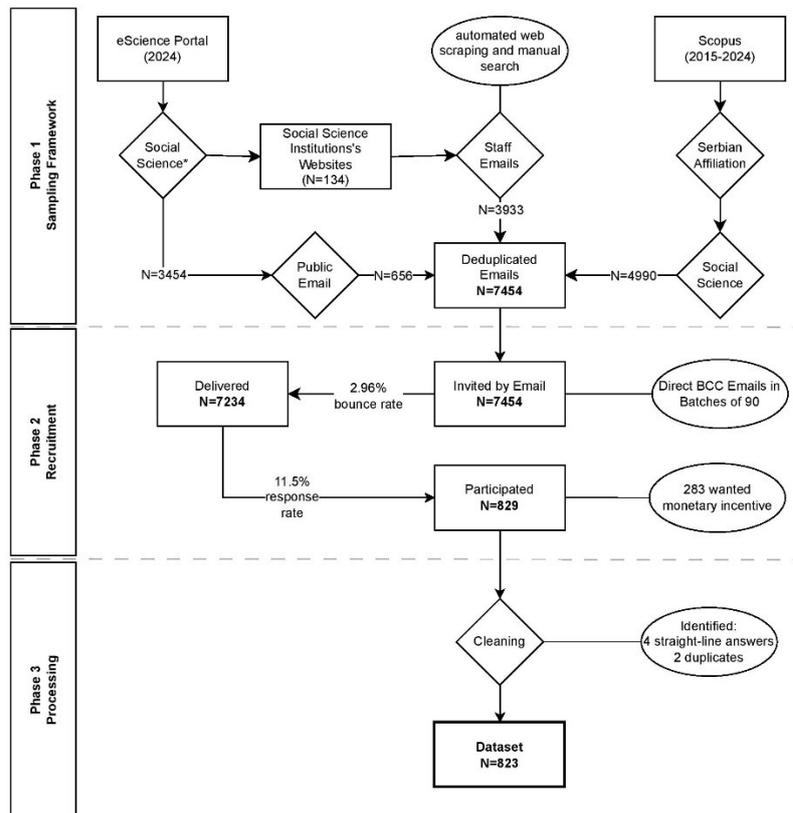


Figure 1. Data collection and cleaning (sampling, recruitment and processing phases)

Using these sources, we obtained 7,454 email addresses, which, after deduplication, resulted in 7,234 unique email addresses. We sent direct email invitations in small batches (90 recipients per batch using BCC) in order to maximize response rates and avoid spam filtering. The recruitment took place over a five-month period (October 2024 - February 2025).

Eligibility was limited to researchers who were either employed by social science institutions in Serbia or had published social science research as identified through our three data sources. Only researchers with valid email addresses who received invitations were eligible to participate.

The survey was administered using LimeSurvey, an open-source survey platform. We conducted a survey pretest by inviting 12 colleagues to complete the survey and provide feedback, with six participants. We have received positive feedback and corrected two typos. The authors also completed the survey as part of the pretest. The mean time to fill out the survey, based on the first eight responses, was 10 minutes.

In total, we surveyed 823 social science researchers in Serbia, achieving an 11.5% response rate.

## 2.2 Sample validation

To assess whether our sample reflects the population of social science researchers in Serbia, we compared our respondents to a list of researchers ( $n = 3,889$ ) obtained from the publicly accessible government portal *eNauka*. From that source we extracted first names and academic titles and inferred sex using the gender R package (Mullen, 2021); for 416 ambiguous cases we used a GPT-4o prompt (details, code and prompt text provided in the R code file in the repository). The authors manually validated both the conventional approach to gendering and the one using GPT-4o, gendered names, and found 7 problematic cases (out of 713 unique names, i.e., 0.98%), which were then corrected. We acknowledge the inherent limitations of this approach. Inferring gender from names is a probabilistic method that cannot capture an individual's gender identity and is restricted to a binary classification. Automated tools may also reflect biases present in their training data. While not perfect, this method provides a basis for comparing the aggregate demographic distributions of our sample against the population.

Only aggregated distributions (sex and academic title) are reported. Chi-square and Kolmogorov–Smirnov tests showed no significant overall difference by academic title ( $\chi^2 = 4.03$ ,  $p = 0.40$ ); separate sex-stratified tests detected modest differences (females:  $\chi^2 = 11.90$ ,  $p = 0.018$ ; males:  $\chi^2 = 14.50$ ,  $p = 0.006$ ; Cramer's  $V = 0.07$ ) (Figure 2). Given that our sample does not deviate significantly from the population and the sensitivity analysis (included in the Supplementary Information), we have decided to report the results without poststratification weighting for the reasons of parsimony and ease of interpretation.

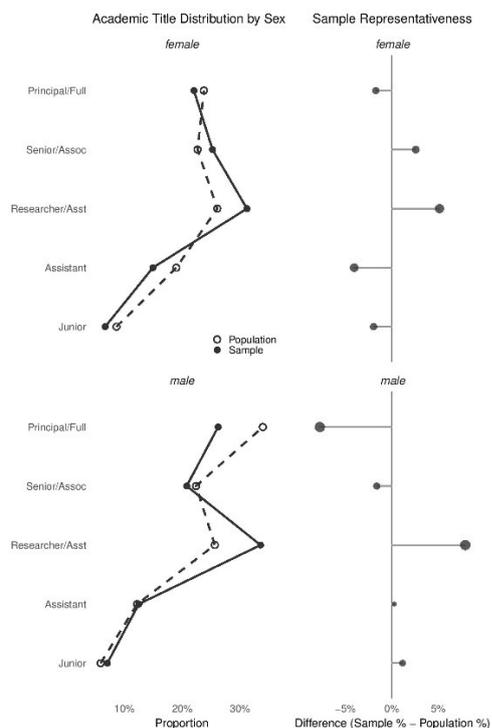


Figure 2. Population vs. sample comparison of academic title distribution by sex

## 2.3 Statistical analysis

Our analytical strategy proceeded in three phases. First, we examined descriptive patterns of AI adoption across age groups to establish whether a generational gradient existed. Second, we used logistic regression to quantify the relationship between age and AI adoption, beginning with a simple bivariate model and progressing to a multivariable model that controlled for career stage (academic title) and sex. This sequential approach allowed us to determine whether observed age differences reflected true generational divides or simply proxy effects of career position or gender. Third, we conducted diagnostic analyses to assess model assumptions and test whether the age-adoption relationship was linear or required more complex functional forms.

The dataset used for this analysis was complete, as the survey items pertaining to AI use, age, sex, and academic title were mandatory for all participants. Therefore, no cases were excluded, and no methods for handling missing data were required.

### 2.3.1 Items, variable definitions, and coding

The data for this study were collected as part of a larger survey on research practices among Serbian social scientists (all items and responses are available in the data repository).

For this study, the dependent variable is a response to the question: *“Do you use or have you used any form of generative artificial intelligence (e.g., ChatGPT) to assist in writing a scientific paper?”* Responses were coded as 1 (Yes) or 0 (No). We chose a broad, inclusive measure of any use rather than frequency or intensity because we wanted to capture the fundamental divide in technology adoption, whether researchers have crossed the threshold to using AI at all, rather than variations in usage patterns among adopters.

Age, as a primary predictor, was measured as a continuous variable in years, calculated from participants' reported birth year. Academic title was measured categorically with six levels reflecting the Serbian academic system: PhD Student (reference category), No Scientific or Research Title, Research Assistant or Teaching Assistant, Research Associate or Assistant Professor, Senior Research Associate or Associate Professor, and Principal Research Fellow or Full Professor. Academic title was included as a covariate because career stage may confound the relationship between age and technology adoption; older researchers tend to hold senior positions that may afford different incentives or constraints regarding AI use. These categories were dummy-coded with PhD Student as the reference group in regression models. Sex was measured categorically with three response options: Female (reference category), Male, and Prefer not to disclose, dummy-coded in the analysis. Sex was included, given documented gender differences in technology adoption patterns in prior literature (Morris & Venkatesh, 2000).

### 2.3.2 Statistical approach

Bivariate associations between AI adoption and demographic/institutional characteristics were first analyzed using Pearson's chi-square tests for categorical predictors (sex, workplace type, academic rank) with the binary outcome (AI use). Since academic rank functions as both nominal and ordinal data, chi-square testing identified differences among ranks, followed by Kruskal-Wallis testing for monotonic trends from junior to senior positions. The Cochran-Armitage test examined linear trends in adoption rates across age groups.

Logistic regression modeled AI adoption probability with the binary dependent variable. Initial bivariate models included age alone, then expanded to incorporate academic title and sex as covariates. This approach separated age effects from potential confounding by career stage and demographics.

Model diagnostics included testing for nonlinear age-adoption relationships using restricted cubic splines (four knots), examining whether the adoption logit changes non-linearly with age. Model comparisons used AIC, BIC, and likelihood ratio tests to evaluate whether covariates improved model fit. Nagelkerke  $R^2$  served as the effect size measure, with its 0-1 scale providing an accessible approximation of variance explained compared to McFadden's  $R^2$ .

### 2.3.3 Software used

We used the programming language R version 4.3.1 (R Core Team, 2023) for all statistical analyses. We used dplyr (Wickham et al., 2023) and tidyr (Wickham et al., 2024) packages for data wrangling, and ggplot2 (Wickham, 2016) together with ggthemes (Arnold, 2024) for visualization. We fitted two logistic regression models: a simple model with age as the sole predictor, and a full model controlling for academic title and sex. Model fit indices were calculated directly in base R. Nagelkerke  $R^2$  was computed with the DescTools package (Signorell, 2024). We estimated confidence intervals with the binom package (Dorai-Raj, 2022), using the Wilson method. To assess whether the association between age and AI writing use was nonlinear, we fit restricted cubic spline logistic regression models with four knots and evaluated nonlinearity using Wald  $\chi^2$  statistics utilizing rms package

(Harrell, 2024). To conduct sensitivity analysis with post-stratification, we used the survey package (Lumley, 2004).

## 2.4 Reproducibility

The questionnaire items in the original language (Serbian) and English, together with all response data and R code used for analysis in this paper, are available at ([anonymized link](#)).

## 2.5 Ethical approval and informed consent

Ethical approval for this research was granted by the Ethics Board of the ANONYMIZED, Republic of Serbia, following their review of the project "ANONYMIZED" (Decision No. 2-19, July 11, 2024). Participants were informed about the purpose and nature of the study at the beginning of the survey and provided their informed consent by checking the appropriate boxes.

## 2.6 Declaration of generative AI

During the preparation of this work, the authors used the Claude Opus 4.1 model in order to generate code for statistical analysis and visualization, Gemini 2.5 Pro for text editing, and the GPT-4o model was used for data processing via API as described in the Methods and data section. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

## 3 Results

Our survey of 823 Serbian social science researchers found that 27.2% (95% CI: 24.3-30.4%) report using AI for academic writing. Table 1 presents adoption rates across multiple demographic and institutional dimensions, revealing substantial variation in AI use patterns.

Table 1 Sample characteristics and AI adoption rates (N = 823)

Dimension	Category	n (%)	AI Users	AI Adoption Rate % (95% CI)
Overall		823 (100.0%)	224	27.2 (24.3-30.4)
Age (mean ± SD)	42.0 ± 10.1	42.0 ± 10.1	—	—
	20-29	84	36	42.9 (32.3-54.0)
	30-39	274	89	32.5 (27.0-38.4)
	40-49	278	67	24.1 (19.2-29.6)
	50-59	139	25	18.0 (12.0-25.4)
	60-69	42	6	14.3 (5.4-28.5)
	70+	5	1	20.0 (0.5-71.6)
Sex	Female	471 (57.2%)	133	28.2 (24.4-32.5)
	Male	349 (42.4%)	91	26.1 (21.7-30.9)
Academic Rank	No Scientific or Research Title	70 (8.5%)	18	25.7 (16.9-37.0)
	Jr. Researcher Assistant/Jr. Teaching Assistant	52 (6.3%)	24	46.2 (33.3-59.5)
	Research Assistant/Teaching Assistant	105 (12.8%)	38	36.2 (27.6-45.7)
	Research Associate/Assistant Professor	242 (29.4%)	59	24.4 (19.4-30.2)
	Sr. Research Associate/Associate Professor	175 (21.3%)	45	25.7 (19.8-32.7)
	Principal Research Fellow/Full Professor	179 (21.7%)	40	22.3 (16.9-29.0)
Workplace	University	494 (60.0%)	130	26.3 (22.6-30.4)

Institute	193 (23.5%)	55	28.5 (22.6-35.2)
Other	136 (16.5%)	39	28.7 (21.7-36.8)

### 3.1 AI adoption across multiple dimensions

Gender differences in AI adoption were minimal, with 28.2% of female researchers and 26.1% of male researchers reporting AI use ( $\chi^2(1) = 0.37, p = .543$ ), suggesting that technology adoption in this context transcends traditional gender divides. Workplace type showed remarkably consistent adoption rates across universities (26.3%), research institutes (28.5%), and other organizations (28.7%), with no significant differences ( $\chi^2(2) = 0.51, p = .775$ ). Academic rank revealed an inverted U-shaped pattern, with junior researchers showing the highest adoption (46.2%) and full professors the lowest (22.3%). While this association was statistically significant ( $\chi^2(5) = 17.09, p = .004$ ), the Kruskal-Wallis test treating rank as ordinal was not significant ( $H = 7.25, p = .123$ ), and our subsequent regression analysis reveals this pattern largely reflects age differences rather than rank-specific effects.

### 3.2 Age as the primary driver of AI adoption

Our results show that 224 out of the 823 researchers surveyed (27.2%, 95% CI: 24.3-30.4%) report using AI for academic writing. Adoption rates showed an age gradient, with usage decreasing from 42.9% among researchers in their 20s to 14.3% among those in their 60s (Cochran-Armitage trend test:  $Z = 4.574, p < .001$ ). The youngest quartile of researchers (ages 23-34) was more than twice as likely to use AI writing tools compared to the oldest quartile (ages 49-80): 37.7% vs. 17.1%,  $\chi^2(3) = 21.96, p < .001$  (Table 1).

Logistic regression showed a statistically significant negative relationship between a researcher's age and their use of AI for academic writing ( $z = -4.581, p < .001$ ). For every year increase in age, the odds of a researcher using AI were lower by 3.8% (OR = 0.962, 95% CI [0.946, 0.978]). Restricted cubic spline analysis showed a strong overall effect of age ( $\chi^2(3) = 24.15, p < 0.0001$ ), but no evidence of a nonlinear component ( $\chi^2(2) = 2.02, p = 0.365$ ). Younger researchers are more likely to use AI tools for writing than their senior colleagues. For example, a 25-year-old researcher has a predicted probability of AI use of approximately 42%, whereas a 65-year-old researcher's probability drops to around 19% (Figure 3). This association was still significant after controlling for sex and academic title ( $z = -3.318, p < .001$ ; see Table 2 and Table 3 for model comparison). Adding controls for academic title and sex did not significantly improve model fit ( $p = .403$ ); both AIC and BIC criteria indicated the simpler age-only model was superior. This means that the age gradient in AI adoption is not explained by career stage, i.e., institutional position. The persistence of age effect after controlling for academic title suggests a generational divide that differences in job security or institutional authority may not fully explain. Different age groups use AI tools differently, regardless of their academic title.

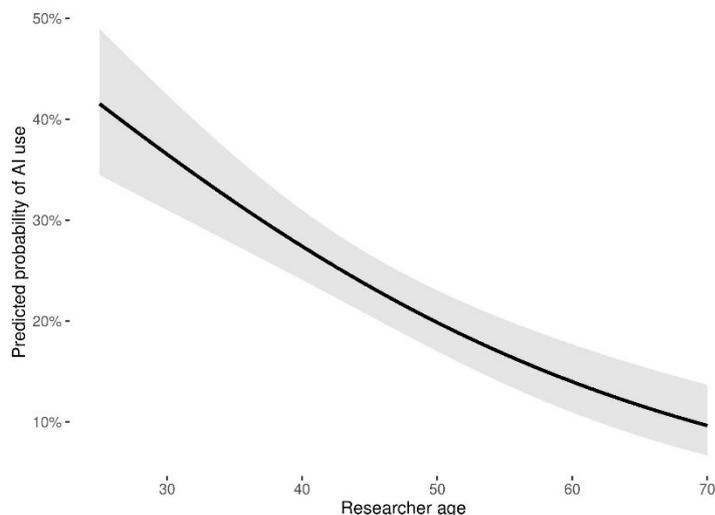


Figure 3. Predicted probability of AI writing tool use by researcher age

Note: The shaded area - 95% CI.

Table 2. Logistic regression models predicting AI use in academic writing

Predictor	Model 1		Model 2		Model 3		Model 4	
	B (SE)	OR [95% CI]						
<b>Intercept</b>	0.615 (0.351)	1.85 [0.93, 3.70]	1.076 (0.458)*	2.93 [1.19, 7.21]	0.593 (0.355)	1.81 [0.90, 3.63]	1.110 (0.474)*	3.03 [1.21, 7.75]
<b>Age</b>	-0.039 (0.008)***	0.96 [0.95, 0.98]	-0.040 (0.012)***	0.96 [0.94, 0.98]	-0.041 (0.008)***	0.96 [0.94, 0.98]	-0.043 (0.012)***	0.96 [0.94, 0.98]
<b>Academic title (ref: Junior Researcher Assistant/Junior Teaching Assistant)</b>								
No Scientific or Research Title	---	---	-0.871 (0.443)*	0.42 [0.17, 0.99]	---	---	-0.871 (0.443)*	0.42 [0.17, 0.99]
Principal Research Fellow/Full Professor	---	---	-0.135 (0.427)	0.87 [0.38, 2.03]	---	---	-0.135 (0.427)	0.87 [0.38, 2.03]
Research Assistant / Teaching Assistant	---	---	-0.291 (0.353)	0.75 [0.37, 1.50]	---	---	-0.291 (0.353)	0.75 [0.37, 1.50]
Research Associate / Assistant Professor	---	---	-0.555 (0.340)	0.57 [0.29, 1.12]	---	---	-0.555 (0.340)	0.57 [0.30, 1.12]
Senior Research Associate /Associate Professor	---	---	-0.261 (0.378)	0.77 [0.37, 1.62]	---	---	-0.261 (0.378)	0.77 [0.37, 1.62]
<b>Sex (ref: Female)</b>								
Male	---	---	-0.088 (0.163)	0.92 [0.66, 1.26]	---	---	-0.088 (0.163)	0.92 [0.66, 1.26]
Prefer not to disclose	---	---	-13.26 (509.53)	0.00 [0.00, ∞]	---	---	-13.26 (509.53)	0.00 [0.00, ∞]
<b>Workplace (ref: University)</b>								
Institute	---	---	---	---	-0.015 (0.198)	0.99 [0.67, 1.45]	-0.019 (0.198)	0.98 [0.66, 1.44]
Other	---	---	---	---	0.369 (0.286)	1.45 [0.82, 2.53]	0.373 (0.286)	1.45 [0.82, 2.53]
<b>Model Fit Statistics</b>								
<b>N</b>	823		823		823		823	
<b>-2 Log Likelihood</b>	941.05		933.80		940.80		931.98	
<b>AIC</b>	945.05		951.80		948.80		953.98	
<b>BIC</b>	954.48		994.22		967.65		1005.83	
<b>Nagelkerke R<sup>2</sup></b>	.039		.052		.040		.055	
<b>Model <math>\chi^2</math> (df)</b>	22.53*** (1)		29.79*** (8)		22.79*** (3)		31.61*** (10)	

Note: B = unstandardized coefficient; SE = standard error; OR = odds ratio; CI = confidence interval; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Model 1: Age only. Model 2: Age + Academic Title + Sex. Model 3: Age + Workplace. Model 4: Age + Academic Title + Sex + Workplace (comprehensive model). \* $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

Table 3. Model comparison

Comparison	$\chi^2$	df	p	$\Delta$ AIC	$\Delta$ BIC
<b>Comparisons to Null Model</b>					
Model 1 vs. Null Model	22.53	1	<.001	-20.53	-15.82
Model 2 vs. Null Model	29.79	8	<.001	-13.53	24.18
Model 3 vs. Null Model	22.76	3	<.001	-16.53	-1.82
Model 4 vs. Null Model	31.62	10	<.001	-11.53	36.18
<b>Pairwise comparisons</b>					
Model 2 vs. Model 1	7.26	7	0.403	7	40
Model 3 vs. Model 1	0.25	2	0.882	4	14
Model 4 vs. Model 2	1.82	2	0.403	2	12
Model 4 vs. Model 3	8.82	7	0.266	5	38

Note: Positive  $\Delta$ AIC and  $\Delta$ BIC values favor the simpler model. The likelihood ratio test comparing Model 2 to Model 1 was not significant ( $p = .403$ ), suggesting that adding current title and sex did not significantly improve model fit despite the significant effect of age in both models.

## 4 Discussion

We found age differences in AI adoption among social scientists; as usage is 42.9% among researchers in their 20s compared to 14.3% among those in their 60s. This fits with how new technology usually spreads (Rogers, 2003), but the size of the gap, even after accounting for career stage (academic title) and gender, points to changes in how academic work gets done and knowledge gets passed between generations.

The rapid global adoption of ChatGPT, reaching 700 million weekly users within three years (Sigalos, 2025), suggests that generative AI diffusion in broader society is occurring quickly. The 27.2% usage rate among surveyed researchers indicates that academic adoption may follow different patterns. The age gradient invites examination of future trends, such as whether younger researchers retain higher usage over time (cohort effect) or adoption rises for all groups (period effect). Generational replacement in academia occurs slowly over decades, but technological diffusion typically happens more rapidly, creating potential tensions in academic practices and knowledge transmission during this transitional period.

Tenured staff may experience less pressure to engage with gen AI tools, while early career and middle career researchers might perceive themselves as facing an adopt-generative-AI-or-perish dilemma, as the users of this technology can easily outcompete them. Young academics facing job insecurity may perceive AI tools as necessary for survival in a system where publication quantity often matters more than quality (Watermeyer et al., 2024). Young academics cannot afford to avoid these tools. The concept of this structural pressure is supported by recent research from Al-Bukhrani et al. (2025). The same authors report that perceived barriers (ethical concerns, high costs, steep learning curves) fail to deter researchers from intending to use AI writing tools, unlike in typical adoption models. When the alternative is to perish professionally, such barriers seem minor in comparison. The pressure to publish may lead early-career researchers to view AI's productivity benefits as essential, causing them to overlook barriers that

might otherwise deter adoption. Another force that is driving this adoption of AI is a monetary incentive for publishers to publish an increasing number of articles, and in the past couple of years, we have witnessed journals publishing articles riddled with obvious signs of AI usage (Glynn, 2024; Tang and Eaton, 2024).

Following Storey's (2025) novice-expert framework, early-career researchers work mostly with explicit, codifiable knowledge that AI can help with: literature reviews, argument refinement, and prose polishing. Senior academics have spent decades building intuitive knowledge: knowing what makes a good argument, spotting theoretical connections, and developing their scholarly voice. For them, AI tools might threaten the expertise that defines their career. These forces reinforce each other. The same pressures pushing younger academics toward AI may be preventing them from developing the deep knowledge their mentors have. Senior academics' investment in traditional practices insulates them from the economic pressures that might otherwise push them toward new tools.

This affects more than individual writing practices. Academic knowledge has traditionally moved through apprenticeship - junior scholars learn both explicit techniques and tacit practices through mentorship (Alavi et al., 2024). When mentors and mentees use different writing technologies, traditional knowledge transfer mechanisms may face challenges. A Supervisor unfamiliar with AI might struggle to guide students who rely on these tools for writing. Students might not understand feedback based on pre-AI ideas about originality and voice. When younger researchers adopt AI writing tools that their senior mentors do not use, these tacit exchanges risk becoming disrupted. This hinders effective knowledge sharing and retention (Costa and Monteiro, 2016; Idrees et al., 2023).

Boyd and Harding (2025) document how students now turn to AI for support traditionally provided by supervisors, creating what they call a "covert third wheel" in supervision. This changes how academic knowledge and norms pass between generations. The apprenticeship model assumes shared practices between mentor and mentee. When this assumption fails, the transmission of experiential knowledge may be affected.

Peer review faces similar problems. Although we have not asked about the use of AI in peer review, the stakes of using AI are much lower than for manuscript preparation. Given that younger researchers accept more review invitations (Bravo et al., 2019; Horta and Santos, 2024) and the age gradient we observed in AI adoption suggests peer review processes may increasingly involve reviewers with divergent approaches to and comfort with these tools, potentially affecting consistency in evaluation standards. Despite calls for strict anti-AI policies in peer review (Mollaki, 2024), and explicit prohibitions from some publishers, we lack evidence about enforcement mechanisms or the actual prevalence of AI use in reviewing. This creates potential inconsistencies: senior reviewers may penalize manuscripts they perceive as lacking a "human touch" (Hadan et al., 2024), while younger reviewers, more comfortable with AI tools based on our findings, may have different thresholds for what constitutes appropriate use. Without clear guidelines and intergenerational dialogue about AI in peer review, evaluation standards risk becoming increasingly inconsistent across reviewer cohorts.

Universal policies face contradictions. Mandating AI use might increase adoption among skeptical senior faculty, but could reduce innovation among early adopters who see mandates as limiting autonomy (Bezrukova et al., 2023). Restrictive policies might preserve traditional practices, but could disadvantage younger researchers competing internationally, where AI use becomes standard.

The challenge runs deeper: institutions must develop frameworks for a technology whose implications remain contested. Senior academics worry about research integrity and the erosion of scholarly craft (Chen et al., 2024). Younger academics might need these tools to manage a system demanding more productivity with fewer resources. Any response must acknowledge both perspectives. Perspectives vary; some believe AI assistance is simply plagiarism (Chomsky, 2023), while others see it as a natural step toward automating research (Lu et al., 2024). This generational reluctance may not stem from a failure to

recognize the technology's power, but from a more complex tension; one study on faculty adoption found that higher perceived usefulness of GenAI can paradoxically lead to more negative attitudes, likely due to concerns that the tools threaten academic integrity and established pedagogical roles (Tony, 2025).

The generational divide in AI adoption that exists globally (Dorta-González et al., 2024) is not a simple resistance or inevitable progress. It shows tensions in how academia produces and validates knowledge.

#### 4.1 Implications for Academic Writing Quality

The generational divide in AI adoption raises questions about the future quality and character of academic writing. The relationship between AI use and writing quality is more complex than simple dichotomies of 'authentic' versus 'artificial' suggest. AI tools may improve surface-level features—grammatical correctness, sentence clarity, organizational coherence, while potentially undermining deeper intellectual work. Capraro et al. (2024) suggest these tools could democratize academic writing by reducing barriers for non-native English speakers and researchers at under-resourced institutions.

This tension between productivity and depth, between access and expertise, between efficiency and intellectual growth, defines the quality paradox at the heart of AI adoption debates. What constitutes 'quality' may itself be generationally contested. Younger researchers who have integrated AI tools into their workflows may develop different standards for evaluating writing, perhaps valuing clarity and efficiency over stylistic distinctiveness—while senior scholars maintain fidelity to traditional markers of scholarly voice and originality. The emergence of such divergent quality standards would fundamentally alter how academic communities evaluate and validate knowledge claims.

The generational gap has implications for writing quality and scholarly communication. Early-career researchers' reliance on AI for efficiency may alter conventions of voice and argumentation, while senior mentors' skepticism can hinder alignment in writing standards. Institutions should therefore integrate AI literacy into mentorship frameworks to preserve productivity. We note the tension between productivity gains and concerns about "industrialization" of academic writing, as AI tools can be used for surface-level polish (grammar, clarity) and also for deeper intellectual work (argumentation, theoretical synthesis).

The technology that could democratize academic writing by lowering barriers (Capraro et al., 2024) might also erode the experiential knowledge that has defined scholarly expertise. While AI helps early-career researchers manage workload pressures, it may prevent them from developing necessary scholarly skills. This pattern is symptomatic of what recent literature reviews term "intergenerational digital tensions," a dynamic where younger generations act as early adopters while their older colleagues exhibit more caution (Umar Baki and Mohd Yusri, 2025). The generational divide exists alongside other significant demographic cleavages in AI adoption. A large-scale survey by Kim et al. (2025) revealed that attitudes toward generative AI also vary significantly by academic discipline and gender, with male students in STEM fields showing the most positive attitudes and highest adoption rates, while female students in non-STEM fields were the least likely to embrace the technology. This trend has serious consequences for the educational research community and universities. This gap may be an example of what Ma et al. (2024) refer to as a "learning divide" or a "belief trap," where older users are slower to change their minds and may abandon the technology after a single negative experience. The disparity may stem from differing perceptions of the technology's utility and trustworthiness (Shata and Hartley, 2025), factors that are themselves built on deeper cognitive perceptions and emotional responses that shape the human-AI relationship (Bao et al., 2021). This pattern aligns with foundational research on technology adoption, which established that younger users are often driven by personal attitudes about a technology's benefits, while older users weigh social pressures and ease of use more heavily (Morris and Venkatesh, 2000).

Senior academics need support in understanding not just how to use AI tools but why their junior colleagues find them necessary. Early-career researchers need opportunities to develop tacit knowledge that AI cannot provide, even while using these tools for survival. We need knowledge transfer methods

that bridge technological differences, such as hybrid mentorship models that address both AI-augmented and traditional practices.

## 4.2 Policy implications

The generational divide in AI adoption documented here might reflect asymmetric institutional pressures rather than differential technological competence. Junior researchers may be adopting AI tools primarily because publish-or-perish demands leave them little choice, not because they prefer algorithmic assistance over traditional scholarly practices. This reframes the policy challenge: institutions cannot address AI adoption without confronting the underlying labor conditions that compel its use. Policies targeting AI use while ignoring workload pressures and publication metrics will either fail or drive usage underground, particularly given the practical impossibility of reliably detecting AI-generated text after human editing. Senior faculty resistance similarly reflects rational calculation; established scholars face neither the productivity pressures nor the precarity that make AI adoption necessary for survival. Any institutional response must acknowledge these differential stakes. Universal policies mandating either adoption or prohibition will inevitably harm one cohort: restrictions disadvantage junior researchers competing internationally, while an uncritical embrace undermines quality standards and marginalizes senior expertise in evaluation processes.

The breakdown of shared methodological practices creates an institutional design problem. Traditional knowledge transmission through apprenticeship fails when mentors and mentees use incompatible tools, risking permanent loss of tacit scholarly expertise before it can be codified or transferred. Peer review faces similar fragmentation when evaluators apply inconsistent standards based on their own relationship to AI tools rather than explicit criteria. Institutions have perhaps 5-10 years before demographic replacement and technology diffusion make AI-augmented practice the default, potentially without quality controls being formalized. This temporal constraint demands that policymakers abandon the search for optimal AI policy and instead develop governance structures capable of accommodating methodologically pluralistic practices. Specifically, institutions need: explicit guidelines for AI use in peer review that separate tool usage from evaluation standards; hybrid mentorship models that preserve tacit knowledge transmission while acknowledging new writing technologies; and transparent criteria for assessing scholarly contribution that remain valid regardless of production methods. The core challenge is not managing a technology, but maintaining epistemic standards when institutional pressures fracture the methodological consensus that academic evaluation has historically assumed.

## 5 Limitations

The data used for this study are self-reported, cross-sectional, and specific to social scientists in Serbia. Our yes/no measure does not show how researchers use AI for different writing tasks; future research should explore this in detail. Response rate of 11.5%, while consistent with cold email recruitment outcomes documented in the literature (Vehovar and Manfreda, 2008), is low and may indicate some non-response bias beyond the demographic variables that the sample response was assessed. Because the survey was framed as investigating mentorship and research practices broadly, with no indication of AI-related content, respondents could not have self-selected based on their AI attitudes or experience. This reduces concerns that the AI usage rates or age differences we observed were inflated by differential participation.

As with all surveys, there is a danger of social desirability bias. The effect of this bias on self-reported AI use may differ between age groups. Older researchers could face greater stigma for admitting to AI assistance because of their established expertise, whereas younger researchers may find such tools more aligned with professional standards.

Our analysis did not differentiate by sub-discipline within the social sciences (due to data limitations), which may also influence adoption patterns. While our study demonstrates that age strongly predicts AI use, but other individual factors like personality, technostress, and self-efficacy also matter (Symasek et

al., 2025). Future research could explore trends in other national and disciplinary contexts and use longitudinal designs to track adoption over time. While identifying AI-generated text is becoming very difficult and unreliable due to false positives, future research could combine bibliometric analysis of published research between 2023 and 2025 with self-reported data.

## 6 Conclusion

This study presents the first systematic evidence of a generational gap in AI use among Serbian social scientists; younger researchers are 2.5 times more likely to employ these tools than their older colleagues. Whether this difference signals a temporary adoption trend or a long-term division in academic work is an open question.

The trend of a growing number of journals and journal articles, and questions of quality vs quantity, existed well before the generative AI boom (Goel and Faria, 2007; Onwuegbuzie and Poth, 2016). The capabilities of generative AI seem like a “perfect” way to deal with the pressures of publish-or-perish, especially to young researchers who are both more exposed to publish-or-perish and more likely to adopt new technology. These factors may help explain why younger researchers report higher adoption rates in our sample.

Institutions might be tempted to respond with restrictive policies, but accurate detection of AI-generated text remains unreliable, especially after human editing (Matsubara, 2025; Yu et al., 2023), making punitive approaches both impractical and likely to drive usage further underground.

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