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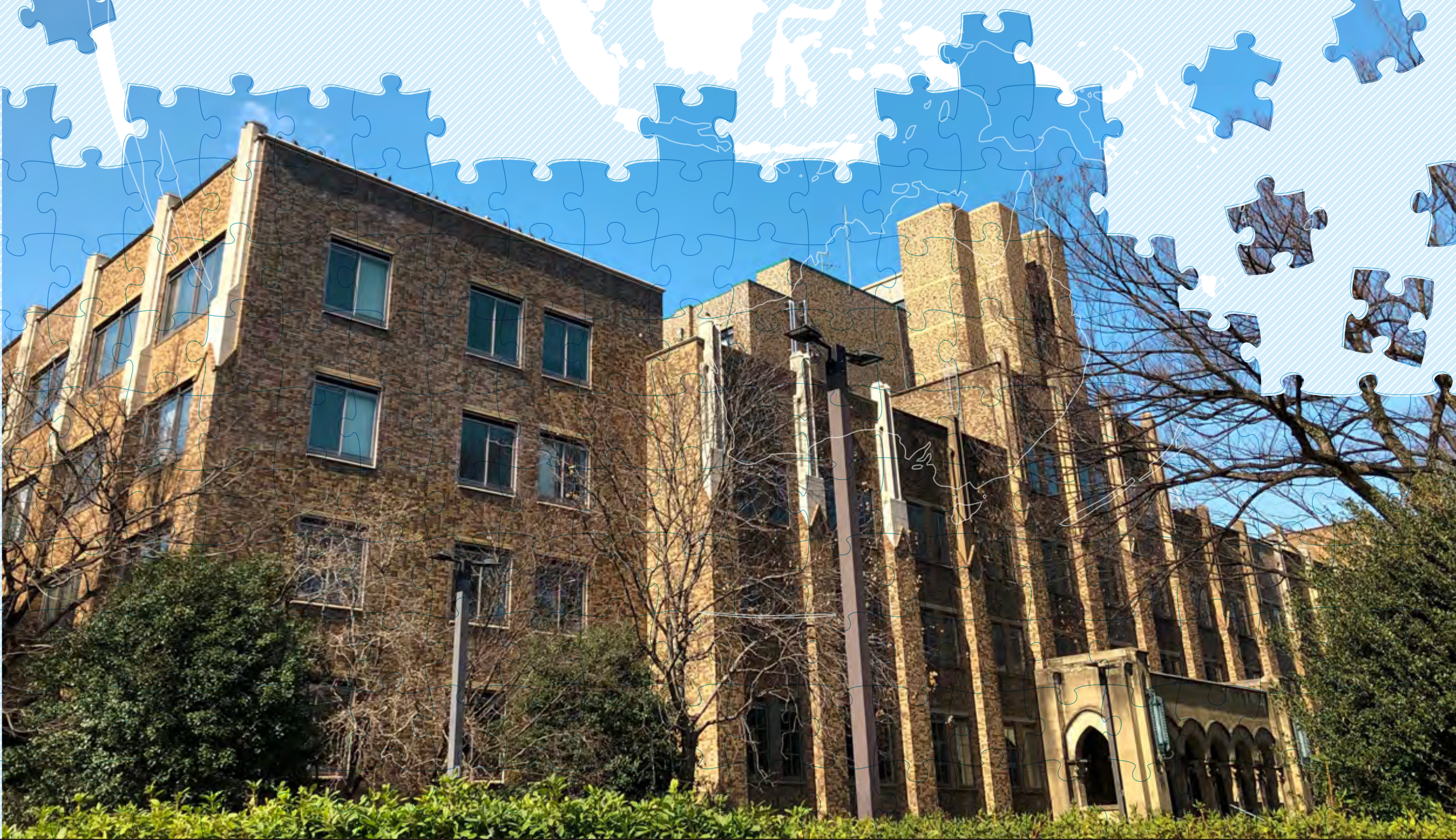
What Determines Acceptance of the Generative AI Age?

Associations Among Generative AI Use, Misinformation Encounters, and Life Satisfaction, and Attitudes Toward Generative AI Diffusion



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What Determines Acceptance of the Generative AI Age?

Associations Among Generative AI Use, Misinformation Encounters, Life Satisfaction, and Attitudes Toward Generative AI Diffusion

Hiroko Kanoh (Yamagata University)

Abstract

As generative artificial intelligence (GenAI) becomes increasingly visible in everyday life, public acceptance of its societal diffusion remains uneven and may be shaped by both direct experience with the technology and broader concerns such as misinformation and well-being. This study examined factors associated with acceptance of GenAI diffusion in Japan, focusing on how GenAI use, misinformation encounters (including non-GenAI online environments), and subjective well-being indicators relate to acceptance.

Using microdata from the SSJDA Panel Wave 6 survey (October 2023; N = 1,528), we analyzed welcoming ratings of GenAI diffusion together with demographic attributes (gender, age group, employment, living arrangement), GenAI use, misinformation/harassment encounters, and well-being indicators. Group differences were assessed using Pearson's χ^2 tests and one-way ANOVAs with effect sizes, bivariate associations were examined using rank-based correlations, and independent predictors were identified using ordinal logistic regression models. Open-ended comments were analyzed with KH Coder using Japanese morphological processing and a co-occurrence network analysis.

Across analyses, acceptance of GenAI diffusion was higher among men, and the most robust correlate of acceptance was prior GenAI use. In contrast, well-being indicators showed only small associations overall: perceived adaptability and self-efficacy were the most consistent positive correlates, whereas negative affect indicators showed small negative associations. Misinformation encounters were common but showed limited association with acceptance. Qualitative themes suggested a pragmatic yet conditional stance, in which respondents emphasized practical benefits (e.g., efficiency and learning support) while simultaneously calling for governance conditions such as privacy protection, copyright clarity, and misuse prevention.

Keywords: Generative AI; technology acceptance; AI use; misinformation exposure; subjective well-being

1. Introduction

Generative artificial intelligence (GenAI)—including text generation (e.g., ChatGPT) and image generation (e.g., Stable Diffusion)—is rapidly diffusing across information search, summarization, translation, and creative support contexts (Dwivedi et al., 2023). At the same time, societal risks such as opaque sourcing, hallucinations (plausible but incorrect outputs), and downstream harms from large-scale language technologies have been repeatedly highlighted (Bender et al., 2021; Ji et al., 2023). Because GenAI can produce persuasive but inaccurate content at scale, its spread intersects with broader concerns about misinformation and the need for cognitive defense in everyday media environments (van der Linden, 2022). This perspective aligns with an AI literacy framing that extends beyond operational skills to cognitive defense—evaluating credibility, recognizing epistemic risks, and developing equitable capacities to navigate generative outputs in everyday life (Kanoh, 2025).

In Japan, the 2025 White Paper on Information and Communications reports that the proportion of individuals who have used any generative AI service increased from 9.1% (FY2023 survey) to 26.7% (FY2024 survey), indicating rapid expansion of user experience. The same report also shows a pronounced age gradient (44.7% in the 20s in the FY2024 survey) and notes that usage has increased in the United States, Germany, and China as well. Together, these figures suggest that GenAI is spreading quickly, while the pace and level of uptake vary across countries and demographic groups (Ministry of Internal Affairs and Communications [MIC], 2025).

This cross-national and demographic variation suggests that acceptance of the "GenAI era" is not simply a function of availability; it is likely shaped by individual experience with GenAI, perceived benefits and risks, and broader life circumstances (Dwivedi et al., 2023).

Classic technology acceptance research indicates that perceived usefulness and ease of use influence adoption, while social influence and facilitating conditions further contribute to intention and behavior (Davis, 1989; Venkatesh et al., 2003). For GenAI in particular, acceptance may additionally depend on trust, quality judgments, and perceived exposure to incorrect information—factors that can weaken confidence and amplify uncertainty (Ji et al., 2023; van der Linden et al., 2024).

However, empirical evidence remains limited on how (a) everyday GenAI usage, (b) encounters with incorrect information in GenAI and in non-GenAI online spaces (including social media), and (c) subjective well-being indicators jointly relate to individuals' acceptance of GenAI (Dwivedi et al., 2023). Using a large-scale Japanese panel survey (Wave 6, October 2023), this study examines determinants of acceptance of GenAI diffusion ("welcome" attitude) by integrating (1) patterns of GenAI use (text, API use, and image generation), (2) exposure to incorrect information (within GenAI and in online environments more broadly, including exposure to online harassment), and (3) well-being indicators such as life satisfaction, happiness, and self-rated health.

Specifically, we address the following research questions: (RQ1) How do GenAI use, misinformation encounters, and acceptance differ by demographic characteristics (age, gender), employment status, and living arrangement? (RQ2) How is acceptance of GenAI diffusion associated with well-being indicators? (RQ3) When modeled simultaneously, which factors best explain acceptance of GenAI diffusion in an ordinal regression framework?

2. Method

2.1 Data Source and Participants

We conducted a secondary analysis using microdata from SSJDA Panel Wave 6, October 2023 (Survey No. SP060), deposited by the SSJDA Panel Project and distributed via the Social Science Japan Data Archive (SSJDA), Institute of Social Science, The University of Tokyo. The survey was administered in Japan as a self-administered web-based questionnaire (CAWI) during 3–29 October 2023. The Wave 6 dataset comprises two probability-based cohorts: the "2021 sample" (Japanese residents aged 20–39 as of the end of December 2020) and the "2022 sample" (Japanese residents aged 21–40 as of the end of December 2021). The original sampling employed a stratified two-stage random sampling design based on the Basic Resident Register. A total of 1,528 respondents provided valid responses (2021 sample: 588; response rate = 73.1%; 2022 sample: 940; response rate = 74.2%). Analyses used all available cases; therefore, effective sample sizes vary by item due to missing responses. Participant characteristics are summarized in Table 1.

Table 1

Participant characteristics

Variable	Category	*N*	%
Gender	Male	603	39.6
	Female	904	59.4
	Other	5	0.3
	Prefer not to say	11	0.7
Employment status	Working for income	1341	88.3
	Not working for income	177	11.7
Living arrangement	Living alone	255	16.7
	Not living alone	1273	83.3

Note. Percentages are valid percentages. Gender: valid n = 1,523 (missing = 5). Employment status: valid n = 1,518 (missing = 10). Living arrangement: valid n = 1,528 (no missing). For analyses focusing on binary gender differences, respondents who selected “other” or “prefer not to say” were excluded from those specific comparisons/models.

Respondents were aged 20–42 years ($M = 33.58$, $SD = 5.78$). The sample included more women (59.4%) than men (39.6%). Most respondents reported working for income (88.3%), and 16.7% reported living alone. Quantitative analyses were conducted using IBM SPSS Statistics (Version 28), and the open-ended responses were analyzed using KH Coder.

2.2 Measures

Demographics. Age (continuous), gender (male, female, other, prefer not to say), employment status (working for income vs. not working), and living arrangement (living alone vs. not) were included as key background variables.

GenAI use frequency. Respondents reported frequency of (a) text-based GenAI use (e.g., ChatGPT), (b) GenAI API use, and (c) image-generation AI use (e.g., Stable Diffusion) on a four-level ordinal scale: daily, several times per week, several times per month, and never.

Misinformation/harassment encounters. Respondents rated the frequency of encountering incorrect information (a) when using text-based GenAI, and (b) in online environments other than GenAI (including social media). They also rated the frequency of encountering online harassment/abusive content in non-GenAI online environments. Each item was answered on a 10-point scale anchored at 1 (no encounters) and 10 (frequent encounters).

Attitudes toward GenAI diffusion (welcoming). In this study, acceptance of the generative AI age was operationalized as welcoming attitudes toward generative AI diffusion. Respondents rated how much they welcome GenAI diffusion on a 10-point ordered scale from 1 (do not welcome) to 10 (welcome).

Subjective well-being and mental health-related indicators. Measures included multi-domain life satisfaction items (overall life, work, family relationships, and relationships with friends/acquaintances), overall happiness, self-rated health, and multiple items related to mood/anxiety (e.g., depressed mood, irritability, worry) and sleep (e.g., time to fall asleep, nighttime awakenings, sleep medication use), as well as perceived control/agency items.

Open-ended response. Respondents provided free-text comments about their views on the GenAI era and, if applicable, recommended prompts, APIs, and specific use cases.

2.3 Analytic Strategy

First, we summarized overall distributions and computed descriptive statistics (*M*, *SD*, and percentages) for all key variables. Group differences by gender, age group, employment status, and living arrangement were examined using Pearson's χ^2 tests for categorical/ordinal distributions and one-way analyses of variance (ANOVA) when treating ordinal scale scores as approximately continuous. For group comparisons, we reported effect sizes (Cramer's *V* for χ^2 tests, and partial eta-squared ηp^2 for ANOVA) following APA-style reporting conventions.

Second, we examined associations between welcoming attitudes toward GenAI diffusion and well-being indicators through group comparisons and correlation analyses, as appropriate for the measurement level of each variable.

Third, to explain welcoming attitudes toward GenAI diffusion while adjusting for covariates, we estimated an ordinal logistic regression model (proportional odds model) with the 10-point welcoming rating as the dependent variable. Predictors were selected based on the descriptive and bivariate findings and theoretical relevance from technology acceptance and misinformation-risk perspectives.

3. Results

3.1 Prevalence of any GenAI use in the sample

The 2025 White Paper on Information and Communications reports that the share of individuals in Japan who have used generative AI services increased to 26.7% (FY2024 survey), while remaining lower than in several peer countries. In the present Wave 6 panel sample, 325 of 1,501 respondents (21.7%) reported any GenAI use (a binary indicator coded as "Yes" if the respondent reported any non-"never" use of text-based GenAI, GenAI APIs, or image-generation AI). This suggests that GenAI use was uncommon in this cohort, providing an important baseline for interpreting subsequent analyses of welcoming attitudes toward GenAI diffusion.

Bivariate associations between any GenAI use and key demographic characteristics were examined using chi-square tests of independence with effect sizes (Cramér's V). Use prevalence differed by gender: 27.7% of men (166/600) versus 17.6% of women (159/901), $\chi^2(1, N = 1{,}501) = 21.31$, $p < .001$, Cramér's $V = .12$. Use was also higher among respondents living alone (29.6%, 74/250) than among those not living alone (20.1%, 251/1,251), $\chi^2(1, N = 1{,}501) = 11.17$, $p < .001$, Cramér's $V = .09$. By contrast, differences by age group were not statistically significant (≤33: 23.5%, 162/689; ≥34: 20.1%, 163/809), $\chi^2(1, N = 1{,}498) = 2.48$, $p = .115$, Cramér's $V = .04$, nor were differences by employment status (working for income: 21.7%, 286/1,319; not working for income: 21.4%, 37/173), $\chi^2(1, N = 1{,}492) = 0.01$, $p = .929$, Cramér's $V = .00$.

Overall, although GenAI use was relatively infrequent in this sample, modest demographic patterning—especially by gender and living arrangement—was evident. These baseline differences motivate the subsequent analyses examining whether welcoming attitudes toward GenAI diffusion, misinformation encounters, and subjective well-being indicators show similar demographic patterning and how they jointly relate in multivariable models.

3.2 Gender differences in GenAI use, misinformation encounters, and related indicators

Building on the prevalence patterns in Section 3.1, we compared male and female respondents on the frequency of GenAI use, misinformation/harassment encounters, and welcoming attitudes toward GenAI diffusion. After excluding respondents who selected “other” or “prefer not to say” for gender, we examined gender differences (male vs. female) across the outcomes listed in Table 2. For each outcome measured on ordinal/continuous rating scales, we conducted a one-way analysis of variance (ANOVA) with gender as the between-subjects factor, treating the scale scores as approximately continuous as described in the Method section.

Means and standard deviations by gender are presented in Table 2. Overall, GenAI use was infrequent on the 4-point frequency scales, with means close to the lower end of the scales. Encounters with incorrect information (both during GenAI use and elsewhere online) and exposure to online harassment were also relatively low on the 10-point scales. In contrast, welcoming attitudes toward GenAI diffusion showed a wider spread and a clearer male–female gap, with men reporting higher welcoming ratings on average.

ANOVA results indicated that age did not differ significantly by gender, $F(1, 1502) = 2.677$, $p = .102$, $\eta p^2 = .002$. In contrast, gender differences were statistically significant for GenAI use frequency measures, including text-based GenAI use frequency, $F(1, 1502) = 19.326$, $p < .001$, $\eta p^2 = .013$; GenAI API use frequency, $F(1, 1497) = 7.990$, $p = .005$, $\eta p^2 = .005$; image-generation AI use frequency, $F(1, 1501) = 4.901$, $p = .027$, $\eta p^2 = .003$; and the overall GenAI use frequency score, $F(1, 1495) = 16.326$, $p < .001$, $\eta p^2 = .011$.

Gender differences were also significant for misinformation/harassment encounters. Men reported higher frequencies of encountering incorrect content when using text-based GenAI, $F(1,$

1463) = 21.424, $p < .001$, $\eta_p^2 = .014$; encountering incorrect content in non-GenAI online environments (including social media), $F(1, 1473) = 27.616$, $p < .001$, $\eta_p^2 = .018$; and encountering online harassment/abusive content in non-GenAI online environments, $F(1, 1478) = 15.205$, $p < .001$, $\eta_p^2 = .010$.

Finally, welcoming attitudes toward GenAI diffusion were higher among men than women, $F\ (1, 1489) = 49.883$, $p < .001$, $\eta_p^2 = .032$. Across outcomes, the direction of differences was consistent with Table 2: men reported slightly higher levels of GenAI use and more positive welcoming attitudes toward GenAI diffusion, and they also reported higher frequencies of encountering incorrect information and online harassment. Effect sizes were small overall ($\eta_p^2 \approx .003$–$.032$), indicating that statistically significant differences accounted for modest proportions of variance in this large sample.

Table 2

Descriptive statistics by gender (male vs. female) for GenAI use, information encounters, and acceptance

Variable	Gender	*N*	%	*M*	*SD*	*Missing*
Text-based GenAI use frequency	Male	601	40.0	1.35	0.690	
Text-based GenAI use frequency	Female	903	60.0	1.21	0.573	
Text-based GenAI use frequency	Total	1504	100.0	1.27	0.626	3
GenAI API use frequency	Male	599	40.0	1.22	0.566	
GenAI API use frequency	Female	900	60.0	1.14	0.494	
GenAI API use frequency	Total	1499	100.0	1.17	0.525	8
Image-generation AI use frequency	Male	601	40.0	1.12	0.434	
Image-generation AI use frequency	Female	902	60.0	1.08	0.323	
Image-generation AI use frequency	Total	1503	100.0	1.10	0.372	4
Overall GenAI use frequency score	Male	599	40.0	3.69	1.471	
Overall GenAI use frequency score	Female	898	60.0	3.42	1.146	
Overall GenAI use frequency score	Total	1497	100.0	3.53	1.293	10
Encountering incorrect content when using text-based GenAI	Male	591	40.3	2.42	2.418	
Encountering incorrect content when using text-based GenAI	Female	874	59.7	1.90	1.875	
Encountering incorrect content when using text-based GenAI	Total	1465	100.0	2.11	2.125	42
Encountering incorrect content online (non-GenAI; incl. social media)	Male	595	40.3	3.39	2.783	
Encountering incorrect content online (non-GenAI; incl. social media)	Female	880	59.7	2.68	2.403	
Encountering incorrect content online (non-GenAI; incl. social media)	Total	1475	100.0	2.97	2.586	32
Encountering online harassment/abusive content (non-GenAI; incl. social media)	Male	593	40.1	3.43	3.076	
Encountering online harassment/abusive content (non-GenAI; incl. social media)	Female	887	59.9	2.83	2.765	
Encountering online harassment/abusive content (non-GenAI; incl. social media)	Total	1480	100.0	3.07	2.908	27
Welcome attitude toward GenAI diffusion	Male	597	40.0	6.13	2.844	
Welcome attitude toward GenAI diffusion	Female	894	60.0	5.14	2.480	
Welcome attitude toward GenAI diffusion	Total	1491	100.0	5.54	2.675	16

Note. Percentages are valid percentages within each variable. Missing indicates the number of excluded cases due to missing responses for the variable after filtering to male/female.

3.3 Age-Group Differences in Generative AI Use and Exposure to Misinformation/Harassment

To examine age-group differences in GenAI use and related experiences, we conducted one-way analyses of variance (ANOVAs) comparing younger adults (≤ 33 years) and older adults (≥ 34 years). The cutoff was set at 34 years (the sample median) to create two approximately equal-sized groups. Descriptive statistics are summarized in Tables 3 and 4. As intended by the age-group definition, the younger group was younger *(M* = 28.13, *SD* = 3.16, *n* = 700) than the older group (*M* = 38.22, *SD* = 2.55, *n* = 823).

Tables 3 and 4 indicate that mean levels of GenAI use were generally low in both age groups on the 4-point frequency scales. Consistent with the prevalence analysis in Section 3.1, the binary "any GenAI use" indicator did not significantly differ by age group; therefore, the present section focuses on group differences in the frequency measures and related exposure outcomes.

Table 3

Descriptive statistics for GenAI use measures by age group

Measure		**≤33**			**≥34**			**Total**	
	N	***M***	***SD***	***N***	***M***	***SD***	***N***	***M***	***SD***
Text-based GenAI use frequency	699	1.29	0.626	821	1.25	0.632	1520	1.27	0.629
GenAI API use frequency	696	1.19	0.535	819	1.16	0.523	1515	1.17	0.528
Image-generation AI use frequency	700	1.10	0.371	819	1.10	0.371	1519	1.10	0.371
Overall GenAI use frequency	696	3.57	1.319	817	3.49	1.279	1513	3.53	1.297

Note. Age groups were defined as ≤33 years and ≥34 years. Cell sizes vary across outcomes due to item-level missingness. Values are unadjusted means and standard deviations.

Table 4

Descriptive statistics for exposure outcomes and welcoming attitude by age group

Measure	≤33			≥34			Total		
	N	***M***	***SD***	***N***	***M***	***SD***	***N***	***M***	***SD***
Incorrect content during text GenAI use (past 6 months)	679	2.22	2.138	802	2.02	2.114	1481	2.11	2.126
Incorrect content online (non-GenAI, past 6 months)	687	3.24	2.650	804	2.75	2.516	1491	2.98	2.589
Harassment online (non-GenAI, past 6 months)	690	3.29	2.970	806	2.90	2.851	1496	3.08	2.912
Welcoming attitude toward GenAI diffusion	698	5.64	2.623	809	5.43	2.705	1507	5.53	2.668

Note. Age groups were defined as ≤33 years and ≥34 years. Cell sizes vary across outcomes due to item-level missingness. Values are unadjusted means and standard deviations.

For GenAI use frequency measures (Table 3), there were no statistically significant age-group differences in text-based GenAI use frequency, GenAI API use frequency, image-generation AI use frequency, or the overall GenAI use frequency score (all *ps* $\geq .158$, $\eta p^2 \leq .001$). These results suggest that within this cohort of adults in their 20s to early 40s, age-group differences in GenAI use intensity were limited.

Regarding exposure outcomes and welcoming attitudes (Table 4), encountering incorrect content during text-based GenAI use did not significantly differ by age group, although the younger group reported slightly higher levels, $F(1, 1479) = 2.99$, $p = .084$, $\eta p^2 = .002$. In contrast, the younger group reported higher exposure to incorrect content in non-GenAI online environments (including social media), $F(1, 1489) = 13.32$, $p < .001$, $\eta p^2 = .009$, and higher exposure to online harassment/abusive content in non-GenAI online environments, $F(1, 1494) = 6.64$, $p = .010$, $\eta p^2 = .004$. Welcoming attitudes toward GenAI diffusion did not differ by age group, $F(1, 1505) = 2.37$, $p = .124$, $\eta p^2 = .002$. Overall, although some age-group differences reached statistical significance for online exposure outcomes, effect sizes were small, indicating modest practical differences in this large sample.

3-4. Employment Status Differences

To examine employment-status differences in GenAI use and related experiences, we compared respondents with income-generating work and those without using one-way analyses of variance (ANOVAs). Descriptive statistics and test results are summarized in Table 5. No statistically significant employment-status differences were observed across the outcomes (all *ps* $\geq .062$), and effect sizes were uniformly small ($\eta p^2 \leq .002$).

For completeness, the one-way ANOVA test statistics are reported for each outcome: Age, $F(1, 1512) = 0.25$, $p = .617$, $\eta p^2 = .000$; text-based GenAI use frequency, $F(1, 1509) = 1.05$, $p = .305$, $\eta p^2 = .001$; GenAI API use frequency, $F(1, 1504) = 3.49$, $p = .062$, $\eta p^2 = .002$; image-generation AI use frequency, $F(1, 1508) = 0.64$, $p = .423$, $\eta p^2 = .000$; overall GenAI use frequency, $F(1, 1504) = 0.00$, $p = .997$, $\eta p^2 = .000$; encountering incorrect information when using text-based GenAI (past 6 months), $F(1, 1474) = 1.06$, $p = .303$, $\eta p^2 = .001$; encountering incorrect information online (non-GenAI; past 6 months), $F(1, 1480) = 0.75$, $p = .387$, $\eta p^2 = .001$; encountering online harassment/abusive content (non-GenAI; past 6 months), $F(1, 1489) = 0.12$, $p = .729$, $\eta p^2 = .000$; and welcoming attitudes toward GenAI diffusion (10-point scale), $F(1, 1500) = 0.80$, $p = .370$, $\eta p^2 = .001$.

The uniformly small effect sizes suggest that employment status, as measured here, explains little variance in GenAI use and related experiences. One likely reason is that the groups were highly imbalanced (employed $n = 1{,}338$ vs. not employed $n = 176$), which limits precision for the smaller group. In addition, the single employment item may combine heterogeneous situations (e.g., full-time work, part-time work, and other forms of income-generating work), which can attenuate between-group differences. These results suggest that more granular employment categories and/or multivariable models may be useful in future analyses to clarify whether employment-related circumstances contribute to GenAI use patterns or attitudes.

Table 5

Descriptive Statistics and One-Way ANOVAs by Employment Status

Variable	**Employed**	**Not employed**	*F*	*df*	*p*	ηp^2
Age	33.61 (5.75), *n*=1338	33.38 (4.56), *n*=176	0.25	1512	.617	.000
Text-based GenAI use frequency	1.29 (0.66), *n*=1337	1.42 (0.84), *n*=176	1.05	1509	.305	.001
API use frequency	1.18 (0.54), *n*=1337	1.07 (0.27), *n*=176	3.49	1504	.062	.002
Image GenAI use frequency	1.09 (0.36), *n*=1338	1.10 (0.43), *n*=176	0.64	1508	.423	.000
Overall GenAI use frequency	3.55 (1.29), *n*=1336	3.54 (1.33), *n*=176	0.00	1504	.997	.000
Encountered misinformation when using text-based GenAI (past 6 months)	2.09 (2.13), *n*=1305	1.96 (2.35), *n*=169	1.06	1474	.303	.001
Encountered online misinformation (non-GenAI; past 6 months)	2.81 (2.57), *n*=1313	2.61 (2.38), *n*=170	0.75	1480	.387	.001
Encountered online harassment (non-GenAI; past 6 months)	3.08 (2.91), *n*=1316	2.99 (2.86), *n*=175	0.12	1489	.729	.000
Welcome GenAI diffusion (10-point scale)	5.55 (2.68), *n*=1327	5.35 (2.62), *n*=175	0.80	1500	.370	.001

Note. Values are *M* (*SD*), *n*. For ANOVAs, df1 = 1 for all tests and df2 is reported. ηp^2 = *partial eta squared.*

3.5. Living arrangement differences (living alone vs. not) in GenAI use and related experiences

To examine differences by living arrangement, we conducted one-way analyses of variance (ANOVAs) comparing participants who reported living alone and those who did not. Descriptive statistics are presented in Table 6. Missing data resulted in small variations in analytic sample size by variable.

Living arrangement was associated with several outcomes (Table 6). Participants living alone were younger on average than those not living alone, $F(1, 1521) = 33.08$, $p < .001$, $\eta p^2 = .021$. They also reported higher frequencies of text-based GenAI use, $F(1, 1523) = 9.57$, $p = .002$, $\eta p^2 = .006$, whereas differences in GenAI API use frequency and image-generation AI use frequency were not statistically significant. In addition, the living-alone group reported more frequent encounters with incorrect GenAI outputs in the past six months, $F(1, 1484) = 18.71$, $p < .001$, $\eta p^2 = .012$, as well as more frequent encounters with incorrect online information in non-GenAI environments, $F(1, 1494) = 17.54$, $p < .001$, $\eta p^2 = .012$, and online harassment/cyberbullying, $F(1, 1499) = 6.62$, $p = .010$, $\eta p^2 = .004$. Finally, participants living alone expressed greater welcoming of GenAI diffusion, $F(1, 1510) = 7.61$, $p = .006$, $\eta p^2 = .005$.

Consistent with the prevalence analysis in Section 3.1, respondents living alone were also more likely to report any GenAI use than those not living alone; therefore, the present section focuses on differences in frequency and exposure outcomes rather than re-testing the binary indicator. Overall, effect sizes were small across outcomes, indicating modest practical differences in this large sample.

Table 6

Descriptive statistics by living arrangement

Variable	Living alone *M* (*SD*)	*N*	Not living alone *M* (*SD*)	*N*	Total *M* (*SD*)	*N*
Age (years)	31.70 (6.000)	255	33.96 (5.662)	1268	33.58 (5.780)	1523
Text-based GenAI use frequency	1.38 (0.717)	253	1.25 (0.607)	1272	1.27 (0.628)	1525
GenAI API use frequency	1.19 (0.571)	253	1.17 (0.519)	1267	1.17 (0.528)	1520
Image-generation AI use frequency	1.09 (0.332)	253	1.10 (0.378)	1271	1.10 (0.370)	1524
Overall GenAI use frequency	3.64 (1.272)	252	3.50 (1.300)	1266	3.53 (1.296)	1518
Encountered incorrect GenAI outputs (past 6 months)	2.64 (2.539)	244	2.00 (2.017)	1242	2.11 (2.124)	1486
Encountered incorrect online info (non-GenAI; past 6 months)	3.59 (2.882)	250	2.85 (2.507)	1246	2.97 (2.588)	1496
Encountered online harassment/cyberbullying (past 6 months)	3.51 (3.109)	250	2.99 (2.862)	1251	3.08 (2.910)	1501
Welcoming GenAI diffusion	5.94 (2.754)	254	5.44 (2.645)	1258	5.52 (2.669)	1512

Note. GenAI = generative artificial intelligence. Ns vary across variables due to missing data.

3.6. GenAI welcoming and well-being (correlational analysis)

To examine how welcoming attitudes toward generative artificial intelligence (GenAI) relate to subjective well-being and psychological experiences, we computed Spearman rank-order correlations (ρ) among GenAI welcoming, life satisfaction domains, mental health symptom indicators, and agency-related beliefs (Tables 7A–7B). Spearman's ρ was selected because most variables were ordinal (e.g., 10-point ratings or Likert-type response categories) and the assumption of normality is unlikely to hold for several indicators; thus, a rank-based statistic provides an appropriate summary of monotonic associations. Correlations were tested two-tailed with $\alpha = .05$. Missing responses were handled with pairwise deletion, so the analytic N varies by pair (range: $N = 1303–1525$). For focal associations involving GenAI welcoming, we additionally report 95% confidence intervals (CIs) for Spearman's ρ (Table 8), estimated using the Bonett and Wright method.

Overall, GenAI welcoming showed only small associations with well-being and psychological indicators. GenAI welcoming was weakly negatively correlated with age ($\rho = -.055$, $p = .033$), indicating slightly higher welcoming scores among younger participants. Regarding positive well-being indicators, GenAI welcoming showed small positive correlations with job satisfaction ($\rho = .061$, $p = .027$) and happiness ($\rho = .055$, $p = .034$). Associations with other satisfaction and health indicators were not statistically significant (overall life satisfaction, family relationship satisfaction, friends/acquaintances relationship satisfaction, and self-rated health; all $ps \geq .05$).

GenAI welcoming was also weakly related to distress indicators. Specifically, welcoming was negatively correlated with anhedonia (little interest/pleasure; $\rho = -.058$, $p = .025$) and with nervous/anxious/irritable feelings ($\rho = -.075$, $p = .004$), whereas depressed/hopeless mood and uncontrollable worry were not significantly associated with welcoming (all *ps* $\geq .05$). No significant association was observed with low autonomy (decisions made by others; $p \geq .05$). In contrast, agency-related beliefs showed the most consistent positive links with welcoming: self-efficacy was positively correlated with welcoming ($\rho = .075$, $p = .003$), and adaptability showed the strongest positive correlation among the psychosocial indicators ($\rho = .119$, $p < .001$). Taken together, the pattern suggests that GenAI welcoming is more closely aligned—albeit modestly—with a general coping orientation (especially adaptability) than with broad differences in life satisfaction or distress symptoms.

Across the correlation matrix (Tables 7A–7B), satisfaction domains were moderately to strongly intercorrelated (e.g., overall life satisfaction with happiness, $\rho = .634$, $p < .001$), mental health symptom indicators were strongly interrelated (e.g., depressed/hopeless mood with uncontrollable worry, $\rho = .599$, $p < .001$), and symptoms were consistently negatively associated with satisfaction and health. Agency-related beliefs (self-efficacy and adaptability) correlated positively with satisfaction indicators and negatively with distress, consistent with their interpretation as protective or resilience-related orientations.

Because these data are cross-sectional, the observed correlations do not support causal conclusions. Nevertheless, the consistently small associations between GenAI welcoming and most well-being indicators suggest that welcoming attitudes may primarily reflect a technology-related orientation and perceived coping resources rather than broad differences in life circumstances or mental health.

Table 7A

Spearman rank-order correlations among study variables (Part A: columns 1–9)

Variable	1	2	3	4	5	6	7	8
1. Age	—							
2. GenAI welcome	-.055*	—						
3. Overall life satisfaction	-.022	.044	—					
4. Job satisfaction	.002	.061*	.494**	—				
5. Family relationship satisfaction	-.057*	.020	.509**	.247**	—			
6. Friends/acquaintances relationship satisfaction	-.126**	.037	.416**	.304**	.474**	—		
7. Happiness	.006	.055*	.634**	.431**	.516**	.379**	—	
8. Health	-.051*	.046	.379**	.319**	.303**	.289**	.407**	—
9. Anhedonia (little interest/pleasure)	-.012	-.058*	-.253**	-.201**	-.205**	-.163**	-.270**	-.249**
10. Depressed/hopeless mood	-.128**	-.046	-.339**	-.322**	-.272**	-.247**	-.337**	-.359**
11. Nervous, anxious, or irritable	-.016	-.075**	-.324**	-.294**	-.273**	-.257**	-.291**	-.375**
12. Uncontrollable worry	-.046	-.037	-.322**	-.293**	-.248**	-.242**	-.290**	-.354**
13. Taking 30+ minutes to fall asleep	-.065*	-.029	-.224**	-.167**	-.175**	-.140**	-.181**	-.275**
14. Low autonomy (decisions made by others)	-.008	.025	-.132**	-.201**	-.083**	-.130**	-.181**	-.154**
15. Self-efficacy (I usually find a way to do what I really want)	.024	.075**	.279**	.230**	.221**	.258**	.300**	.232**
16. Adaptability (I can adapt to changes easily)	.018	.119**	.222**	.234**	.177**	.256**	.235**	.319**

Note. Cells contain Spearman's ρ. * $p < .05$. ** $p < .01$ (two-tailed). Pairwise deletion was used; N varies across pairs (N = 1303–1525). Variable codes: 1 Age; 2 GenAI welcome; 3 Any GenAI use; 4 Overall life satisfaction; 5 Job satisfaction; 6 Family relationship satisfaction; 7 Friends/acquaintances relationship satisfaction; 8 Happiness; 9 Health; 10 Anhedonia; 11 Depressed/hopeless mood; 12 Anxiety/irritability; 13 Uncontrollable worry; 14 Sleep onset latency ≥30 min; 15 Low autonomy; 16 Goal striving; 17 Adaptability.

Table 7B

Spearman rank-order correlations among study variables (Part B: columns 10–17)

Variable	9	10	11	12	13	14	15	16
9. Anhedonia (little interest/pleasure)	—							
10. Depressed/hopeless mood	.427**	—						
11. Nervous, anxious, or irritable	.339**	.599**	—					
12. Uncontrollable worry	.349**	.600**	.579**	—				
13. Taking 30+ minutes to fall asleep	.170**	.294**	.277**	.292**	—			
14. Low autonomy (decisions made by others)	.150**	.183**	.152**	.139**	.101**	—		
15. Self-efficacy (I usually find a way to do what I really want)	-.160**	-.221**	-.216**	-.191**	-.135**	-.190**	—	
16. Adaptability (I can adapt to changes easily)	-.166**	-.277**	-.226**	-.250**	-.173**	-.093**	.343**	—

Note. Cells contain Spearman's ρ. * $p < .05$. ** $p < .01$ (two-tailed). Pairwise deletion was used; N varies across pairs ($N = 1303–1525$). Variable codes: 1 Age; 2 GenAI welcome; 3 Any GenAI use; 4 Overall life satisfaction; 5 Job satisfaction; 6 Family relationship satisfaction; 7 Friends/acquaintances relationship satisfaction; 8 Happiness; 9 Health; 10 Anhedonia; 11 Depressed/hopeless mood; 12 Anxiety/irritability; 13 Uncontrollable worry; 14 Sleep onset latency ≥30 min; 15 Low autonomy; 16 Goal striving; 17 Adaptability.

Table 8

Associations of GenAI welcoming with other variables (Spearman's ρ with 95% CIs)

Outcome variable	ρ	95% CI	p	N
Age	-.055	[-.105, -.004]	.033	1507
Overall life satisfaction	.044	[-.007, .094]	.089	1512
Job satisfaction	.061	[.007, .114]	.027	1326
Family relationship satisfaction	.020	[-.031, .070]	.443	1497
Friends/acquaintances relationship satisfaction	.037	[-.014, .087]	.154	1508
Happiness	.055	[.004, .106]	.034	1463
Health	.046	[-.004, .096]	.072	1511
Anhedonia (little interest/pleasure)	-.058	[-.109, -.007]	.025	1480
Depressed/hopeless mood	-.046	[-.096, .005]	.077	1487
Nervous, anxious, or irritable	-.075	[-.126, -.024]	.004	1486
Uncontrollable worry	-.037	[-.088, .014]	.159	1474
Taking 30+ minutes to fall asleep	-.029	[-.080, .021]	.256	1496
Low autonomy (decisions made by others)	.025	[-.026, .075]	.332	1508
Self-efficacy (I usually find a way to do what I really want)	.075	[.025, .125]	.003	1511
Adaptability (I can adapt to changes easily)	.119	[.069, .169]	< .001	1493

Note. CIs for Spearman's ρ were estimated using the Bonett and Wright method (95% level). Positive values indicate that higher GenAI welcoming is associated with higher scores on the outcome. Symptom indicators are coded so that higher values reflect more frequent symptoms; other variables should be interpreted according to the codebook (e.g., satisfaction items may have been reverse-coded so that higher values indicate higher satisfaction).

3.7 Factors Influencing Welcoming Attitudes Toward the Diffusion of Generative AI

To examine which factors independently explain respondents' welcoming of generative AI diffusion, we estimated three ordinal logistic regression models (proportional-odds cumulative logit) in SPSS (PLUM). The proportional-odds (parallel lines) assumption was examined using the Test of Parallel Lines. The test was significant for Model 1, $\chi^2(24) = 57.78$, $p < .001$, indicating that the proportional-odds constraint was violated. For Models 2–3, SPSS did not return the Test of Parallel Lines because the unconstrained model could not be estimated reliably**;** therefore, results are interpreted with caution. Model improvement was evaluated using likelihood-ratio (LR) χ^2 tests comparing each final model with its intercept-only counterpart (Table 9)

Model 1 included demographic predictors (gender, age group, living arrangement). Model 2 added well-being and agency-related indicators, and Model 3 additionally included any generative AI use. Valid N varies across models due to listwise deletion.

(1) Model comparison and overall fit

As shown in Table 9, within each model's analytic sample, the model including predictors fit significantly better than the intercept-only model. Model 1 (demographics) improved over the intercept-only model, LR $\chi^2(6) = 80.401$, $p < .001$. Model 2 (adding well-being indicators) also improved fit, LR $\chi^2(20) = 111.427$, $p < .001$. Model 3 (additionally including generative AI use) yielded the largest LR χ^2 statistic, LR $\chi^2(22) = 200.834$, $p < .001$, and the highest pseudo-R^2 values (Cox & Snell / Nagelkerke / McFadden = 0.154 / 0.156 / 0.039). Because valid N differed across models due to listwise deletion, these statistics are interpreted as model-specific evidence of fit rather than strict nested comparisons across identical cases.

(2) Model 1: Demographic predictors

In Model 1 (Table 10), gender was a robust predictor: males reported more welcoming attitudes than females ($B = 0.726$, $SE = 0.112$, Wald $\chi^2 = 41.913$, $p < .001$; $OR = 2.07$, 95% CI [1.66, 2.58]). Living alone was not statistically significant ($p = .126$). Age group showed a marginal trend ($p = .052$), suggesting slightly higher welcoming ratings among the younger group ($OR = 1.21$, 95% CI [1.00, 1.47]).

(3) Model 2: Adding well-being and psychological experience indicators

After adding well-being indicators (Model 2; Table 11), adaptability ("adapt to change easily") emerged as a significant positive predictor ($B = 0.366$, $SE = 0.099$, Wald $\chi^2 = 13.826$, $p < .001$; $OR = 1.44$, 95% CI [1.19, 1.75]). Gender remained significant ($OR = 2.24$, 95% CI [1.82, 2.74]), and living alone became significant in this model ($OR = 1.38$, 95% CI [1.02, 1.86]). In contrast, most domain-specific satisfaction indicators and symptom items (e.g., life satisfaction, job satisfaction, depressed mood, anxiety-related items, sleep onset latency) were not significant (all $ps \geq .173$), indicating that—once other covariates were considered—welcoming attitudes were not strongly explained by broad well-being differences.

(4) Model 3: Adding generative AI use

In the fully adjusted model (Model 3; Table 12), generative AI use (coded 1 = no, 2 = yes) showed the strongest association with welcoming attitudes (B = −1.350, SE = 0.167, Wald $\chi^2 = 65.226$, p < .001; OR = 0.26, 95% CI [0.19, 0.36]). Given this coding, the negative coefficient indicates higher welcoming ratings among users than non-users; equivalently, the reciprocal odds ratio (1/0.26 = 3.85) indicates substantially greater odds of being in higher welcoming categories for users. Adaptability remained significant (OR = 1.33, 95% CI [1.08, 1.63]), and gender also remained significant (OR = 2.11, 95% CI [1.62, 2.76]). The previously significant effect of living alone in Model 2 was no longer significant in Model 3 (p = .221), suggesting that differences in technology use may account for part of that association.

Taken together, Model 3 indicates that welcoming attitudes are most clearly differentiated by (a) actual generative AI use, (b) general adaptability, and (c) gender, whereas many well-being indicators show limited incremental predictive value in a multivariable framework.

From an interpretive standpoint, the pattern suggests that welcoming the diffusion of generative AI is more closely aligned with behavioral/experiential proximity to the technology (use vs. non-use) and general coping orientation (adaptability) than with broad differences in life satisfaction or distress symptoms. Because the data are cross-sectional, these findings should not be interpreted causally; however, they provide a strong rationale for examining how people narrate benefits, risks, and conditions of acceptance in their own words, which we address in the next section (**Section 3.8**).

Table 9

Model fit statistics for ordinal logistic regression models

Model	Valid *N*	-2LL (Intercept-only)	-2LL (Final)	$LR\chi^2(df)$	*p*	Pseudo R^2 (C&S / *N* / McF)
Model 1 (Demographics)	1,488	430.120	349.719	80.401 (6)	< .001	0.053 / 0.053 / 0.013
Model 2 (+ Well-being)	1,204	5146.125	5034.698	111.427 (20)	< .001	0.088 / 0.090 / 0.022
Model 3 (+ AI use)	1,200	5129.394	4928.560	200.834 (22)	< .001	0.154 / 0.156 / 0.039

Note. Outcome: welcoming diffusion of generative AI (10-point ordinal scale). Pseudo R^2 values are Cox & Snell (C&S), Nagelkerke (N), and McFadden (McF). LR χ^2 values are likelihood-ratio tests comparing the final model with the intercept-only model, based on the difference in −2 log-likelihood (−2LL).

Table 10

Model 1 coefficients (demographics)

Predictor	B	SE	Wald χ^2	*p*	*OR*	95% *CI* for *OR*
Male (vs. female)	0.726	0.112	41.913	< .001	2.07	[1.66, 2.58]
Living alone: Yes (vs. No)	0.212	0.139	2.346	= .126	1.24	[0.94, 1.62]
Age ≤ 33 (vs. ≥ 34)	0.192	0.099	3.773	= .052	1.21	[1.00, 1.47]

Note. Reference categories: female; not living alone; age ≥ 34. *OR* = exp(B).

Table 11

Model 2 coefficients (demographics + well-being)

Predictor	B	SE	Wald χ^2	*p*	*OR*	95% *CI* for *OR*
Life satisfaction (overall)	0.010	0.081	0.014	= .905	1.01	[0.86, 1.18]
Job satisfaction	0.032	0.058	0.308	= .580	1.03	[0.92, 1.16]
Family relationship satisfaction	-0.125	0.073	2.933	= .087	0.88	[0.76, 1.02]
Friends/acquaintances satisfaction	0.085	0.074	1.296	= .254	1.09	[0.94, 1.26]
Happiness	0.110	0.081	1.859	= .173	1.12	[0.95, 1.31]
Self-rated health	-0.060	0.063	0.898	= .343	0.94	[0.83, 1.07]
Little interest or pleasure	-0.077	0.070	1.227	= .269	0.93	[0.81, 1.06]
Feeling down/hopeless	-0.092	0.110	0.693	= .405	0.91	[0.73, 1.13]
Nervous/anxious/irritable	-0.128	0.105	1.494	= .222	0.88	[0.72, 1.08]
Unable to stop worrying	0.122	0.092	1.770	= .183	1.13	[0.94, 1.35]
Sleep onset > 30 minutes	0.017	0.063	0.072	= .788	1.02	[0.90, 1.15]
Mostly decided by others (external control)	0.089	0.095	0.871	= .351	1.09	[0.91, 1.32]
Find ways to do what I want (self-direction)	0.062	0.101	0.372	= .542	1.06	[0.87, 1.30]
Adapt to change easily	0.366	0.099	13.826	< .001	1.44	[1.19, 1.75]
Male (vs. female)	0.805	0.104	59.829	< .001	2.24	[1.82, 2.74]
Living alone: Yes (vs. No)	0.320	0.152	4.446	= .035	1.38	[1.02, 1.86]
Age ≤ 33 (vs. ≥ 34)	0.165	0.112	2.178	= .140	1.18	[0.95, 1.47]

Note. Reference categories: female; not living alone; age ≥ 34. *OR* = exp(B).

Table 12

Model 3 coefficients (Model 2 + generative AI use)

Predictor	B	SE	Wald χ^2	*p*	*OR*	*95% CI* for *OR*
Life satisfaction (overall)	-0.056	0.085	0.435	= .510	0.95	[0.80, 1.12]
Job satisfaction	0.029	0.061	0.226	= .634	1.03	[0.91, 1.16]
Family relationship satisfaction	-0.097	0.076	1.622	= .203	0.91	[0.78, 1.05]
Friends/acquaintances satisfaction	0.087	0.078	1.257	= .262	1.09	[0.94, 1.27]
Happiness	0.101	0.085	1.412	= .235	1.11	[0.94, 1.30]
Self-rated health	-0.042	0.066	0.414	= .520	0.96	[0.84, 1.09]
Little interest or pleasure	-0.102	0.073	1.944	= .163	0.90	[0.78, 1.04]
Feeling down/hopeless	-0.089	0.116	0.585	= .444	0.91	[0.73, 1.15]
Nervous/anxious/irritable	-0.136	0.111	1.497	= .221	0.87	[0.70, 1.09]
Unable to stop worrying	0.114	0.096	1.410	= .235	1.12	[0.93, 1.35]
Sleep onset > 30 minutes	0.015	0.066	0.054	= .816	1.02	[0.89, 1.16]
Mostly decided by others (external control)	0.087	0.100	0.753	= .385	1.09	[0.90, 1.33]
Find ways to do what I want (self-direction)	0.082	0.106	0.600	= .438	1.09	[0.88, 1.34]
Adapt to change easily	0.283	0.104	7.401	= .007	1.33	[1.08, 1.63]
Male (vs. female)	0.748	0.136	30.276	< .001	2.11	[1.62, 2.76]
Living alone: Yes (vs. No)	0.192	0.157	1.498	= .221	1.21	[0.89, 1.65]
Age ≤ 33 (vs. ≥ 34)	0.120	0.117	1.046	= .307	1.13	[0.90, 1.42]
Generative AI use: Yes (vs. No)	-1.350	0.167	65.226	< .001	0.26	[0.19, 0.36]

Note. Reference categories: female; not living alone; age ≥ 34; no generative AI use. *OR* = *exp(B)*.

Across three models, gender and perceived adaptability were consistently associated with higher welcoming ratings. Importantly, self-reported generative AI use showed a large association with welcoming diffusion of generative AI, suggesting either that exposure/experience is linked to more positive evaluations, or that individuals with favorable attitudes are more likely to adopt these tools. Given the cross-sectional nature of the data and potential omitted variables (e.g., education, digital skills), causal interpretations should be avoided. Future work may examine mediation pathways (e.g., AI use → perceived benefits → welcoming) and test robustness with alternative codings of age groups and additional controls.

3.8. Insights from open-ended responses (co-occurrence network analysis)

We analyzed open-ended comments about living in an era in which generative AI becomes widespread (non-empty responses: $n = 762$). Using KH Coder, we conducted Japanese morphological processing and constructed a co-occurrence network retaining nouns, adjectives, and adverbs. Edges were visualized when the Jaccard coefficient was $\geq .30$, and subgraphs (communities) were identified to summarize dominant themes. Following this specification, we interpreted each community (Subgraphs 01–05 in Figure 1) by considering the most frequent terms and the co-occurrence links, and we then selected representative excerpts to illustrate the themes.

Figure 1 shows five communities that capture the main frames used by respondents. First, a central cluster ("AI–generative–more–widespread–also") indicates that many comments were explicitly situated in the context of societal diffusion.

Second, a pragmatic cluster ("image–document–time–good–thing") reflects concrete use cases—especially generating images and drafting documents—often discussed in terms of saving time or being useful. Third, a future-oriented cluster ("use–future–advance–great") suggests that diffusion was frequently interpreted through the lens of technological progress and expectations for advancement. Fourth, a reflective/ambivalent cluster ("technology–generation–important–very–many–however–interesting–such–actively–information–human") suggests a mixture of interest, perceived importance, and hesitation: respondents often signaled that the topic is important and interesting while simultaneously expressing conditional acceptance and the need for accurate information and human-centered boundaries. Finally, a social–legal cluster ("law–people–sense") highlights that diffusion is also evaluated in normative terms, including fairness, legitimacy, and how people should make sense of AI-generated outputs.

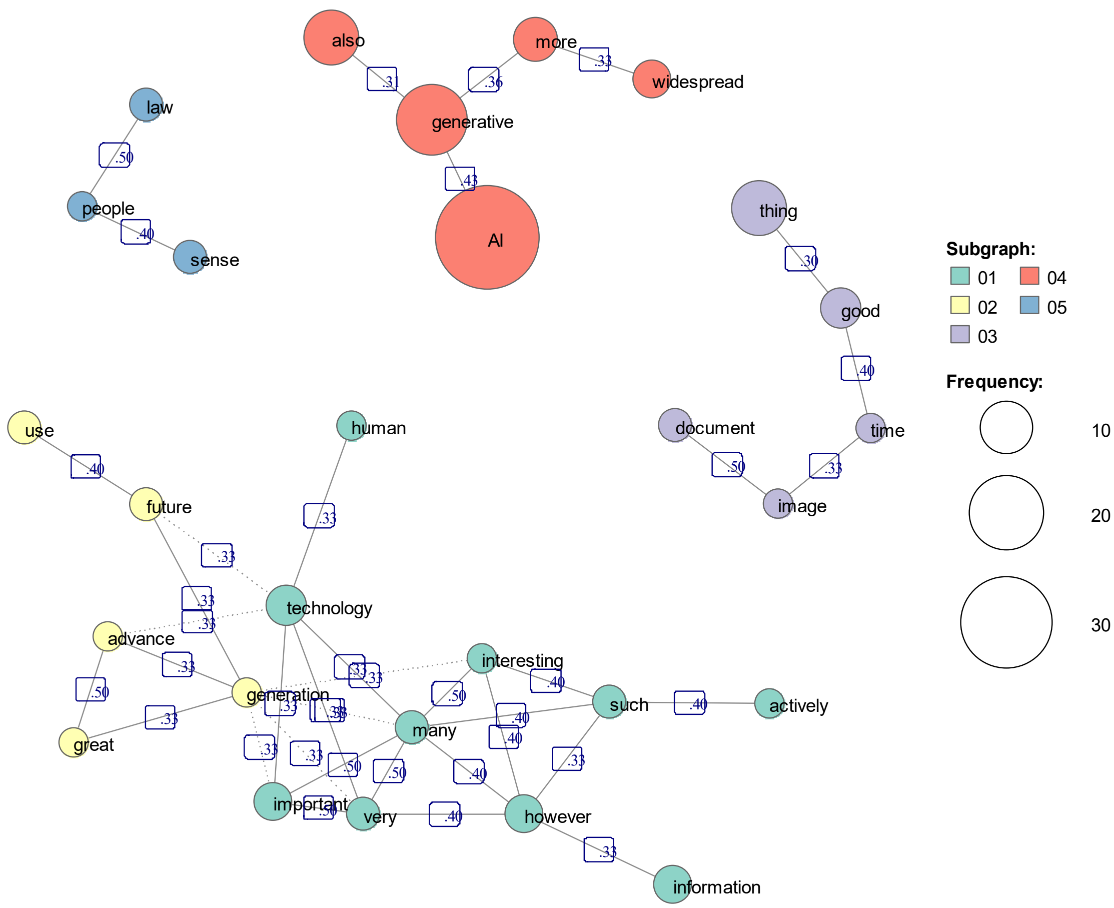

Figure 1

Co-occurrence network of key terms in open-ended comments (nouns/adjectives/adverbs only; Jaccard ≥ .30).

Note. Node size indicates term frequency; edges indicate co-occurrence strength (Jaccard). Colors represent subgraphs detected by KH Coder.

To illustrate the themes identified in the network analysis, Table 13 presents representative excerpts. All excerpts were translated from Japanese into English for reporting, with meanings preserved as closely as possible.

Table 13

Representative excerpts from open-ended comments (English translations)

Theme (illustrative)	Representative excerpt (English translation)
Pragmatic support / efficiency	"GenAI can be convenient as a support function that accelerates creative work. If rules are put in place to prevent misuse, it could become a practical supporter in work and everyday life."
Copyright and creator protection	"Image-generation AI should be used in ways that respect copyright. We need mechanisms that protect the creators whose works are used for training."
Need for legal frameworks	"I feel uneasy because software evolves daily while legal frameworks lag behind. I think prompt legal arrangements are necessary."
Concerns about skill decline	"I want to learn about it once, but I do not want to use it actively. I worry that personal abilities such as imagination and composition may decline."
Cognitive defense against misinformation	"We need the ability to identify fake information, but I am not sure what countermeasures are sufficient to build that ability."
Work-related utility	"GenAI helps me with drafting, translation, and coding suggestions; it is useful for my work. I hope the technology continues to improve."
Employment and social impacts	"While AI may improve convenience and reduce working time, I am concerned about job loss and the need to choose careers that remain needed."
Attribution and rights for AI-assisted works	"Generating images and text easily is convenient, but I worry that creators' status could decline. We also need faster legal clarification about copyrights for AI-assisted works."
General anxiety/uncertainty	"I do not know much about GenAI, but I feel a vague sense of anxiety about its diffusion."
Literacy and inequality concerns	"Rather than rejecting AI, we should disseminate literacy quickly and organize rules beyond direct regulation; otherwise, it may create new disparities."

Note. Original Japanese texts were retained for analysis; English translations are provided for reporting purposes.

4. Discussion

This study examined how adults evaluate the societal diffusion of generative AI (GenAI) in Japan by integrating group comparisons, correlational analyses, ordinal logistic regression models, and open-ended responses. Across analyses, effect sizes for demographic and well-being differences were generally small, but a consistent pattern emerged: welcoming attitudes were most clearly differentiated by experiential proximity to GenAI (use vs. non-use), while associations with broad well-being indicators were modest.

4.1. Adoption gaps and the interpretation of "diffusion"

A key contextual point is that diffusion does not imply uniform adoption. Even in an era where GenAI is widely discussed, many respondents reported limited experience with these tools, underscoring a gap between societal visibility and everyday use. This backdrop matters because attitudes among non-users may be shaped more by indirect information and anticipatory evaluations than by repeated hands-on experience. In policy-oriented discussions of AI risk, the importance of grounding debates in empirical evidence has been emphasized, reflecting a broader shift from abstract claims to data-based risk understanding and solution-oriented research.

4.2. Use as the most salient correlate of welcoming attitudes

In the fully adjusted ordinal logistic regression model, GenAI use showed the strongest association with welcoming attitudes, even after adjusting for demographics and multiple well-being and agency-related indicators. Because the data are cross-sectional and self-reported, directionality cannot be established. It is plausible that individuals who already hold favorable views are more likely to adopt GenAI, but it is equally plausible that adoption increases perceived usefulness and reduces uncertainty through repeated exposure. This bidirectional interpretation—attitudes shaping uptake and experience shaping subsequent attitudes—has also been discussed in educational analyses of GenAI acceptance (Kanoh, 2025b).

The present findings support the practical inference that acceptance is closely tied to "experienced benefits" and "experienced risks," rather than to general life circumstances alone.

Interpretation, however, should remain cautious due to model assumptions. The proportional-odds (parallel lines) assumption was not supported for Model 1, and for Models 2–3 the test was not available because the unconstrained model could not be estimated in SPSS. Accordingly, the regression results are best treated as robust evidence of directional associations—especially the prominent role of use—rather than as definitive parameter estimates under fully satisfied proportional-odds constraints.

4.3. Well-being and "adaptability": acceptance as coping orientation, not global life quality

Correlational analyses indicated that welcoming attitudes showed only small associations with most well-being indicators. In contrast, adaptability (e.g., "I can adapt to changes easily") displayed a more consistent positive relationship with welcoming attitudes. This pattern suggests that welcoming GenAI diffusion may reflect a general coping orientation or openness to change more than it reflects overall well-being per se. Such a profile aligns with the idea that technology acceptance is partly anchored in psychological readiness to navigate change, while global satisfaction or distress may be too broad (and multiply determined) to predict a specific technology attitude strongly once other covariates are considered.

4.4. Risk perception and the "technical vs. social risk" lens

The open-ended responses show that acceptance is not simply enthusiasm or resistance; rather, it is a conditional stance balancing usefulness with governance requirements. This can be sharpened by the risk framework articulated in the attached paper, which distinguishes AI-related risks into (a) technical risks (e.g., erroneous judgments, hallucination-like failures, security issues) and (b) social risks (e.g., privacy and property-rights infringement, misuse/abuse, cognitive load, bias, legal and reputational risks).

Your qualitative clusters map naturally onto this distinction: pragmatic comments about drafting documents or generating images primarily reflect perceived usefulness, while concerns about copyright, legality, and misinformation correspond closely to the social-risk domain (and, in the case of incorrect outputs, also to technical risk). This helps explain why welcoming attitudes can be simultaneously positive about efficiency yet cautious about societal rules and harm prevention.

4.5. Cognitive security and AI literacy as "human-centered defense"

A second interpretive contribution from the attached paper is the emphasis on cognitive security, an interdisciplinary approach integrating AI, human behavior, and social science to address human cognitive vulnerabilities as a core element of security. It frames humans as a potentially vulnerable component in socio-technical systems and highlights a shift from purely technical defenses toward human-centered defenses, including education programs grounded in cognitive and behavioral evidence.

This perspective strongly supports how your qualitative results are already framed: respondents' concerns about being deceived, failing to identify fake information, or losing independent thinking and creative agency are not "peripheral anxieties," but central acceptance conditions. In other words, the public's stance is not only about whether GenAI is useful; it is also about whether individuals and institutions can develop the cognitive and educational infrastructure needed to use GenAI safely and responsibly.

4.6. Governance conditions for social acceptance: hard law, soft law, roles, and public anxiety

The social–legal cluster in the open-ended network (e.g., "law–people–sense") signals that diffusion is evaluated through normative and governance lenses, not merely personal convenience. The attached paper cites a recent Japanese policy framing that emphasizes building an AI governance framework and proposes three strategic approaches: (1) combining application of existing laws with proactive use of soft law such as guidelines, (2) clarifying roles and responsibilities among stakeholders (developers, providers, users), and (3) addressing public anxiety and concerns through concrete measures that build trust(Takemura, 2025).

This governance framing is highly consistent with your data: respondents' acceptance often appears conditional on rules for misuse prevention, rapid legal clarification (especially around copyright), and credible accountability structures. Thus, welcoming attitudes should be interpreted not simply as "positive feelings," but as evaluations of whether a trustworthy socio-technical and institutional environment is emerging.

4.7. Acceptance is service- and context-dependent

Another relevant insight from the attached paper is that social acceptance can require different approaches depending on the service context and the type/size of perceived risk; it illustrates this using multiple AI services with different purposes and risk profiles, including differences in monetary risk exposure.

Applied to GenAI, this implies that public acceptance may vary meaningfully by use case (e.g., casual drafting vs. consequential decision support) and by domain (education, work, healthcare, finance). This helps contextualize why "GenAI use" is such a strong predictor: use is not a single phenomenon but a proxy for multiple contextual experiences (benefits realized, risk encountered, domain of application, and informal learning about limitations).

4.8. Implications for education and policy

Two implications follow. First, diffusion debates should not be framed as a simple pro/anti divide. Respondents articulated both opportunities (efficiency and support for work/creative tasks) and governance conditions (copyright protection, legal clarity, and misuse prevention). Second, AI literacy should be conceptualized as more than tool operation: it should incorporate cognitive defense competencies (verification practices, recognizing error modes, bias awareness, and reflection on how tool use shapes thinking), consistent with the human-centered defense orientation highlighted by cognitive security research.

In teacher education, these findings reinforce the need for structured competency models and assessment rubrics that cover not only tool use but also verification practices, ethical reasoning, and classroom decision-making around GenAI (Kanoh, 2025c).

At the policy level, the three-part governance approach (soft law + clear responsibilities + addressing public anxiety) provides an actionable template for translating public concerns into institutional responses.

4.9. Limitations and future directions

Several limitations should be noted. The co-occurrence network captures word co-occurrence patterns rather than full nuance (e.g., conditional reasoning or minority views). All measures were self-reported and cross-sectional; therefore, causal claims cannot be made. In addition, the proportional-odds assumption was not supported in Model 1, and diagnostics were not available for Models 2–3 due to estimation constraints; robustness checks using alternative ordinal specifications would strengthen inference. Future work should (a) test directionality between use and attitudes using longitudinal designs, (b) examine context-specific acceptance by use domain and perceived risk type (technical vs. social), and (c) evaluate interventions that operationalize cognitive-defense-oriented AI literacy alongside governance mechanisms that build trust.

5. Overall summary and future directions

Using a large-scale secondary dataset, this study found that welcoming the diffusion of generative AI was most strongly associated with respondents' prior GenAI use, whereas demographic and subjective well-being correlates were comparatively modest. In multivariable ordinal models, men and individuals reporting greater adaptability tended to express more welcoming attitudes. Most notably, GenAI users were markedly less likely to report low welcoming ratings, highlighting the central role of experiential proximity to the technology in shaping acceptance.

Open-ended responses complemented these quantitative findings by illustrating how respondents evaluated diffusion in a pragmatic yet conditional manner. Many comments emphasized practical benefits such as saving time and supporting work or learning (e.g., drafting documents and generating images), while simultaneously specifying governance-related conditions such as copyright protection, clearer legal frameworks, privacy safeguards, and prevention of misuse. In addition, concerns about skill decline and vulnerability to misinformation underscore the importance of AI literacy not only as operational competence but also as cognitive defense—supporting verification, critical evaluation, and reflective decision-making about when and how to rely on generative systems.

Several limitations warrant caution. All measures were self-reported and cross-sectional, and missingness required listwise deletion in multivariable models. Accordingly, the directionality between GenAI use and welcoming attitudes cannot be established: favorable attitudes may motivate adoption, and adoption may in turn reduce uncertainty by making benefits more salient. Moreover, qualitative results based on co-occurrence networks summarize lexical patterns and cannot capture nuance such as conditional reasoning, minority perspectives, or context-dependent interpretations.

Future research should (a) test directional pathways between GenAI use and attitudes using longitudinal designs and, where possible, behavioral indicators of use; (b) examine how specific literacy components (verification practices, attribution norms, and critical evaluation) relate to both adoption and well-being; and (c) develop and evaluate educational and communication interventions that help learners and citizens use GenAI responsibly while preserving human creativity, autonomy, and trust in information environments.

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