sociological science

Supplement to:

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A. Sampling Strategy, Sample Statistics, Recruitment Materials

To build our sampling frame we collected all articles published in 50 sociology journals (see Table A.2) in the last 5 years (2021-2026)[1] from the Clarivate Web of Science (WoS) database. This yielded a total of roughly 21,000 authors. Note that we include both sociologists (in title) and their collaborators. We randomly sampled 4,000 authors. To contact the authors, we combined the email addresses from the WoS records with manually searching for addresses posted publicly on faculty pages or connected to their other publications. Where an email "bounced" (i.e., rejected by the receiving server), we made one attempt to find an accurate address and resend the email. This resulted in a total of 3,425 authors receiving an invitation to complete the survey. We began fielding the survey at the end of April 2026, and continued until the beginning of July 2026. We dropped respondents who started the survey but did not complete it. We also filtered out cases where the survey was taken in less than four minutes, which did not appear realistic given the number of questions. One unavoidable limitation of the sampling strategy is that important characteristics of individual authors may correlate with a missing email address. Nevertheless, the distribution of our sociodemographic variables, career status, methods preferences, country of residence, and subfield suggests that our sample includes scholars from diverse segments of the discipline – see Table A.1 for descriptive statistics on the final respondents.

[1] As of May 2, 2026.

Table A.1: Descriptive Statistics

Variable	Level	N	%
Identifies as sociologist		259	86.3%
Resides in North America		158	56.4%
English first language		193	64.8%
Age	25-34 years old	58	19.3%
	35-44 years old	109	36.3%
	45-54 years old	90	30%
	55-64 years old	27	9%
	65+ years old	16	5.3%
Tenured		126	44.5%
Identifies as white		223	75.3%
Gender	Man	149	49.8%
	Other	150	50.2%
Methods typically used	Mixed-Methods	92	30.8%
	Qualitative	85	28.4%
	Quantitative	122	40.8%
Use frequency	Never	69	23%
	At least once	62	20.7%
	At least monthly	69	23%
	At least weekly	64	21.3%
	Daily	36	12%

Note: The table shows the statistics of our sample of 300 sociologists and their collaborators. Percentages are based on observations without missing values for the respective variable.

Below, we present the email we sent to the authors we sampled.

Dear [FIRST NAME] [LAST NAME],

We hope this email finds you well. We are writing to invite you to participate in a brief survey on the ethics of generative AI (GenAI) use in sociological research.

In a previous round of our survey, the results of which were published in Sociological Science, we found that many sociologists have adopted GenAI in their research practices, but that there is also considerable concern about its impact on the discipline. In the current survey, we aim to better understand what kinds of GenAI use sociologists consider acceptable and under what circumstances. By participating, you will shape discussions on generative AI in sociology and help us understand its role in the sociological toolkit. You do not need to be a sociologist to participate.

Most people take between 5 and 10 minutes to complete the survey. To take this survey, please follow this personalized link: [LINK]. If you prefer to take part anonymously, please use this link: [LINK]

Thank you for considering taking part in our survey. Please don't hesitate to contact us if you have any questions.

Table A.2 lists the 50 sociology journals that were used to identify the authors in our sampling frame.

Table A.2: 50 Journals Used to Sample Authors

Acta Sociologica	*Social Currents*
American Journal of Cultural Sociology	*Social Forces*
American Journal of Sociology	*Social Networks*
American Sociological Review	*Social Problems*
Annual Review of Sociology	*Social Psychology Quarterly*
British Journal of Sociology	*Social Science Research*
City & Community	*Society and Mental Health*
Criminology	*Socio-Economic Review*
Cultural Sociology	*Sociological Forum*
Current Sociology	*Sociological Inquiry*
Demography	*Sociological Methodology*
Environmental Sociology	*Sociological Methods and Research*
Ethnic and Racial Studies	*Sociological Perspectives*
European Sociological Review	*Sociological Science*
Gender & Society	*Sociological Theory*
International Journal of Sociology	*Sociology*
Journal for the Scientific Study of Religion	*Sociology Compass*
Journal of Health and Social Behavior	*Sociology of Education*
Journal of Marriage and Family	*Sociology of Health & Illness*
Journal of Mathematical Sociology	*Sociology of Race and Ethnicity*
Poetics	*Sociology of Religion*
Rationality and Society	*Socius*
Rural Sociology	*Symbolic Interaction*
Sexualities	*Work and Occupations*
Social Compass	*Work Employment and Society*

B. Survey Excerpts and Information

The following information was shown to respondents before they were asked to answer any questions about GenAI.

> For the sake of this survey, we use GenAI to refer to generative models that produce content (e.g., GPT-5), as well as specific applications or platforms built on top of them (e.g., ChatGPT). There is a wide variation in how GenAI might be used in sociological research. We aim to find out what kinds of GenAI use you consider acceptable and under what circumstances.

Subsequently, we gave respondents the following instruction for responding to the first three scenarios about using GenAI for ideation and literature research. Instructions were formulated analogously for subsequent scenarios on data collection and analysis, writing, and peer review.

> Below, we present a series of scenarios for the use of GenAI for developing ideas and reviewing literature. For each, indicate whether you think the use is ethically acceptable and whether acceptability requires disclosure of GenAI use in resulting publications or presentations.

The item wordings for the scenarios are documented in Table 1 in the main text. All other item wordings are accessible together with the data in the data repository at https://doi.org/10.7910/DVN/HNK0SO (Stuhler et al. 2026).

C. Item Correlation and Scale Construction

In Panel A of Figure C.1 we present the Pearson correlations between the 19 scenario items. Responses are encoded as continuous, assigning 0 for *generally not acceptable*, 1 for *acceptable if disclosed*, and 2 for *acceptable without disclosure*. We find that most items are strongly correlated, with an average correlation of 0.39. The only two items that are more weakly correlated with the others are those that are rejected by the vast majority of sociologists: using GenAI to interview subjects without telling them and using GenAI to write initial drafts of reviews.

To explore the dimensionality, we perform a principal component analysis on the complete cases (N = 216). The resulting scree plot (Panel B of Figure C.1) suggests that the first dimension captures 45.1% of the total variance, with the subsequent two dimensions accounting for 7.3% and 5.7%, respectively. As we mention in the main manuscript, with our relatively small sample size, the share of variance accounted for by the first dimension is likely to be inflated and the true factor structure in the population is likely to be less clearly unidimensional than our data suggest. Still, these results point to there being a single dimension (GenAI acceptance) that captures much of the variation in these data.

As an additional validation check, we extract this factor by conducting a confirmatory factor analysis. While the category *don't know/can't tell* was chosen only 3.3% of the time, 28% of respondents selected this category at least once. To generate factor estimates for respondents with some missing responses, we use Full Information Maximum Likelihood estimation. In Table C.1 we report the loadings of each of our 19 items. We find that the resulting factor scores are almost perfectly correlated with the average-based measure shown in Figure 2 of the main text ($r = 0.99$), which is unsurprising given the large number of items and the strong correlations between them. In light of this, we decided to go with the less complex measure for our main analyses.

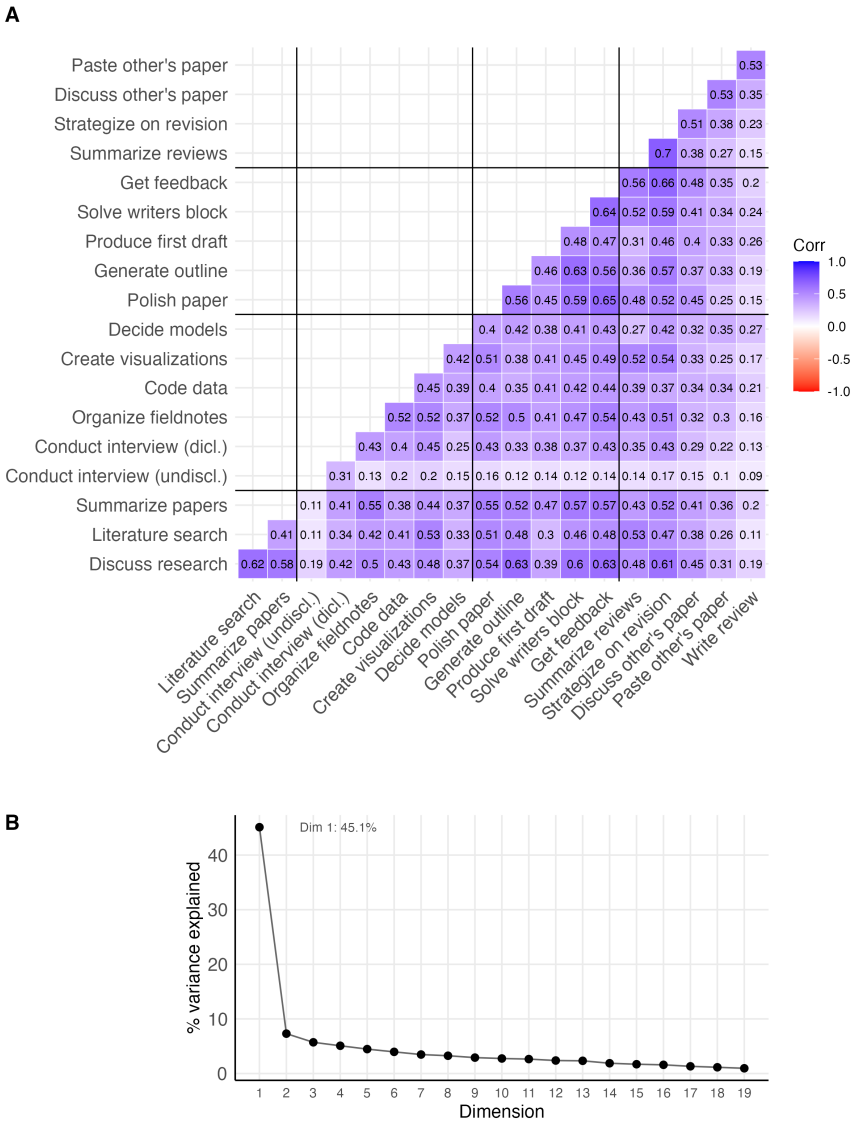


Figure C.1: Correlation of scenario items and dimensionality.

Note: Panel A shows the Pearson correlation between the 19 scenario items, using pairwise-complete observations. Panel B shows the scree plot of a principal component analysis fit on 19 items and based on cases without missing values ($N = 216$). Items were scaled to unit variance. For both plots, responses were encoded as continuous, assigning 0 for *generally not acceptable*, 1 for *acceptable if disclosed*, and 2 for *acceptable without disclosure*.

Table C.1: Standardized factor loadings for confirmatory factor analysis

Item	Loading	SE	p	Missing rate
Get feedback	0.797	0.027	<0.01	0.057
Strategize on revision	0.780	0.027	<0.01	0.040
Discuss research	0.769	0.028	<0.01	0.013
Solve writer's block	0.754	0.032	<0.01	0.063
Polish paper	0.739	0.032	<0.01	0.017
Summarize papers	0.714	0.030	<0.01	0.030
Generate outline	0.707	0.034	<0.01	0.030
Organize fieldnotes	0.674	0.036	<0.01	0.043
Summarize reviews	0.666	0.040	<0.01	0.027
Create visualizations	0.660	0.040	<0.01	0.053
Literature search	0.652	0.040	<0.01	0.007
Produce first draft	0.600	0.035	<0.01	0.040
Discuss other's paper	0.589	0.040	<0.01	0.040
Code data	0.574	0.039	<0.01	0.033
Conduct interview (discl.)	0.551	0.044	<0.01	0.033
Decide models	0.537	0.042	<0.01	0.047
Paste other's paper	0.476	0.039	<0.01	0.037
Write review	0.303	0.047	<0.01	0.037
Conduct interview (undiscl.)	0.221	0.043	<0.01	0.003

D. Regression Models and Correlations

Table D.1: OLS regressions predicting standardized GenAI acceptance.

	Dependent variable: GenAI acceptance						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Identifies as sociologist	−0.211	−0.225	−0.268	−0.184	−0.168	−0.195	−0.193
	(0.166)	(0.166)	(0.170)	(0.164)	(0.162)	(0.164)	(0.163)
Man	0.408†	0.399†	0.443†	0.327†	0.294*	0.315†	0.305*
	(0.116)	(0.116)	(0.117)	(0.117)	(0.116)	(0.119)	(0.118)
White	−0.041	−0.050	0.027	−0.064	−0.007	−0.086	−0.033
	(0.134)	(0.133)	(0.140)	(0.136)	(0.136)	(0.136)	(0.137)
Age (in decades)	−0.071			0.018	0.012	−0.026	−0.024
	(0.054)			(0.061)	(0.060)	(0.064)	(0.064)
35-44 years (vs 25-34)		−0.065					
		(0.160)					
45-54 years		−0.169					
		(0.166)					
55-64 years		−0.530*					
		(0.232)					
65+ years		0.063					
		(0.281)					
Tenured			−0.248*	−0.220	−0.192	−0.169	−0.155
			(0.120)	(0.132)	(0.131)	(0.137)	(0.136)
Qualitative methods				−0.349*	−0.349*	−0.430†	−0.395†
				(0.147)	(0.145)	(0.149)	(0.149)
Quantitative methods				0.373†	0.335*	0.291*	0.290*
				(0.139)	(0.138)	(0.142)	(0.141)
English first language					−0.353†		−0.314*
					(0.121)		(0.149)
Resides in North America						−0.265*	−0.094
						(0.117)	(0.142)
Constant	0.328	0.154	0.097	0.013	0.236	0.446	0.491
	(0.288)	(0.223)	(0.197)	(0.316)	(0.321)	(0.342)	(0.340)
Observations	296	296	280	279	279	269	269
R^2	0.047	0.062	0.067	0.149	0.175	0.170	0.184
Note:	*p<0.05; †p<0.01; no respondents aged 18-24.						

Table D.2: Correlations among independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Man	1.00									
(2) White	0.04	1.00								
(3) Age	0.16	0.12	1.00							
(4) Tenured	0.05	0.21	0.50	1.00						
(5) English first language	−0.12	0.14	0.02	0.10	1.00					
(6) Resides in North America	−0.16	0.03	−0.03	0.05	0.59	1.00				
(7) Qualitative methods	−0.11	−0.10	−0.02	−0.03	0.04	−0.09	1.00			
(8) Quantitative methods	0.19	0.09	−0.16	−0.07	−0.13	−0.08	−0.52	1.00		
(9) Mixed-methods	−0.10	0.00	0.18	0.11	0.10	0.18	−0.42	−0.55	1.00	
(10) Sociologist	0.07	0.00	0.01	0.00	0.03	0.02	0.08	−0.08	0.01	1.00

E. Predicting GenAI Acceptance by Research Stage

In Figure E.1 we compare the effects of researcher characteristics on GenAI acceptance by research stage. For this, we constructed GenAI acceptance scales for each of our four dimensions separately, using the same coding and averaging approach as we did for our general measure. We then fit separate OLS regression models on these scales, which are documented in Table E.1. One point worth highlighting is that the scales for the dimensions are based on fewer items. For instance, the scale for GenAI acceptance for literature review and ideation is based on only three items. This leads to noisier measures and is likely a reason why effects in these models tend to be smaller than in the main model. Generally, the models do not point to any *stark* differences in the effects between dimensions. This does of course not preclude, however, that differences could be found with more items and statistical power.

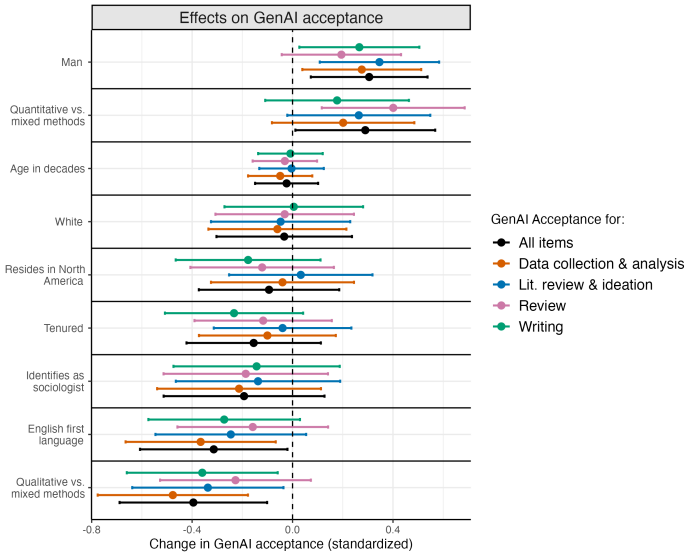


Figure E.1: Predictors of GenAI acceptance by research stage.

Note: The figure shows the effects of the full model's covariates on GenAI acceptance with 95% confidence intervals. The black error bars correspond to the full model in Table D.1 that provides the basis for Panel A of Figure 3 of the main text. The other bars show the effects on GenAI acceptance by research stage, which are based on OLS regressions documented in Table E.1.

Table E.1: OLS regressions predicting GenAI acceptance by research stage.

	Dependent variable				
	All items	Lit. review and ideation	Data collection and analysis	Writing	Review
	(1)	(2)	(3)	(4)	(5)
Identifies as sociologist	−0.193	−0.138	−0.213	−0.143	−0.186
	(0.163)	(0.166)	(0.166)	(0.168)	(0.166)
Man	0.305*	0.346†	0.276*	0.266*	0.194
	(0.118)	(0.121)	(0.120)	(0.121)	(0.121)
White	−0.033	−0.048	−0.060	0.005	−0.031
	(0.137)	(0.141)	(0.140)	(0.140)	(0.140)
Age (in decades)	−0.024	−0.004	−0.049	−0.008	−0.031
	(0.064)	(0.065)	(0.065)	(0.065)	(0.065)
Tenured	−0.155	−0.040	−0.100	−0.233	−0.117
	(0.136)	(0.139)	(0.138)	(0.140)	(0.139)
Qualitative methods	−0.395†	−0.337*	−0.477†	−0.360*	−0.227
	(0.149)	(0.153)	(0.152)	(0.153)	(0.152)
Quantitative methods	0.290*	0.264	0.201	0.177	0.401†
	(0.141)	(0.145)	(0.144)	(0.145)	(0.144)
English first language	−0.314*	−0.246	−0.366*	−0.272	−0.158
	(0.149)	(0.152)	(0.152)	(0.153)	(0.152)
Resides in North America	−0.094	0.033	−0.040	−0.177	−0.121
	(0.142)	(0.145)	(0.145)	(0.146)	(0.145)
Constant	0.491	0.168	0.686*	0.459	0.377
	(0.340)	(0.347)	(0.346)	(0.350)	(0.347)
Observations	269	268	269	267	269
R^2	0.184	0.136	0.174	0.148	0.134

Note: *p<0.05; †p<0.01

F. Predicting GenAI Acceptance by Use Frequency

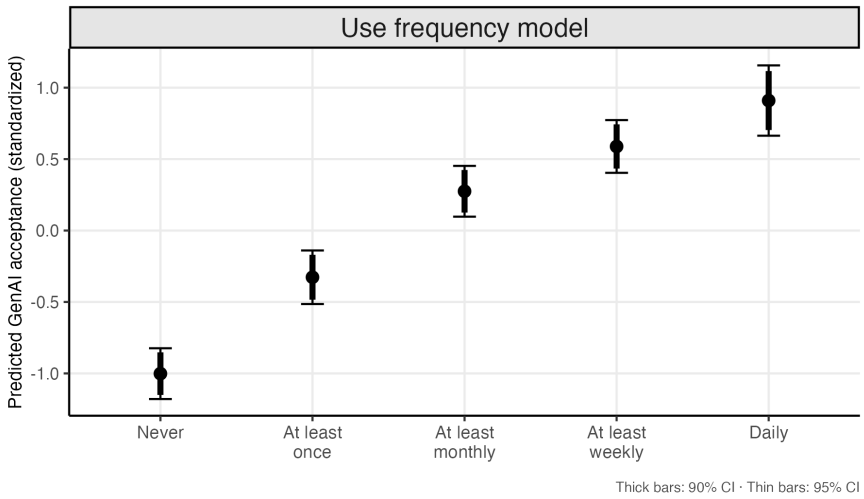


Figure F.1: Predict GenAI acceptance by use frequency.

Note: The figure shows the predicted GenAI acceptance score for the levels of a categorical measure of use frequency. These stem from an OLS regression with use frequency as the sole predictor ($N = 300$, $R^2 = 0.44$), documented in Table F.1.

Table F.1: GenAI acceptance by use frequency.

	Dependent variable: GenAI acceptance
Never	$-1.002^{\dagger}$
	(0.090)
At least once	$-0.327^{\dagger}$
	(0.095)
At least monthly	$0.275^{\dagger}$
	(0.090)
At least weekly	$0.588^{\dagger}$
	(0.094)
Daily	$0.910^{\dagger}$
	(0.125)
Observations	300
R^2	0.445

Note: *p<0.05; †p<0.01
Model without intercept (as shown in Figure F.1). Coefficients are group means of standardized GenAI acceptance. Stars test difference from zero.

G. Perceived Usefulness of GenAI

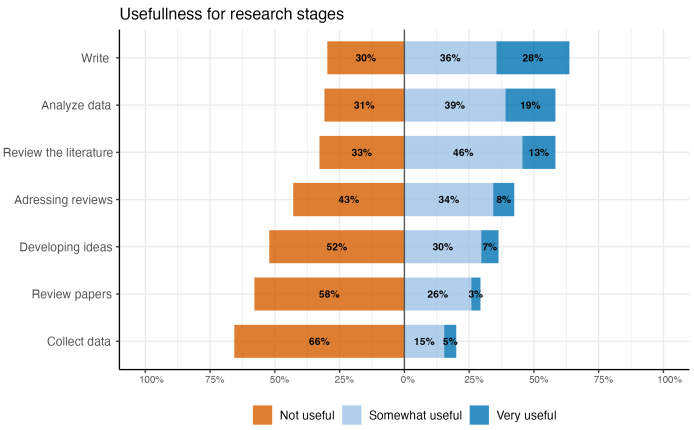


Figure G.1: Perceived usefulness of GenAI.

Note: Respondents were asked how useful GenAI tools are for each research task. The figure is based on responses by those identifying as sociologists ($N = 259$). Items offered a "don't know/can't tell" response, which is reflected in the percentages.

H. Conditions of Using GenAI

We asked respondents the following question: "There are different types of GenAI models and ways to use GenAI tools. In your opinion, how important are the following for making the use of GenAI more acceptable for research purposes?" Respondents were offered the following response options:

- Not important
- Somewhat important
- Very important
- GenAI use in research is unacceptable, regardless of model properties
- Don't know / can't tell

In Figure H.1, we show the distribution of responses for the six different conditions we asked about.

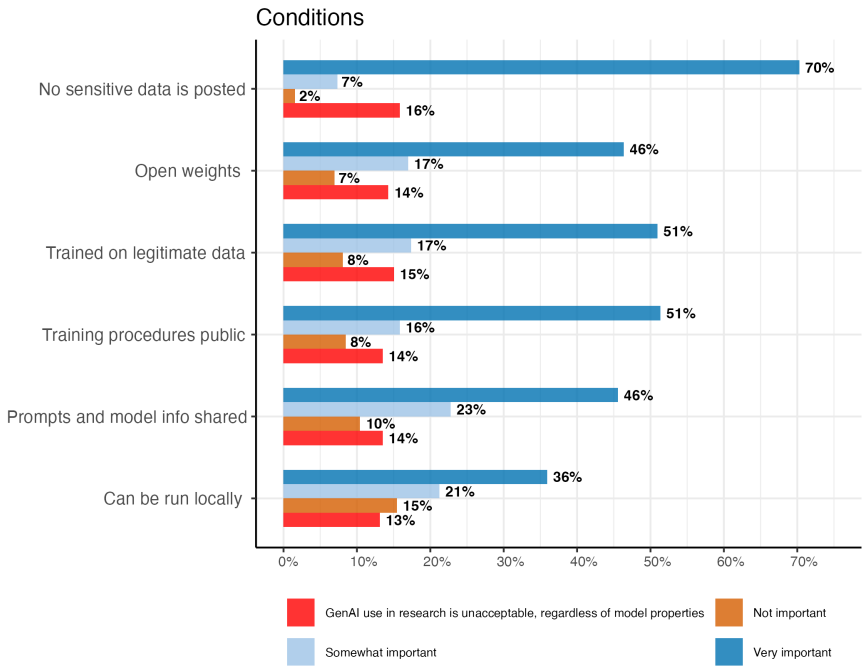


Figure H.1: GenAI acceptability and conditions.

Note: The figure shows the respondents' views on the importance of different conditions for making GenAI use acceptable.

I. GenAI Adoption Within Sociology Over Time

In early 2025, Alvero et al. (2026) fielded a survey contacting authors of papers published in the same 50 sociology journals we use for the present study. In that study, there were 311 self-identified sociologists, but the study included an oversample of "computational" scholars.[2] To make a time-trend analysis between those data[3] and the current study data, we used rake weights to force the weighted proportional distribution of the sample from which the respondent was chosen—the general sample versus the computational oversample—to match the equivalent distribution in the Alvero et al. (2026) sampling frame (5% for the computational subsample and 95% for the general sample). In Figure I.1, we make two comparisons: *unweighted* 2025 use frequency levels compared to use frequency levels in our present study (2026), and *weighted* 2025 use frequency levels compared to 2026 use frequency levels. Our present study (2026) does not include an oversample and therefore is not weighted.

The left panel of Figure I.1 shows the 2026 and 2025 use level estimates. The estimates from 2025 to 2026 are remarkably similar—especially the weighted 2025 estimates. We formally test the difference in each use level's estimates between 2025 and 2026 using a series of bivariate logistic regressions. We merged the 2025 and 2026 data, created a new binary variable for each use case where 1 = the respondent chose that use level and 0 = otherwise, and regressed that variable on a variable capturing whether the response was from 2025 or 2026.[4] We then computed the average marginal effect (AME) on the predicted probability scale for each regression. The AMEs are visualized as a coefficient plot in the right panel of Figure I.1. None of the contrasts are statistically significant; each set of confidence intervals overlap zero.

All together, there are only minor differences in use frequency levels between 2025 and 2026 regardless of weighting.

[2] See Alvero et al. (2026) for more details on the sampling strategy.

[3] Available on Harvard Dataverse (Alvero et al. 2025).

[4] We used simple bivariate logistic regression for testing differences between estimates. We used survey-weighted logistic regression (Lumley 2010) to test differences between 2026 and the weighted 2025 estimates, setting the weight for all 2026 responses to 1.

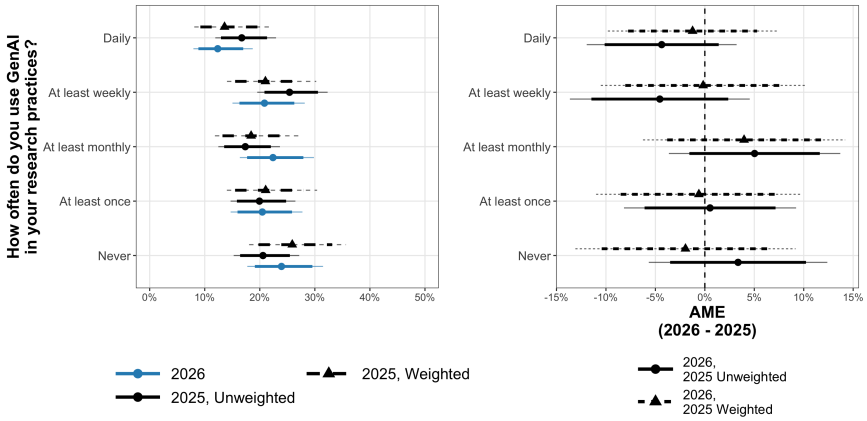


Figure I.1: Comparing use frequency levels between 2025 and 2026.

Note: Solid lines are 95% confidence intervals. Dashed lines are 99% confidence intervals.

J. Journal Policies

To assess how and whether sociology journals currently regulate AI use, we examined the websites of the 50 sociology journals we used to sample our respondents (as of July 28, 2026). For each journal, we assigned one of the following four codes:

- **No statement** (42%): The journal's website does not make any statements about AI use.
- **Publisher's policy** (14%): The journal's website does not make any statements about the permissibility of AI use or on how AI use should be disclosed, but refers to the publisher's policy on AI.
- **Publisher's policy, no AI coauthorship** (8%): The journal's website states that AI cannot be a coauthor but refers to the publisher's policy on AI for anything beyond that.
- **AI statement** (36%): The journal's website makes at least one explicit statement about either the permissibility of AI use, or on how AI use should be disclosed. In addition, they may refer to the publisher's policy.

Our results are listed in Table J.1. We find that currently, most journals do not explicitly mention AI use on their websites (42%). Meanwhile, about a third (36%) have statements about the permissibility of AI use or on how to disclose it. We should highlight, however, that of these, only few journals had very detailed rules. 22% of the journals we surveyed do not state any principles on AI use but refer to their publisher's policy.

Table J.1: Journals by AI policy

Journal	**Publisher**
No Statement	
American Journal of Cultural Sociology	Palgrave/Springer Nature
American Journal of Sociology	Chicago
American Sociological Review	SAGE
British Journal of Sociology	Wiley
City & Community	SAGE
Criminology	Wiley
European Sociological Review	Oxford
Journal of Health and Social Behavior	SAGE
Social Problems	Oxford
Social Psychology Quarterly	SAGE
Society and Mental Health	SAGE
Socio-Economic Review	Oxford
Sociological Methodology	SAGE
Sociological Perspectives	SAGE

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Table J.1 – continued from previous page

Journal	Publisher
Sociological Science	Scholastica
Sociological Theory	SAGE
Sociology	SAGE
Sociology of Education	SAGE
Sociology of Religion	Oxford
Socius	SAGE
Work Employment and Society	SAGE
Publisher's Policy, No AI Coauthorship	
Cultural Sociology	SAGE
Current Sociology	SAGE
Social Currents	SAGE
Sociology of Race and Ethnicity	SAGE
Publisher's Policy	
Acta Sociologica	SAGE
Annual Review of Sociology	Annual Reviews
Journal of Mathematical Sociology	Taylor and Francis
Rationality and Society	SAGE
Sexualities	SAGE
Social Compass	SAGE
Work and Occupations	SAGE
AI Statement	
Demography	Duke
Environmental Sociology	Taylor and Francis
Ethnic and Racial Studies	Taylor and Francis
Gender & Society	SAGE
International Journal of Sociology	Taylor and Francis
Journal for the Scientific Study of Religion	Wiley
Journal of Marriage and Family	Wiley
Poetics	Elsevier
Rural Sociology	Wiley
Social Forces	Oxford
Social Networks	Elsevier
Social Science Research	Elsevier
Sociological Forum	Wiley
Sociological Inquiry	Wiley
Sociological Methods and Research	SAGE
Sociology Compass	Wiley
Sociology of Health & Illness	Wiley
Symbolic Interaction	Wiley

There are several caveats that we would like to highlight. First, we did not try to submit a paper to these journals. It is possible that some of the journals that we

coded as having no explicit policy or as referring to the publisher's policy actually do have more specific rules about GenAI displayed in their submission portals. More generally, the table is based on an examination of 'submission guidelines' or the 'instructions for authors' web pages—where we usually found statements about AI for those journals that did have policies. It is possible that we missed some statements about AI if they were located elsewhere.

Second, journals that do not mention AI on their website do not necessarily have *no* AI policy. Many journals' websites link to their publisher's general ethics code, which often includes sections on AI (even if not explicitly referenced on the journal page). Finally, for journals that do make statements about AI use, we do not know anything about the origin of the rules and these may still stem from the publisher. The journals *Poetics*, *Social Science Research*, and *Social Networks*, for instance, are all published by Elsevier and appear to have identical, relatively detailed rules on GenAI use, suggesting that these were written by the publisher.

Taken together, then, Table J.1 is a good faith effort to collect the information that is accessibly displayed on sociology journals' websites as of July 2026. A more systematic analysis would require contacting journals, which we did not do.

K. AI Use Statement

In Table K.1 we provide a summary of how GenAI was used in conducting the research for this paper. We follow the same structure as our survey, dividing our work into four research stages. One point worth acknowledging is that we found ourselves in a somewhat unusual situation with regard to using GenAI for this project: the acceptability of such use is precisely our topic, and our analyses suggest that sociologists have rather heterogeneous opinions on this. This had some disciplining effects in the sense that we avoided GenAI use where in other projects we might not have. Had we taken the survey ourselves, we would fall somewhere in the middle of our acceptance scale. That said, all four authors of this study have adopted GenAI into our research workflows to varying extents. While our attitudes toward GenAI use in research are still evolving, and we may differ in our current stances with each other and others in our discipline, we share with the vast majority of sociologists the position that there are some acceptable uses of GenAI—especially when these are disclosed transparently.

Table K.1: AI use Disclosure

Research stage	**Use**
Literature review & ideation	• For literature review in this paper, we relied on traditional means such as tracing citations or searching via Google Scholar. However, we note that GenAI is now integrated with many tools as a default. For instance, typing the following into Google triggers an AI-generated summary: "Has the American Sociological Association made any statement on generative AI and what uses it considers legitimate or something along these lines?" • We did not use any GenAI tools for brainstorming or ideation.

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Table K.1 – continued from previous page

Research stage	**Use**
Data collection and analysis	• When constructing our survey questionnaire, we used a Claude model in chat mode to 'think through' and refine some of our items. For instance, we would prompt an item we had written and would ask the model whether there is potential for misunderstandings. We adopted some of the model's suggestions to clarify or shorten items where we deemed them helpful. We also asked the model to come up with suggestions for important aspects or uses that we might be missing (it confirmed we covered the main ones). • We used Qwen (local) and GLM (Ollama cloud) models to debug coding errors via OpenCode during the sample construction phase. The models offered code solutions for these errors, which were refined in OpenCode's "plan" mode and then copied into the active R session where deemed useful. • We used Claude and Gemini models to generate initial R code templates for different aspects of our analysis, notably creating figures and regression tables. We then manually adjusted this code to fit our data and analytic goals. For instance, the following is a minimally adjusted version of the prompt we used in the creation of Figure 2 of the main text: "I would like to make a ggplot where in the bottom, I show the histogram of a variable, and then in the top, I want to show select quotes illustrating specific points on that continuum. The qotes should be text boxes and a vertical line should be drawn to the x-axis to where that case sits. The idea is to have this be a large, landscape plot in a paper. Can you give me R code to do this? Create some fake data so that we can discuss the plot. You can use a separate dataframe for the quotes." We then took the template code and adjusted it to work for our data. Importantly, we used Claude and Gemini in *chat mode* and copied over code into an active R session. **At no point did a GenAI model see any data collected via the survey.** • We used Claude to prepare our code for the replication repository. Specifically, we pasted all scripts into Claude (script by script) and asked it to identify ways to make the code easier to follow as well as redundancies or dead code. We then adopted these suggestions where we found them useful.

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Table K.1 – continued from previous page

Research stage	**Use**
Writing	• We used Claude models and GLM 5.3 via OpenCode, both in chat mode, to help with LaTeX formatting problems. • All text in this manuscript was written by us. That said, the text editor we used to prepare this manuscript (Overleaf) contains an enhanced spell-checker (similar to Grammarly) that detects genuine errors but also occasionally suggests refining word choice. In some instances, we adopted its suggestions. Besides, the first author is not a native English speaker and regularly uses Claude to help with word choice, similar to a thesaurus.
Review	• We did not use GenAI in the revision of this manuscript.

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