Artificial Intelligence as a Health Communication Infrastructure for Metro and Nonmetro Residents

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The Illinois Institute for Rural Affairs (IIRA) works to improve the quality of life for rural residents by partnering with public and private agencies on local development and enhancement efforts.

Abstract

This paper explores whether AI use for health information is skewed towards young people, for example, less than 35 years of age, and living in the metro. Statistical analysis of survey data from 1,343 adults indicates that one's age has the strongest association with AI use ($r = .23$) and one's place of residence, metro / nonmetro, has little or no influence on AI use behavior.

Introduction

In a report titled "AI as a Healthcare Ally", OpenAI reveals that 40 million ChatGPT users ask health-related questions every day[2]. The report goes on to highlight that geographically, hospital deserts, defined as places that are more than 30-minute drive from a hospital, averaged 580,000 ChatGPT health messages per week[3].

In an earlier *Research Brief* about health-related Internet use among Midwesterners, I concluded that technological diffusion is moderated by one's age (less than 35 years of age), sex (male), race (Asian), and metro location[4]. Is this profile valid for users of AI for health information? What motivates people to use AI for health-related information; is it the cost of seeing a provider, or not having a regular healthcare provider? How satisfied are users with AI responses about healthcare? This paper addresses these and other related questions using survey responses from 1,343 adults, a weighted equivalent of 252.99 million adults.

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2 https://cdn.openai.com/pdf/2cb29276-68cd-4ec6-a5f4-c01c5e7a36e9/OpenAI-AI-as-a-Healthcare-Ally-Jan-2026.pdf.

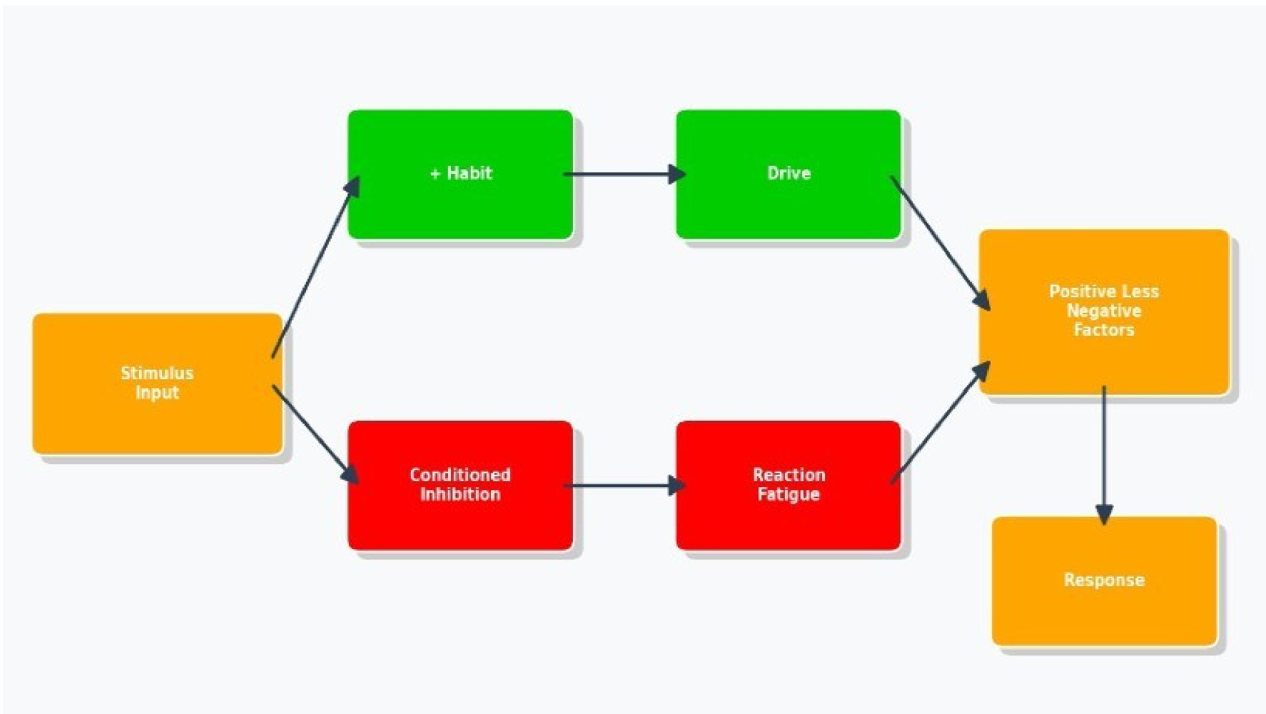
3 For research on healthcare deserts in Illinois, see Athiyaman, A. (2024). Geographic Variation in Trauma Deaths in Rural Illinois: A Hypothesis about Trauma Deserts, Research Brief, 6(7), April 16. Available online: https://iira.org/wp-content/uploads/2024/04/Geographic-Variation-in-Trauma-Deaths-in-Rural-Illinois_published.pdf.

4 Athiyaman, A. (2025). Health-Related Internet Use among Adults In The Midwest, Metro and Nonmetro Geographies, *Research Brief*, 7(13), August 1. Available: https://iira.org/wp-content/uploads/2025/08/RB7_13-Health-Related-Internet-Use-among-Adults-In-The-Midwest-p.pdf.

Concepts and their Relations

Hull's Systematic Behavior Theory[5] could be used to explain AI use; the theory explains how and why organisms made the responses they did. Theoretical constructs such as 'habit strength' and 'inhibition' are used to explain behavior (Figure 1); specifically, positive factors for a response combine with negative factors that inhibit the response to determine behavior. Table 1 lists the conceptual definitions.

Figure 1: Hull's Theory, Schematic Summary



5 Albery, I., Davey, G., Sterling, C., & Field, A. (2014). *Complete Psychology*. Routledge.

Table 1: Conceptual Definitions

Construct	Definition
Stimulus Input	Stimulus that triggers behavior
Positive Habit, H	Positive associative strength of a response to the stimulus
Drive	Motive for behavior
Conditioned Inhibition	Negative strength to respond to the stimulus
Reaction fatigue	Temporary response inhibition, weariness
Reaction potential	Difference between net positive and negative factors
Response	Behavior

Methodology

Data are from a survey of SSRS panel members of US adults age 18 and above[6]. The survey on "health information and trust" polled 1,343 national adults, SSRS panelists, during February 24 – March 2, 2026. Survey was implemented using both online and telephone.

Table 2 lists the operational definitions of variables, measures of constructs listed in Table 1. Descriptive and confirmatory data analyses were performed to establish the face validity of the theory and to describe metro / nonmetro differences in AI use.

6 See, www.sssrs.com. Microdata from the survey were accessed from iPoll, https://ropercenter.cornell.edu/ipoll/.

Table 2: Measures [7]

Construct	Operational Definition
Positive habit, H, Attitude towards AI	Four-step satisfaction with the quality of AI responses to physical and mental health questions. Scores range from a maximum of 8 to a minimum of 2.
Drive	Problem removal and problem avoidance, were the primary motives for AI use. Ordinal, “Major reason”, “Minor reason”, and “Not a reason” responses, were obtained for the following motives for AI use: 1) You don’t have a regular health care provider, or could not get an appointment; 2) You could not afford the cost of seeing a provider; 3) You wanted to look up information before deciding whether to see a health care provider; 4) You felt more comfortable looking up things related to your health privately; 5) You felt the information from AI Chatbots was as reliable as what a health care provider would tell you; 6) You received medical test results before being able to discuss them with a provider; and 7) You wanted quick or immediate information or support.
Conditioned inhibition	Privacy concerns for health data submitted to AI were assessed using a four point “Very Concerned” (4) to “Not at all concerned” (1) scale.
Response behavior	How often do you actively use artificial intelligence (AI) tools, such as typing questions into a chatbot like ChatGPT, Google Gemini, or Claude? Answers ranged from “Several times a day” (5) to “Never” (1). For crosstabulations, the 5-step scale was converted to a binary measure with “0” for “Never” and “1” for all other values.
Demographics:	
I. Gender	1 = Male; 2 = Female
ii Age	1 = 18 – 29; 2 = 30 – 49; 3 = 50 – 64; 4 = 65 and above
iii. Race	1 = White; 2 = Nonwhite
iv. Education	1 = LT High School; 2 = HS Graduate; 3 = Some College; 4 = College degree
v. Income	1 = LT $40k; 2 = $40k - <90k; 3 = $90k and above
vi. Geography	1 = Suburban; 2 = Urban; 3 = Rural
vii. IL	State of residence: 1 = IL; 0 = all other states
viii. Weight	Person weight

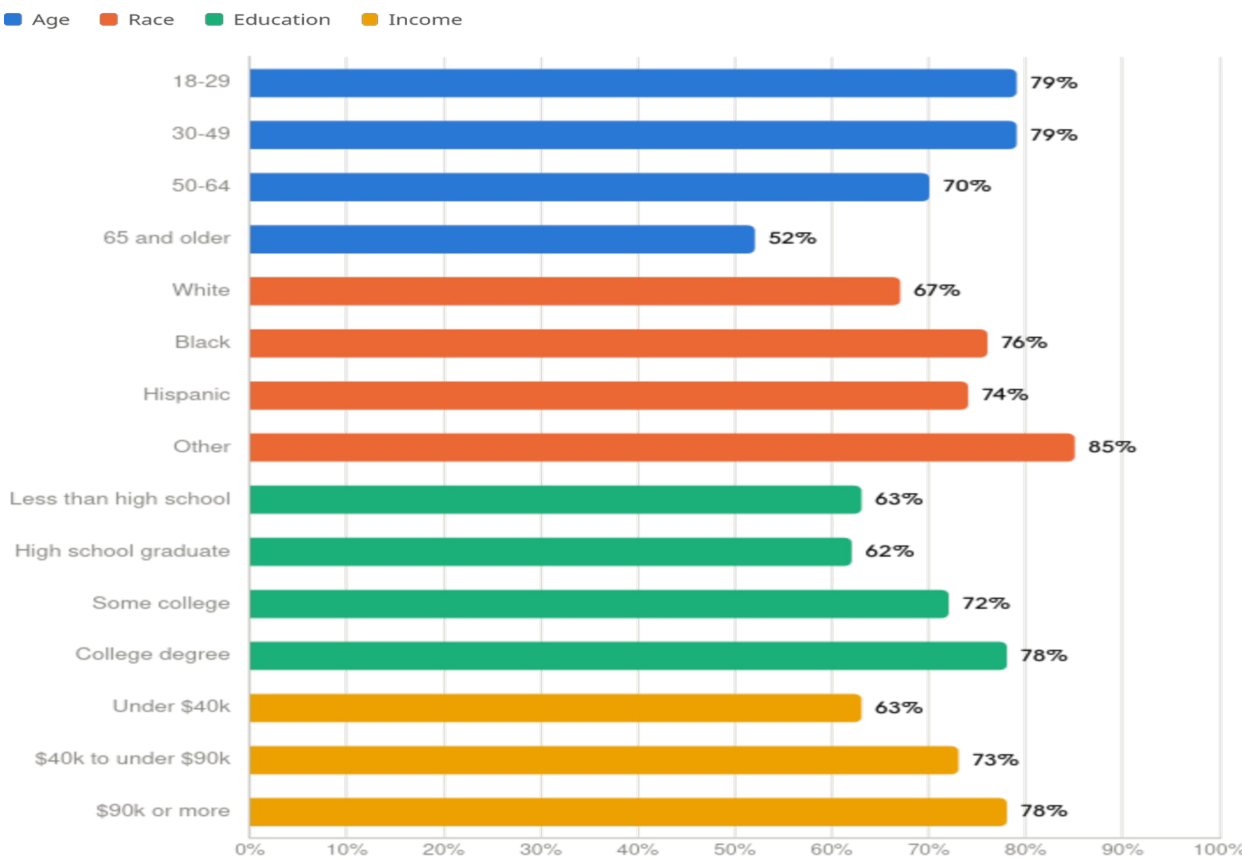
7 Appendix 1 lists the questions for all the variables.

Findings

AI User Profile

A typical, active, AI user is young[8], non-White, has a college degree, and reports an annual income greater than $90,000 (modal values in Figure 2). Table 3 shows that age has the strongest association with AI use (r = .23); one's place of residence, metro / nonmetro, has little or no influence on one's AI use behavior.

Figure 2: Demographics of AI Users



8 The "age" variable was bimodal, both 18-29 and 30-49 age groups registered a 79% response rate for the AI use question.

Table 3: Impacts of Demographics on Respondents' AI Use [9]

	Gender (%)	
AI Use	**Male**	**Female**
Yes	73%	70%
No	27%	30%
N, Weighted	113.18 mil	134.53 mil

Note: chi2 = 0.334, p = 0.5635, Cramer's V = 0.020

	Age Group			
AI Use	**18-29**	**30-49**	**50-64**	**GTE 65**
Yes	79%	79%	70%	52%
No	21%	21%	30%	48%
N, Weighted	46.49 mil	93.25 mil	60.45 mil	47.86 mil

Note: chi2 = 45.742, p = 0.0000, Cramer's V = 0.233

	Race			
AI Use	**White**	**Black**	**Hispanic**	**Other**
Yes	67%	76%	74%	85%
No	33%	24%	26%	15%
N, Weighted	128.55 mil	38.36 mil	58.04 mil	22.80 mil

Note: chi2 = 13.492, p = 0.0037, Cramer's V = 0.127

	Level of Education			
AI Use	**LT High School**	**High School Grad**	**Some College**	**College Grad**
Yes	67%	76%	74%	85%
No	33%	24%	26%	15%
N, Weighted	21.95 mil	61.64 mil	70.04 mil	94.09 mil

Note: chi2 = 18.400, p = 0.0004, Cramer's V = 0.148

	Household Income		
AI Use	**LT $40,000**	**$40k – LT $90k**	**GTE $90k**
Yes	63%	73%	78%
No	37%	27%	22%
N, Weighted	89.27 mil	84.44 mil	74.00 mil

Note: chi2 = 15.462, p = 0.0004, Cramer's V = 0.136

	Residential Geography		
AI Use	**Suburban**	**Urban**	**Rural**
Yes	73%	70%	63%
No	27%	30%	37%
N, Weighted	125.96 mil	97.67 mil	24.85 mil

Note: chi2 = 3.995, p = 0.1356, Cramer's V = 0.069

	State of Residence	
AI Use	**IL**	**Other States**
Yes	82%	70%
No	18%	30%
N, Weighted	8.20 mil	239.52 mil

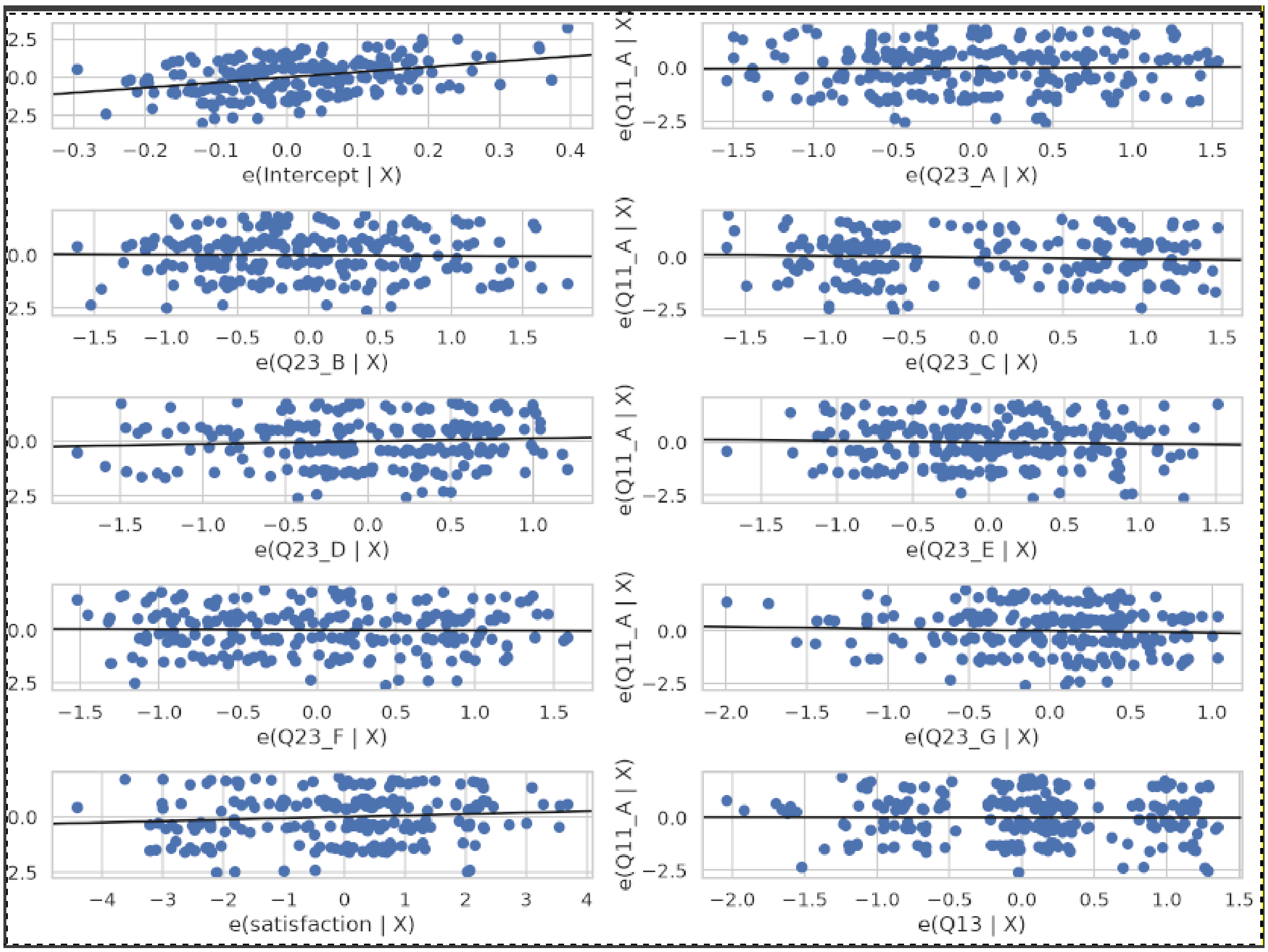
Note: chi2 = 2.156, p = 0.1420, Cramer's V = 0.051

9 The 5-step AI use response was converted to a binary scale with 1 indicating AI use and 0 otherwise; see Table 2.

Empirical Support for the Theoretical Model

The conceptual framework in Figure 1 was validated using regression procedures; Figure 3 shows each predictor's unique contribution to variability in the criterion, AI use. One's satisfaction with AI use reinforces them to repeat use AI to gather health information. As predicted, privacy concerns inhibit AI use.

Figure 3: Nomological Analysis, AI Use and its Predictors



Note: See Appendix 1 for questions related to the measures.

Table 4 shows the correlations among the constructs. All correlations were in the expected direction. The seven motives, all negatively originated[10], indicate that AI use is triggered by the drive to "gain information quickly".

10 Negatively originated motives are conerned with problem removal, or problem avoidance behavior; see Athiyaman, A. (2022). Youth E-Cigarette Use in Illinois and the Midwest: Insights from A Panel Study. Research Brief, Short Paper 4(18). Available at https://iira.org/wp-content/uploads/2023/07/Youth-E-Cigarette-Use-_-RB418.pdf

Table 4: Correlations among the Constructs in Figure 1

	AI Use	Satisfaction	Lack of PCP	Cost of Care	Pre-PCP	Privacy Motive	Reliable Info Check	Test Results
AI Use	1	0.09	-0.02	-0.05	0.02	0.08	-0.04	0.02
Satisfaction		1	0.00	0.02	0.06	0.09	0.18	0.12
Motive: Lack of PCP			1	0.50	0.22	0.18	0.20	0.21
Motive: Cost of Care				1	0.19	0.21	0.28	0.12
Motive: Pre-PCP Consult					1	0.26	0.21	0.26
Motive: Privacy Motive						1	0.24	0.16
Motive: Reliable Info							1	0.26
Motive: Check Test Results								1
Motive: Quick Info								
Inhibition								

Note: See Appendix 1 for survey questions related to the constructs; see Table 2 for operational definitions.

<u>Multivariate Analysis</u>

Table 3 presented zero-order, bivariate, correlational measures of demographic variables with the criterion “AI use”; Cramer’s *V* ranged from a high of .23 for the age variable to a low .02 for gender[11]. In this section, we explore propositions of the form “If *p, q, r, …, v*, then *y*”. The focus is on the combined influences of the independent variables, demographics, on the dependent variable and of the relative amounts of the influences of the predictors.

Table 5 shows variable frequencies, unweighted cases by levels. For example, 43 respondents were from Illinois and females were in the majority, 683 respondents. Of the total 1,254 respondents who provided responses to the “AI use” question, 74% said that they use AI.

11 Cramer’s V is a measure of association between two nominal variables; see, Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish journal of emergency medicine*, *18*(3), 91-93.

Table 5: Frequency Distributions of Predictor Variables

variable	level	n
gendervar	Male	571
gendervar	Female	683
recage2	18-29	225
recage2	30-49	482
recage2	50-64	308
recage2	65+	239
race_R	White	653
race_R	Black	194
race_R	Hispanic	293
race_R	Other	114
receduc	HS grad	313
receduc	LT HS	106
receduc	Some college	361
receduc	College degree	474
recincome	LT $40k	444
recincome	$40k-<$90k	430
recincome	$90k+	380
USR_NEW	Suburban	639
USR_NEW	Urban	488
USR_NEW	Rural	127
IL	Other states	1211
IL	Illinois	43

A Logit model of the form:

AI Use ~ C(Gender) + C(Age) + C(Race) + C(Education) + C(Income) + C(Metro/Nonmetro) + C(Resides in IL)

was calibrated. The reference categories for the categorical variables are given in Table 6; Table 7 shows the results of model calibration. Appendix 2 shows model fit statistics.

Table 6: Reference Categories for Nominal Variables

```
Categorical coding (reference category is listed first)
--------------------------------------------------------------------------------
  gendervar    ref = 'Male'   levels: ['Male', 'Female']
  recage2      ref = '18-29'   levels: ['18-29', '30-49', '50-64', '65+']
  race_R       ref = 'White'   levels: ['White', 'Black', 'Hispanic', 'Other']
  receduc      ref = 'HS grad'   levels: ['HS grad', 'LT HS', 'Some college', 'College degree']
  recincome    ref = 'LT $40k'   levels: ['LT $40k', '$40k-<$90k', '$90k+']
  USR_NEW      ref = 'Suburban'   levels: ['Suburban', 'Urban', 'Rural']
  IL           ref = 'Other states'   levels: ['Other states', 'Illinois']
```

Table 7: Results of Model Run

Coefficients, odds ratios and 95% confidence intervals

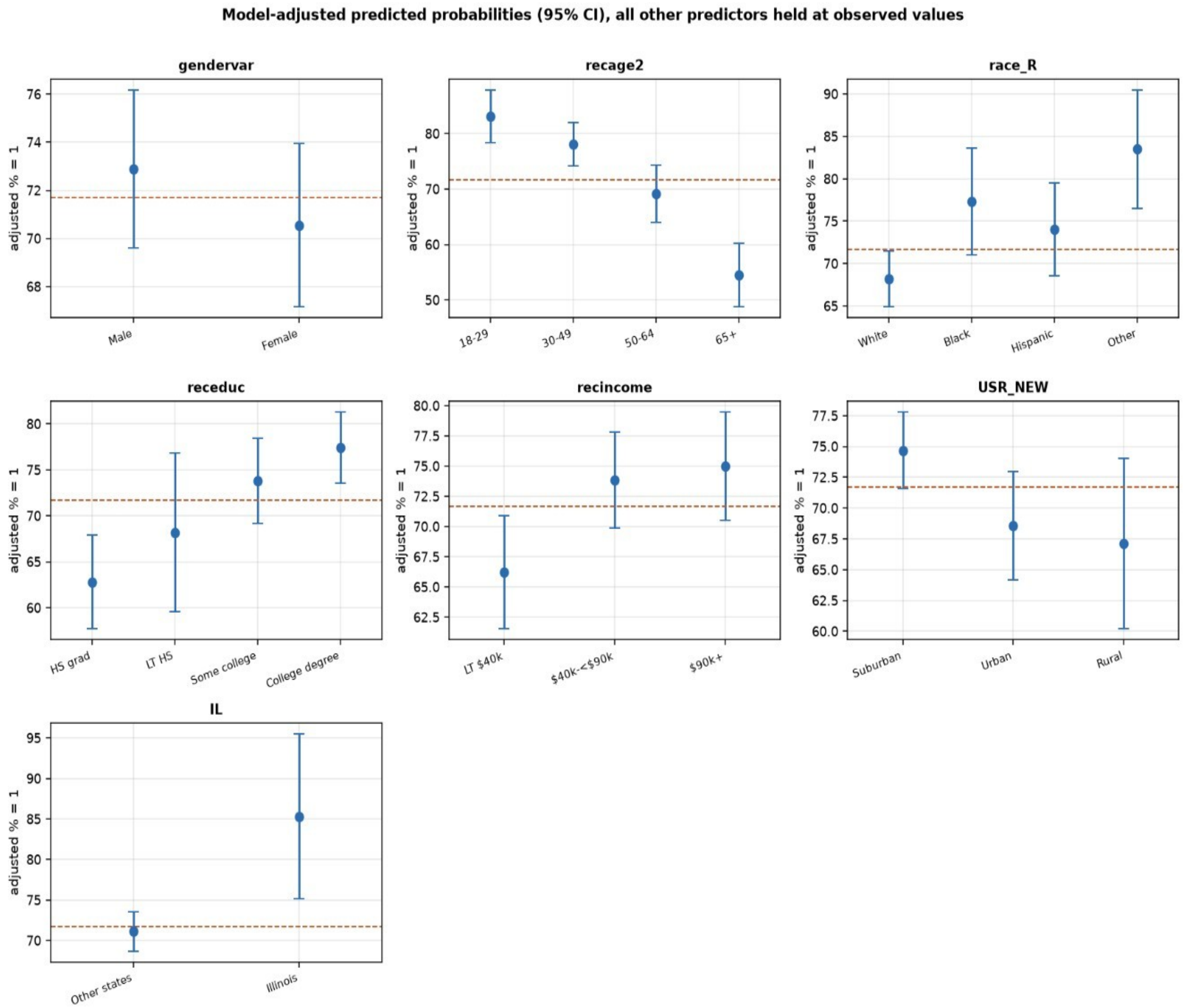
term	b	SE	z	p	OR	OR_lo95	OR_hi95	sig
Intercept	0.9146	0.2462	3.7143	0.0002	2.4959	1.5403	4.0441	***
gendervar: Female	-0.1295	0.1345	-0.9632	0.3355	0.8785	0.6750	1.1434	
recage2: 30-49	-0.3401	0.2183	-1.5575	0.1193	0.7117	0.4639	1.0918	
recage2: 50-64	-0.8285	0.2268	-3.6528	0.0003	0.4367	0.2800	0.6812	***
recage2: 65+	-1.4973	0.2215	-6.7596	0.0000	0.2237	0.1449	0.3454	***
race_R: Black	0.5136	0.2211	2.3229	0.0202	1.6713	1.0836	2.5778	*
race_R: Hispanic	0.3165	0.1847	1.7136	0.0866	1.3724	0.9555	1.9711	.
race_R: Other	0.9424	0.2917	3.2304	0.0012	2.5662	1.4487	4.5457	**
receduc: LT HS	0.2643	0.2503	1.0561	0.2909	1.3025	0.7976	2.1273	
receduc: Some college	0.5655	0.1799	3.1435	0.0017	1.7603	1.2373	2.5044	**
receduc: College degree	0.7812	0.1817	4.2993	0.0000	2.1840	1.5297	3.1183	***
recincome: $40k-<$90k	0.4051	0.1655	2.4473	0.0144	1.4995	1.0840	2.0742	*
recincome: $90k+	0.4724	0.1919	2.4616	0.0138	1.6039	1.1011	2.3364	*
USR_NEW: Urban	-0.3390	0.1531	-2.2149	0.0268	0.7125	0.5278	0.9617	*
USR_NEW: Rural	-0.4131	0.2053	-2.0118	0.0442	0.6616	0.4424	0.9894	*
IL: Illinois	0.9502	0.4575	2.0769	0.0378	2.5862	1.0549	6.3399	*

Significance: *** p<.001 ** p<.01 * p<.05 . p<.10
OR > 1 => higher odds of Q11_binary = 1 than the reference level.

The logistic coefficients, the ***b*** values in Table 7, give the change in the log odds of the outcome for changes in predictor values. For example, compared to a person in the 18-29 age category, an individual in the 65+ age group would have a -1.5 change in the log odds of using AI.

Figure 4 shows the predicted probabilities of AI Use given the predictor levels. The highest probabilities of AI use are associated with the “other” race, 18-29 age category, college education, household income greater than or equal to $90,000, suburban living, and Illinois state residency.

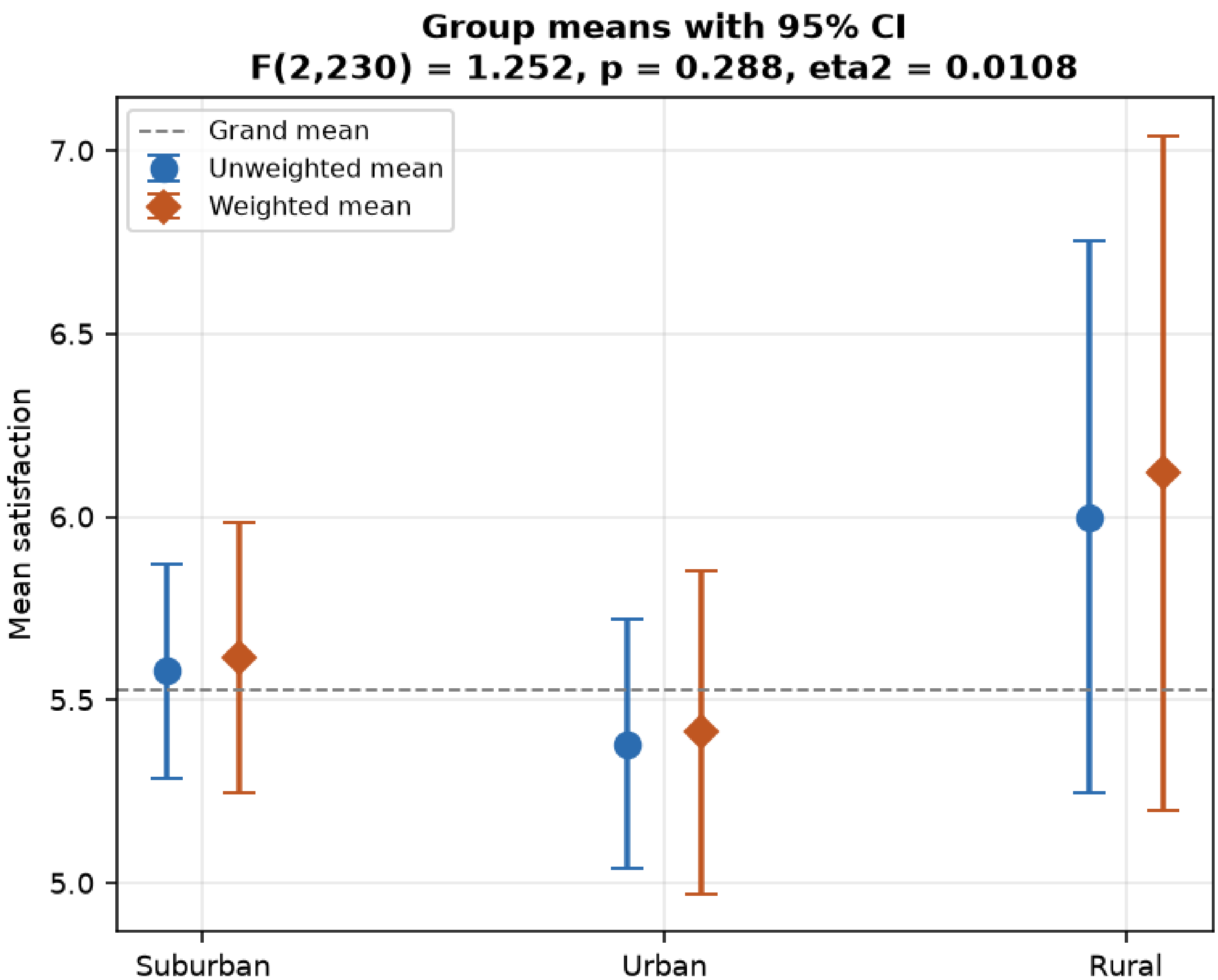
Figure 4: Predicted Probabilities of AI Use



<u>Descriptive Analysis of Theoretical Constructs, Hull's Theory</u>

Satisfaction with AI use and inhibition, privacy concerns for AI use, did not differ among the geographies (Figures 5 and 6). However, motives for AI use did differ among urban/suburban and rural residents (Table 8); for instance, rural residents do not feel the need to use AI Chatbots as a substitute for PCP, but urban and suburban residents do. For all the three geographical segments, the need for quick or immediate health information is the salient driver for AI use.

Figure 5: Mean Differences in AI-Use Satisfaction among Suburban, Urban, and Rural Residents



Note: Satisfaction scores range from 2 to 8; see Table 2.

Figure 6: Mean Differences in Inhibition Scores among Suburban, Urban, and Rural Residents

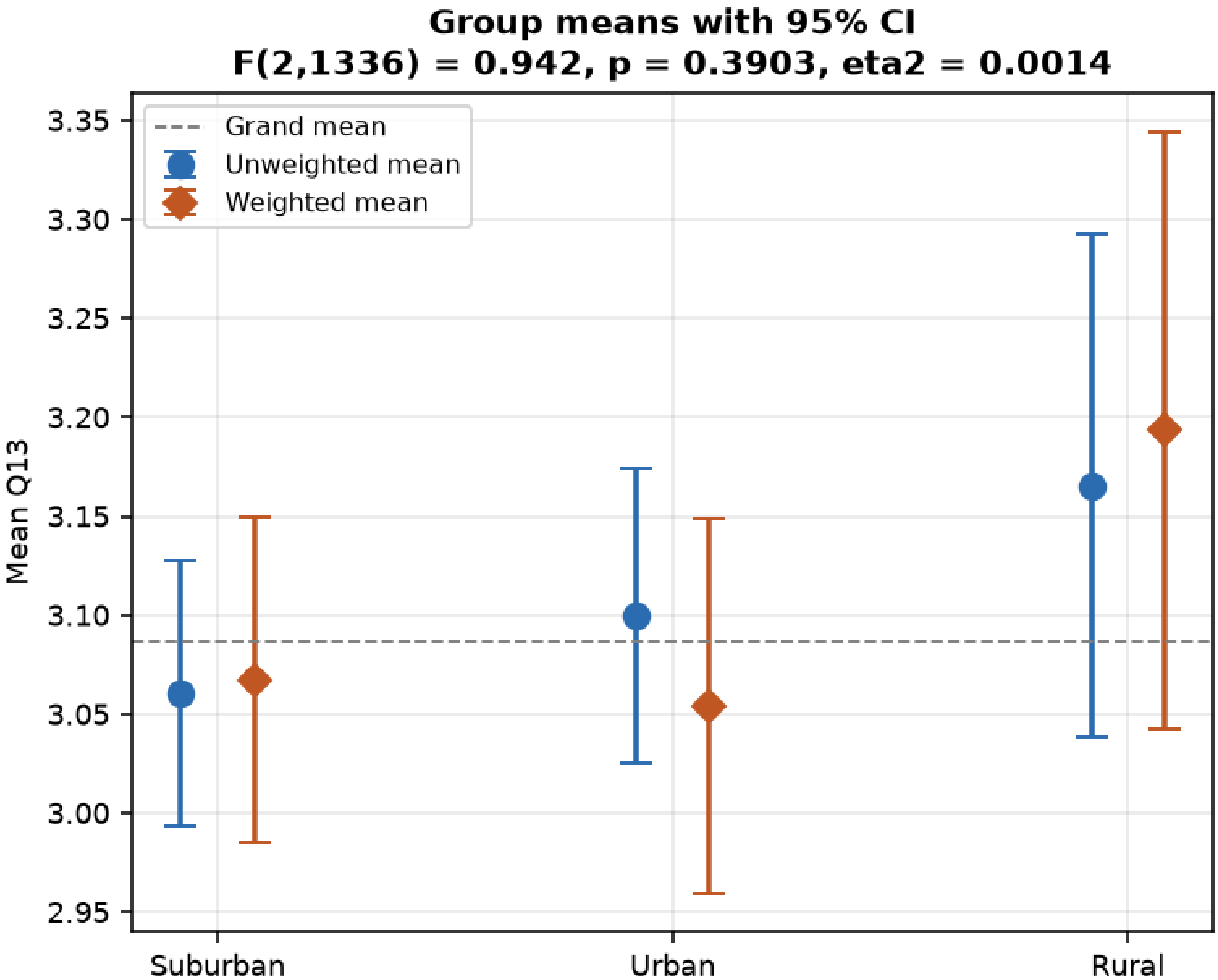


Table 8: Motives for AI Use for Health Information by Geography, Unit = %

Motive, Major Reason for AI Use	Suburban	Urban	Rural	p
Don't have a PCP, or could not get an appointment	15	18	32	0.69
Couldn't afford the cost of seeing a provider	16	24	16	0.07
Look up information before seeing a provider	38	45	40	0.63
More comfortable looking up things related to health privately	35	40	28	0.64
Felt that AI Chatbots can provide information as reliable as a PCP	17	22	14	0.10
Received medical test results before being able to discuss them with a provider	31	31	12	0.17
Wanted immediate health information or support	65	68	55	0.04

Note: p values are associated with the Chi-square tests.

Summary and Conclusion

This paper explores metro and nonmetro residents' use of AI for health information. Data are from a survey of 1,343 adults, a weighted equivalent of 252.99 million individuals, conducted during February 24 – March 2, 2026.

Hull's Systematic Behavior Theory provided the structure for the report. Specifically, the constructs 'attitude', 'drive', and 'inhibition' were used to discuss AI use among the US population. Key findings from the survey are provided below in a question-answer format.

i. What motivates people to use AI for health information?

   The need for quick or immediate health information is the salient driver for AI use.

ii. Does attitude towards AI differ among respondents from urban/suburban and rural geographies?

   No, respondents from all three geographies hold positive attitude towards AI.

iii. What factors, if any, inhibit AI use?

   None; people are "somewhat concerned" about the privacy of personal medical information that they provide to AI tools, but it exhibits a low, statistically zero, correlation with AI-use satisfaction.

iv. What is the profile of a typical AI user?

   A typical, active, AI user is 18-49 years old, non-White, has a college degree, and reports an annual income greater than $90,000.

In conclusion, AI is a critical health communication infrastructure for both metro and nonmetro residents, but questions remain about people's ability to understand the information they receive – a topic for future research.

Appendix 1: Questionnaire

Inhibition [1]

How concerned, if at all, are you about the privacy of personal medical or health information that people provide to artificial intelligence (AI) tools or chatbots?

- → Very concerned
- → Somewhat concerned
- → Not too concerned
- → Not at all concerned

AI Use

How often do you actively use artificial intelligence (AI) tools, such as typing questions into a chatbot like ChatGPT, Google Gemini, or Claude?

- → At least several times a week
- → About once a day
- → Several times a week
- → Less often
- → Never

Drive [2]

People use AI tools for health information for different reasons. For each of the following, please indicate whether it was a major reason, a minor reason, or not a reason you used an AI tool or chatbot for health information.

- → You don't have a regular health care provider, or could not get an appointment
- → You could not afford the cost of seeing a provider
- → You wanted to look up information before deciding whether to see a health care provider
- → You felt more comfortable looking up things related to your health privately
- → You felt the information from AI chatbots was as reliable as what a health care provider would tell you
- → You received medical test results before being able to discuss them with a provider
- → You wanted quick or immediate information or support

Satisfaction / Attitude (Two items – one for physical and one for mental health)

How satisfied were you, if at all, with the quality of the response you received from AI tools or chatbots when you used it for information or advice related to your physical health / mental health?

- → Very satisfied
- → Somewhat satisfied
- → Not too satisfied
- → Not at all satisfied

1 Labeled Q13 in Figure 3.
2 The 7 motives were labeled Q23_A to Q23_G in Figure 3.

Appendix 2: Model Fit Statistics

```
Global model tests and pseudo R-squared
---------------------------------------------------------------------------------
Log-likelihood (full)          :    -677.3999
Log-likelihood (intercept only):    -747.2369
Likelihood-ratio chi2(15)       :     139.6739   p = 2.669e-22
Robust Wald chi2(15)            :     122.8305   p = 5.334e-19   <- use this one when weighting
Deviance                       :    1354.7998  df = 1238
Pearson chi2                   :    1269.8749
Deviance / df                  :       1.0943   (~1 indicates no gross over/under-dispersion)
AIC                            :    1386.7998
BIC                            :    1468.9453
McFadden pseudo R2             :       0.0935
McFadden adjusted pseudo R2    :       0.0734
Cox-Snell pseudo R2            :       0.1054
Nagelkerke pseudo R2           :       0.1514

Note: pseudo R2 values of .05-.20 are typical and respectable for
individual-level survey attitude models; they are not comparable to OLS R2.
```