MSE 609 - Quantitative Data Analysis

University of Waterloo

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Group 11 Project Report

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1 Introduction

This project replicates key results from the paper "Knowledge is not all you need for comfort in use of AI in healthcare" by Li *et al.* (2025) [1]. The original paper was published in *Public Health*, an established academic journal. The study examined how demographic factors shape Canadians' knowledge of AI and comfort with AI use in healthcare. Importantly, it found that fostering trust and integrating AI in healthcare systems may depend on strong data governance, transparency, and inclusive AI design. This work is influential because it provides a timely exploration of public perceptions of AI in healthcare, particularly as the technology is rapidly expanding across multiple disciplines.

The goal of our project was to replicate key results from the original paper. Specifically, we replicated Table 1, which reports descriptive statistics; Appendix 1, which presents ordinal logistic regression models for four outcomes (Q40–Q43); and Figures 1–4, which required multivariate polynomial regression. Following the replication of these components, we extended the analysis by examining two additional datasets from the Canadian Digital Health Survey (CDHS) for 2023 [2] and 2024 [3]. In this report, we outline our data pipeline, assess the reproducibility of results, and discuss our replication findings and the subsequent extension.

2 Data

2.1 Data Source

The data for this replication were obtained from the ATS2021 dataset of the 2021 Canadian Digital Health Survey, hosted on Borealis Dataverse (N = 12,052 respondents) [4]. The dataset includes demographic characteristics, health-related behaviours, and attitudes toward AI in healthcare. All datasets used, including those for the extension, are accessible through the reference list and Appendix.

2.2 Variables Used

This section outlines the variables included in the replication study. A complete data dictionary is provided in the Appendix.

2.2.1 Dependent Variables (Q40–Q43)

The cleaned dataset includes four dependent variables, each measured on a four-point Likert scale (1 = Not at all, 4 = Very):

- Q40: Knowledge of what AI is
- Q41: Comfort with AI as a tool in healthcare
- Q42: Comfort with AI research with consent
- Q43: Comfort with AI research without consent (deidentified)

2.2.2 Independent Variables

The four independent variables are demographic controls treated as categorical factors:

- Age_new: Age group (5 categories)
- Gender: Male, Female, Other/Non-binary
- Income (Q55): Total annual household income (7 categories)
- Education (Q66): Highest level of education completed (7 categories)

2.3 Data Cleaning Pipeline

Our cleaning pipeline follows the logic implied in the original study.

1. **Missing values:** Values coded between 96–99 were treated as missing (NA), representing "other," "unsure," or non-responses. Valid responses for the four demographic controls ranged from 1–4.

2. **Data filtering:** Two filtering strategies were implemented:
   - **Standard filtering:** All four independent variables must have valid values. Invalid responses (96–99) were removed. For Q40–Q43, all responses were retained. Each outcome produced a different sample size, aligned with Appendix A1 of the original paper.
   - **Strict filtering:** Only respondents with valid values for all eight variables (independent and dependent) were retained. Invalid responses for Q40–Q43 were also removed, resulting in a final sample size of $n = 9{,}198$, matching Table 1 in the original paper.
3. **Final samples:** Standard filtering produced a sample of $n = 10{,}553$, used for reproducing Appendix A1 and Figures 1–4. Strict filtering yielded $n = 9{,}198$, used exclusively for replicating Table 1.

We also identified differences in age-bin definitions between the original study and our dataset. The paper uses categories such as "35–54," "55–64," and "65+" [1], whereas the dataset provides "35–44," "45–54," and "55+" [4]. Because these bins are embedded directly in the source data and no additional information is available, we retained the dataset's original categorization.

3 Replication Results

When reviewing our replication of the 2021 dataset, we found that our results were highly similar to those reported in the original paper. Although minor differences emerged, no major discrepancies were observed in the underlying trends.

3.1 Replication of Table 1

3.1.1 Data Cleaning for Table 1

1. **Defining Variables:** We defined eight independent and dependent variables. Following the original article, Table 1 includes only respondents who provided complete responses for all variables.

2. **Data Filtering:** Participants with missing or incomplete responses were removed to avoid skewing the replicated results.

3. **Final Sample:** After filtering, the final sample contained $n = 9{,}198$ respondents, used exclusively for the replication of Table 1.

3.1.2 Side-by-Side Comparison

A comparison between the original Table 1 and our replicated version shows an almost perfect match, aside from the differences in "Age" bins previously discussed. Partial results illustrating this comparison can be found in Appendix 1.

3.2 Replication of Appendix A1

The original paper's Appendix A1 applied ordinal logistic regression (proportional odds model) to the four Likert-type outcomes Q40–Q43 [1]. We replicated this model using the same predictors and reference categories.

3.2.1 Data Cleaning for Appendix A1

1. **Defining Variables:** As with Table 1, we defined eight variables.

2. **Data Filtering:** Standard filtering procedures were used, while the strict filtering was reserved only for Table 1.

3. **Final Sample:** This produced varying sample sizes across the four dependent variables.

3.2.2 Side-by-Side Comparison

Our replicated estimates align closely with the original Appendix A1. Both analyses show that older adults tend to report lower AI knowledge and lower comfort with AI tools. Female respondents also consistently show lower comfort across Q41–Q43 and lower odds of being knowledgeable about AI. Higher household income increases the likelihood of reporting greater comfort with AI and acceptance of data usage, mirroring the findings of the original paper.

Although some differences in p-values appear—e.g., Age 25–34 category ($p = 0.137$ in the original vs. $p = 0.02$ in our replication) and the "Apprenticeship/Trades" category ($p = 0.935$ vs. $p = 0.54$)—all effect-size patterns remain consistent. Differences in odds ratios remain modest, never exceeding 0.4, and confidence intervals differ by less than 0.2. Trends such as the steadily increasing odds ratios for the Education variable until the PhD category (followed by a decline for Medical/Paramedical respondents) were fully replicated.

These small differences may reflect variations in data-cleaning procedures. Nonetheless, the replication is successful overall.

3.3 Replication of Figures 1–4

3.3.1 3D Surface Findings

Replication of Figure 2 closely matches the pattern shown in the original paper [1].

Note: All findings reported here are restricted to respondents with university-level education and annual household incomes between \$80,000 and \$99,000.

Middle-aged and older women show the lowest comfort with both AI use in healthcare and data use for AI training, revealing a strong interaction between age and gender. Across demographic groups, comfort with data being used for AI training without consent is generally low, even when data are de-identified. The main exception is males aged 16–24, who display higher comfort levels; all other groups remain at or below a comfort rating of 2 out of 4.

Older adults (55+) consistently exhibit lower AI knowledge and lower comfort with AI in healthcare, yet the 3D surface plots show that they report comparatively higher willingness to allow their data to be used for AI training.

In the polynomial model, most nonlinear and interaction effects are statistically insignificant. Only quadratic age and gender terms show notable contributions. This aligns with the 3D plots, where curvature is concentrated along age and gender, and additional higher-order terms provide little analytical benefit.

Full replicated figures are available in the Appendix. Interpretation of 2021 patterns is revisited after the extension for a unified analysis.

4 Extension (New Dataset 2023 & 2024)

4.1 Purpose of Extension

We examined how AI knowledge and comfort evolved over time using the publicly available 2023 and 2024 CDHS datasets. These datasets include direct analogues to the 2021 variables (Q31–Q34 in 2023; Q28_A1, Q28_A3, Q28_A5 in 2024), along with additional questions unique to 2024. We applied the same modelling structure and data-cleaning strategies used in the 2021 replication.

4.2 Analysis Results

Table 1A

Demographic patterns in 2023 and 2024 closely mirror those found in 2021. Younger groups show higher AI knowledge and comfort, while older groups remain significantly less familiar and less trusting. Gender patterns remain stable: women consistently report lower knowledge and comfort, while the “Other” category reports the highest levels. Income and education gradients persist across both datasets. Numerical differences between years do not meaningfully alter interpretation.

3D Surface Plots

Knowledge about AI In 2021, knowledge declined steadily with age, forming a valley-shaped surface, with the ‘Other” gender highest and women lowest. In 2023, the surface flattened, reducing curvature and narrowing age gaps; young males became the peak, while young ‘Other“ respondents reported lower knowledge than older “Other” respondents. In 2024, overall predicted scores increased and the surface more closely resembled 2021. Knowledge still declined with age, but the age slope flattened, suggesting diminishing generational differences in older groups while the youth advantage widened. Plots appear in Appendix 3.1, 3.5, and 3.9.

Comfort with AI In 2021, comfort exhibited a U-shaped pattern: highest in youth, lowest in middle age, then a slight rebound among seniors. Women consistently showed the lowest comfort, while ‘Other” respondents were highest. In 2023 (Q32), the surface was flatter with a gentler slope, indicating narrowing age gaps. In 2024 (Q28_A3), the surface was nearly planar, with young males again forming the peak and older ‘Other” individuals elevated. Plots appear in Appendix 3.2, 3.6, and 3.10.

Comfort with Identified Data (With Consent) In 2021 (Q42), middle-aged women formed the lowest comfort group; young males and “Other” respondents were the highest. In 2023 (Q33), the structure remained similar, though peaks and valleys were less pronounced, suggesting narrowing gaps but not convergence. Plots appear in Appendix 3.3 and 3.7.

Comfort with De-identified Data (Without Consent) In 2021 (Q43), young males reported the highest comfort; comfort declined with age. In 2023 (Q34), the pattern persisted but included a slight rebound among seniors. In 2024 (Q28_A5), the pattern inverted: older respondents showed the highest comfort, young respondents moderate, and middle-aged groups lowest. Gender gaps narrowed substantially. Plots appear in Appendix 3.4, 3.8, and 3.11.

New 2024 Questions

Additional 2024 questions show shifting patterns. Knowledge of AI in healthcare (Q28_A2) decreased for most groups except young males. Trust in unbiased AI (Q28_A4) followed a U-shaped age pattern with young and older individuals reporting the highest trust; young females exceeded males. Privacy concerns (Q28_A7) were high across all groups, with males reporting the lowest concerns and women moderate levels. Plots appear in Appendix 3.12–3.15.

Cross-Year Synthesis

Across 2021–2024, several demographic patterns remain stable: women consistently report lower knowledge and comfort; young males and "Other" respondents show the highest levels; and middle-aged adults remain the least comfortable and most sceptical. Higher income and education consistently predict greater knowledge and comfort and lower privacy concerns. Over time, surfaces flatten, suggesting shrinking gender differences, while generational divides in AI knowledge widen. Notably, in 2024 seniors show unexpectedly high comfort with de-identified data use. Overall, attitudes toward AI in healthcare are becoming more positive, while privacy and fairness concerns remain persistent.

5 Reflection

5.1 What We Learned About Data and Filtering

Replicating the paper required careful attention to how data was cleaned and filtered. We learned that small variations in cleaning decisions directly influenced sample size and interpretation. Using structured filtering strategies improved data quality, enhanced reliability, reduced analytic errors, and enabled a more faithful replication of the original study.

5.2 Lessons About Modeling and Reference Categories

When working with categorical predictors, reference categories play a central role in interpretation. Changing the baseline for age, gender, income, or education alters coefficient signs, odds ratios, and substantive conclusions. To ensure comparability, we aligned all reference categories with those used in the original paper.

5.3 Reproducibility Challenges

Reprocessing Differences. Minor discrepancies emerged due to unavoidable differences in data handling. Although we followed the procedures described in the original study, slight variations and human judgment may have introduced small deviations.

Age Group Mismatch. We also found inconsistencies in age groupings between the dataset and the original publication. Because the dataset already contained predefined categories, we lacked the necessary raw detail to reconstruct the original bins precisely.

Overall Outcome. Despite these issues, the replication was successful: major trends aligned closely with the original findings, and differences were minor and did not alter the overall interpretation.

5.4 Limitations

Self-Report Bias. The CDHS relies on self-reported information, which introduces recall errors and social-desirability bias. Because responses cannot be independently verified, the precision and validity of key measures remain uncertain.

Question Wording Differences. Although the 2021 and 2023 waves use identical wording, several 2024 questions were modified. Even subtle changes in phrasing can alter respondent interpretation, reducing comparability across years.

Scale Differences. The response scale also changed: 2021 and 2023 used a 1–4 Likert scale without a neutral option, while 2024 used a 1–5 scale including a midpoint. This structural shift affects distributional patterns and may introduce artificial differences when examining trends over time.

6 Reproducibility Appendix

In the Appendix, we have included all the relevant information documenting the reproducibility of our work. This includes the data dictionary, the exact commands to reproduce our figures, software information, a file tree, and the data usage information.

References

[1] A. K. C. Li, I. A. Rauf, and K. Keshavjee, "Knowledge is not all you need for comfort in use of AI in healthcare," **Public Health**, vol. 238, pp. 254–259, Jan. 2025. [Online]. Available: https://doi.org/10.1016/j.puhe.2024.11.019 pages 3, 5, 6, 7

[2] Canada Health Infoway, "2023 Canadian Digital Health Survey," 2024. [Online]. Available: https://doi.org/10.5683/SP3/5C7HSO pages 3

[3] ——, "2024 Canadian Digital Health Survey," 2025. [Online]. Available: https://doi.org/10.5683/SP3/MI0HZP pages 3

[4] ——, "2021 Canadian Digital Health Survey," 2021. [Online]. Available: https://doi.org/10.5683/SP3/CEYG42 pages 4, 5

Appendix

Teamwork and Division of Work

Our group collaborated across all project phases to replicate the targeted results. All members contributed to selecting the paper and identifying dataset sources. Gary, Kai, and Agam led data acquisition, while the whole group searched for access pathways. During Phase 2, we coordinated regular meetings to handle data cleaning, regression modeling, and plotting (Gary, Kai, Aymen, Leila, Agam). Documentation and planning were shared among all members. Zayn led the final report writing, with additional contributions from Leila and Agam for the presentation. The entire group revised the final report for accuracy and alignment.

AI Use Declaration

AI tools (ChatGPT, GPT-5.1, Gemini 3) were used only for prose refinement, formatting, organizational tasks, and referencing clarification. All statistical procedures—data cleaning, modelling, and code execution—were performed by the authors, with AI providing limited code-adjacent assistance (vibe coding). All analyses comply with the project's AI-use guidelines.

File Structure

```
MSE609-Group11-Project/
 R/
    00_project_setup.R
    01_data_cleaning.R
    02_descriptives_table1.R
    03_ordinal_logistic_regression.R
    04_plots_Q40_to_Q43.R
    05_different_dataset.R
    06_plots_different_dataset.R
    07_extension_tables.R
       utils/common_utils.R
 data/
    data_raw/
        readme.md
 artifacts/
    tables/
    plots/
    models/
 docs/examples/
```

```
   q40_2021.png
renv/
renv.lock
run_all.R
MSE609-Group11-Project.Rproj
README.md
```

Exact Commands to Reproduce

1. **Clone the repository:**

```
git clone https://github.com/CorelessXeon/MSE609-Group11-Project.git
cd MSE609-Group11-Project
```

2. **Restore the R environment:**

```
renv::restore()
```

3. **Execute full pipeline:**

```
source("run_all.R")
# Runs scripts 00{07 sequentially
# Approx. 3{7 minutes depending on hardware
```

Data Usage Note

Data originate from the Canadian Digital Health Survey (CDHS), hosted on Borealis under the University of Victoria Dataverse Collection. Access requires acceptance of Infoway's Custom Dataset Terms, restricting use to Canadian educational and research contexts. Redistribution is prohibited. Only anonymized microdata were used. Raw datasets are excluded from this document and must be independently obtained via Borealis.

Data Dictionary

Independent Variables

Variable	Type	Values	Description
age_new	Ordered factor	1–5	Age group (16–24 through 55+)
gender	Factor	1–3	Self-reported gender
Q55	Ordered factor	1–7	Household income
Q66	Ordered factor	1–7	Highest education completed

Dependent Variables (4-level Likert)

Variable	Values	Meaning
Q40	1–4	AI knowledge
Q41	1–4	Comfort with AI in healthcare
Q42	1–4	Comfort with AI research (with consent)
Q43	1–4	Comfort with AI research (without consent)

Missing Value Coding

Raw Code	Meaning	Treatment
96	Other (specify)	NA
97–98	Refused / Prefer not	NA
99	Don't know	NA

Strict Dataset Definition

A strict filtered dataset (`cleaned_dataset_strict.rds`) was created by removing any observation with NA in Q40–Q43. Final sample size: **9,198 respondents**. Used only for Table 1 and descriptive outputs. All regression models and 3D plots use `cleaned_dataset.rds`.

Variable Usage Across Scripts

Script	Dataset	Purpose
01_data_cleaning	raw → cleaned	General cleaning
02_descriptives_table1	strict	Table 1
03_ordinal_logistic_regression	cleaned	Models
04_plots_Q40_to_Q43	cleaned	3D surfaces
05_different_dataset	raw 2023/24	Cleaning 23/24
06_plots_different_dataset	cleaned 23/24	3D surfaces
07_extension_tables	cleaned 23/24	Additional tables

Tables and Plots

Table 1

Original Table 1 (Paper)

Factor	Age Category (Code)	Sample Size (Male - 1)	Sample Size (Female - 2)	Sample Size (Other - 3)
Age in years	16-24 (1)	274	549	28
	25-34 (2)	676	802	18
	35-54 (3)	870	815	19
	55-64 (4)	983	851	12
	65+ (5)	1841	1444	16
Income	< $24,999 (1)	321	455	26
	$25,000-$49,999 (2)	737	871	21
	$50,000-$79,999 (3)	1035	1044	18
	$80,000-$99,000 (4)	804	685	7
	$100,000-$149,999 (5)	1054	860	13
	$150,000-$249,999 (6)	556	457	5
	$250,000+ (7)	137	89	3
Education	Highschool (1)	827	975	37
	Apprenticeship/Trades (2)	323	185	2
	College/CEGEP (3)	1027	1195	17
	University degree (4)	1716	1578	23
	Masters (5)	597	432	11
	PhD (6)	105	66	0
	Medical/paramedical (7)	49	30	3

Replication of Table 1 (2021)

Table 1. Descriptive statistics of respondents based on socioeconomic and demographic characteristics.

Category (Code)	Sample Size (male)	Sample Size (female)	Sample Size (other)
Age in years			
16–24 years (1)	274	549	28
25–34 years (2)	676	802	18
35–44 years (3)	870	815	19
45–54 years (4)	983	851	12
55+ years (5)	1,841	1,444	16
Income			
< $24,999 (1)	321	455	26
$25,000-$49,999 (2)	737	871	21
$50,000-$79,999 (3)	1,035	1,044	18
$80,000-$99,000 (4)	804	685	7
$100,000-$149,999 (5)	1,054	860	13
$150,000-$249,999 (6)	556	457	5
$250,000+ (7)	137	89	3
Education			
Highschool (1)	827	975	37
Apprenticeship/Trades (2)	323	185	2
College/CEGEP (3)	1,027	1,195	17
University degree (4)	1,716	1,578	23
Masters (5)	597	432	11
PhD (6)	105	66	0
Medical/paramedical (7)	49	30	3

Age uses the five bins present in this export (16–24, 25–34, 35–44, 45–54, 55+). The article used 16–24, 25–34, 35–54, 55–64, 65+.

Appendix Table 1A

Original Appendix A1 (Paper)

Appendix

Table A1. Likelihood of being highly knowledgeable about or comfortable with AI compared to reference group

Dependent Variable	Factor	Categories	Odds Ratio	95% CI	p-value
Q.40 -How knowledgeable are you about what artificial intelligence is? (n = 10,553)	Age	16-24	1.00 (ref)		
		25-34	0.87	(0.73-1.04)	0.137
		35-54	0.72	(0.60-0.85)	<0.001
		55-64	0.55	(0.47-0.65)	<0.001
		65+	0.44	(0.38-0.52)	<0.001
	Gender	Male	1.00 (ref)		
		Female	0.47	(0.43-0.51)	<0.001
		Other	1.99	(1.24-3.18)	<0.05
	Income	< $24,999	1.00 (ref)		
		$25,000-$49,999	0.95	(0.81-1.13)	0.572
		$50,000-$79,999	1.09	(0.92-1.28)	0.330
		$80,000-$99,000	1.01	(0.85-1.21)	0.897
		$100,000-$149,999	1.14	(0.96-1.35)	0.124
		$150,000-$249,999	1.36	(1.12-1.66)	<0.05
		$250,000+	1.45	(1.07-1.98)	<0.05
	Education	Highschool	1.00 (ref)		
		Apprenticeship/Trades	0.99	(0.82-1.21)	0.935
		College/CEGEP	1.37	(1.21-1.56)	<0.001
		University degree	1.71	(1.51-1.92)	<0.001
		Masters	2.34	(1.99-2.75)	<0.001
		PhD	3.65	(2.61-5.12)	<0.001
		Medical/paramedical	2.23	(1.38-3.62)	<0.05

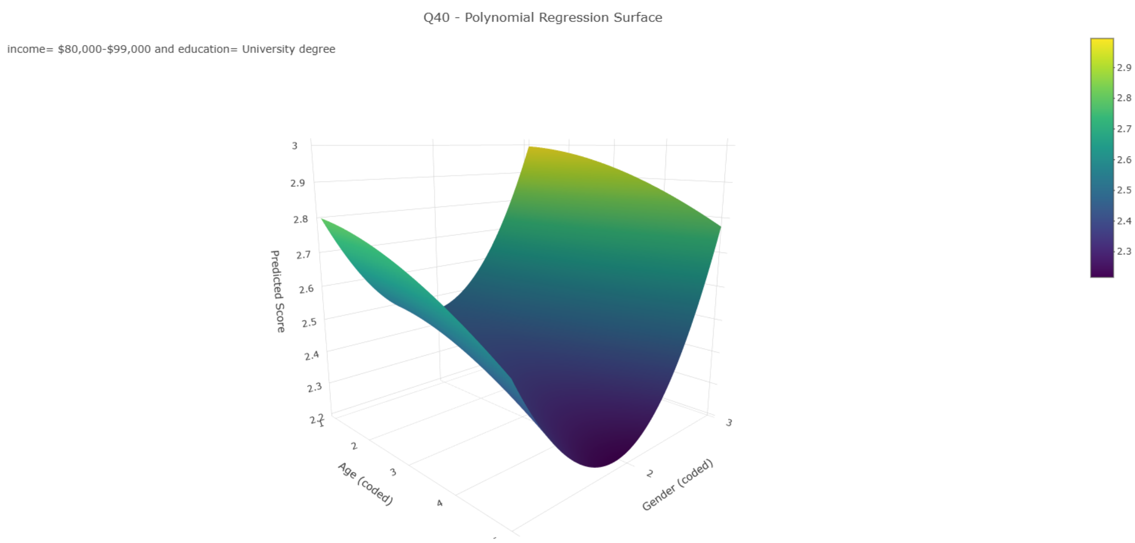
Replication of Appendix A1 (2021)

Appendix Table 1A (Replication): Ordinal logistic regression — Odds ratios (95% CI) and p-values			
Factor	**Categories**	**Odds Ratio (95% CI)**	**p-value**
Q.40 – How knowledgeable are you about what artificial intelligence is?			
Age	16–24 years	1.00 (ref)	
Age	25–34 years	0.83 (0.71–0.97)	0.02
Age	35–44 years	0.74 (0.64–0.86)	0.00
Age	45–54 years	0.57 (0.49–0.66)	0.00
Age	55+ years	0.46 (0.40–0.52)	0.00
Gender	male	1.00 (ref)	
Gender	female	0.47 (0.44–0.50)	0.00
Gender	other	1.88 (1.27–2.78)	0.00
Income	< $24,999	1.00 (ref)	
Income	$25,000-$49,999	0.95 (0.82–1.10)	0.50
Income	$50,000-$79,999	1.05 (0.91–1.21)	0.49
Income	$80,000-$99,000	1.00 (0.86–1.16)	0.96
Income	$100,000-$149,999	1.13 (0.98–1.31)	0.09
Income	$150,000-$249,999	1.30 (1.10–1.53)	0.00
Income	$250,000+	1.43 (1.09–1.87)	0.01
Education	Highschool	1.00 (ref)	
Education	Apprenticeship/Trades	1.05 (0.89–1.25)	0.54
Education	College/CEGEP	1.39 (1.25–1.55)	0.00
Education	University degree	1.74 (1.57–1.93)	0.00
Education	Masters	2.35 (2.05–2.71)	0.00
Education	PhD	3.73 (2.78–5.00)	0.00
Education	Medical/paramedical	2.27 (1.51–3.43)	0.00

3D Surface Plots

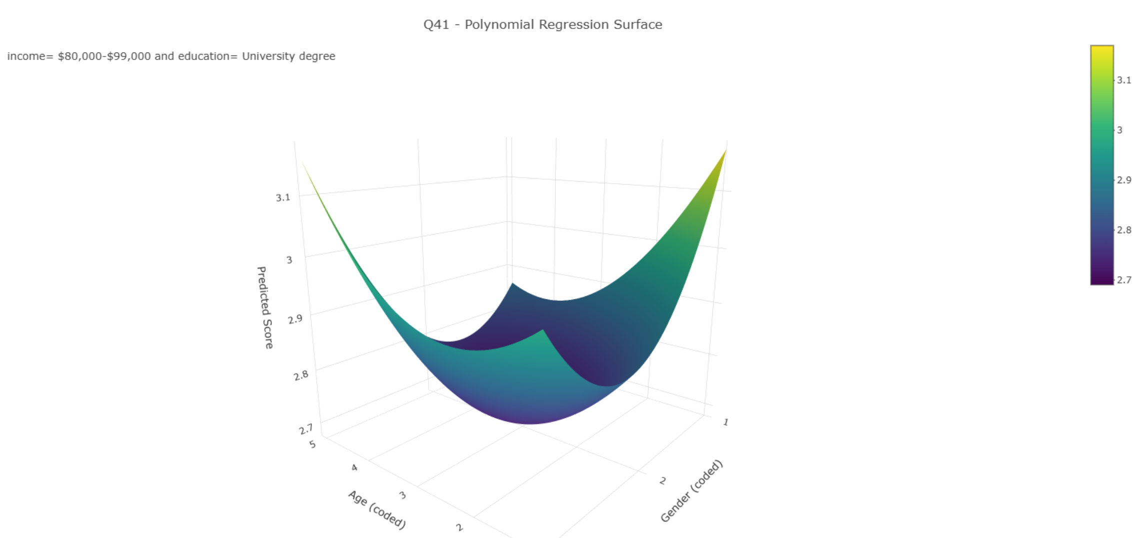
2021 Q40

On a scale of 1–4 … How knowledgeable are you about what artificial intelligence is?



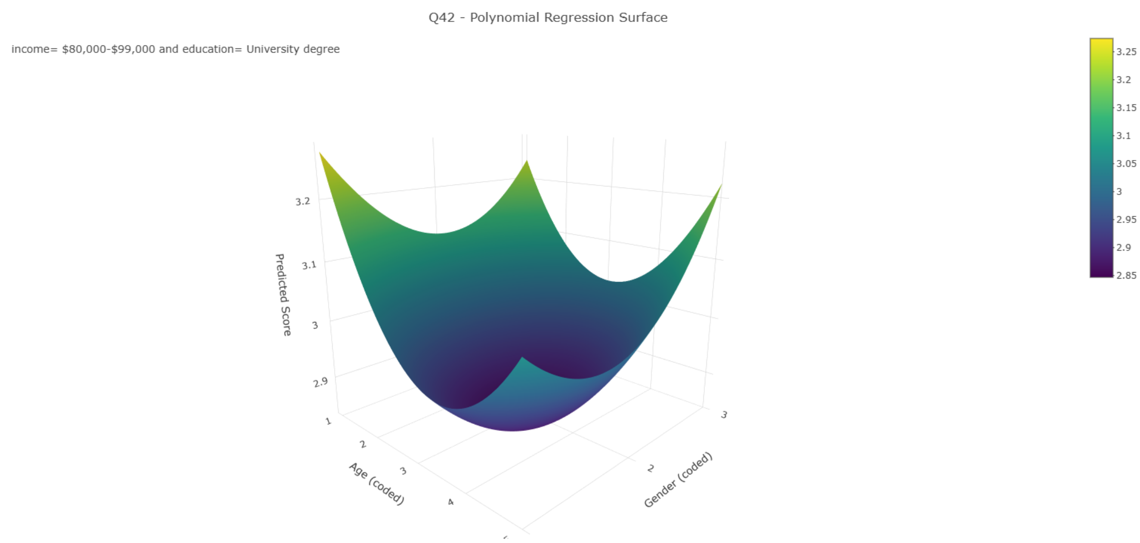
2021 Q41

How comfortable are you with AI being used as a tool in healthcare?



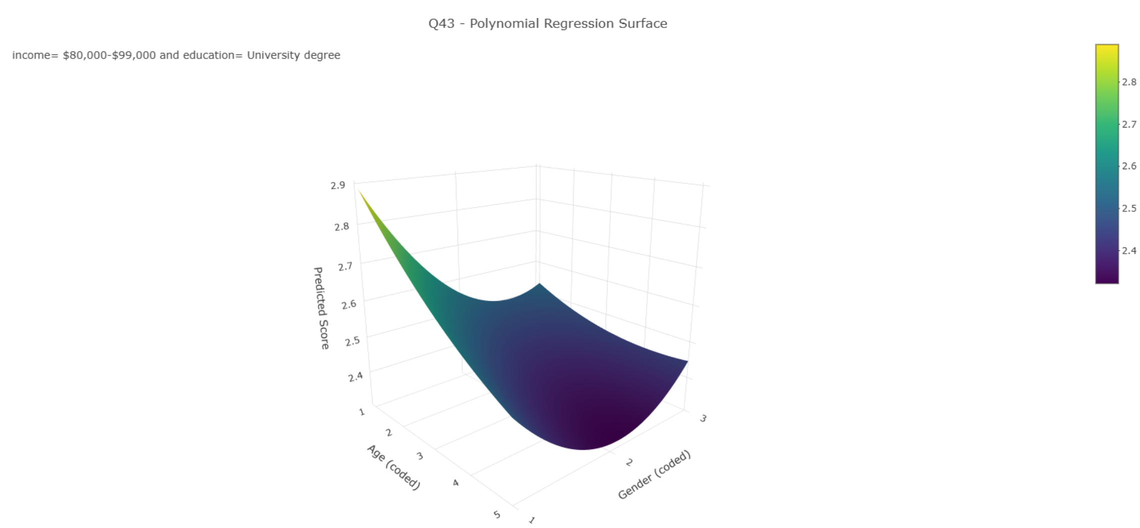
2021 Q42

Comfort using personal health data for AI research with informed consent.



2021 Q43

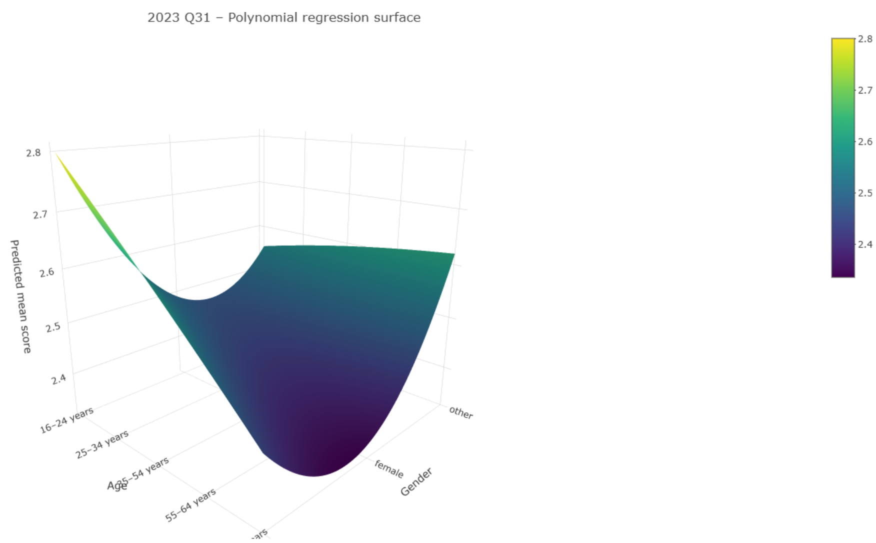
Comfort using de-identified data for AI research without consent.



3D Surface Plots — 2023

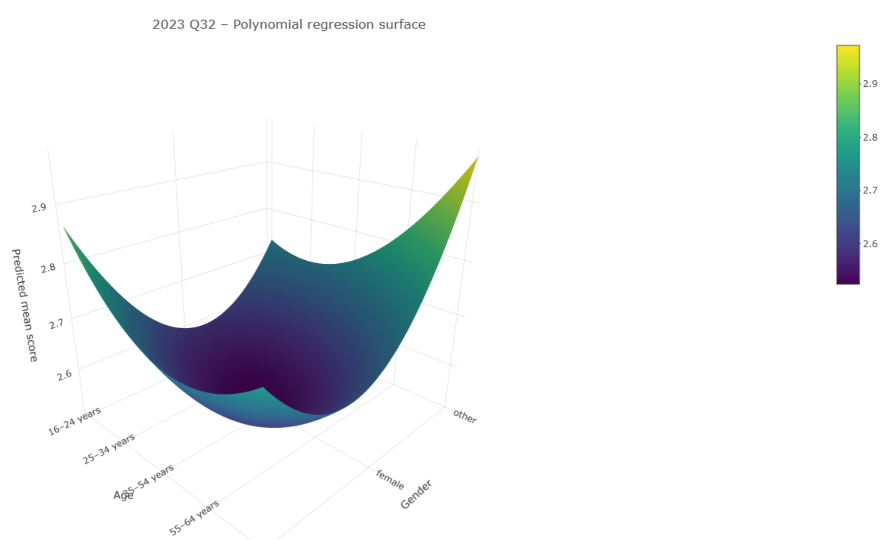
2023 Q31

Knowledge about what artificial intelligence is.



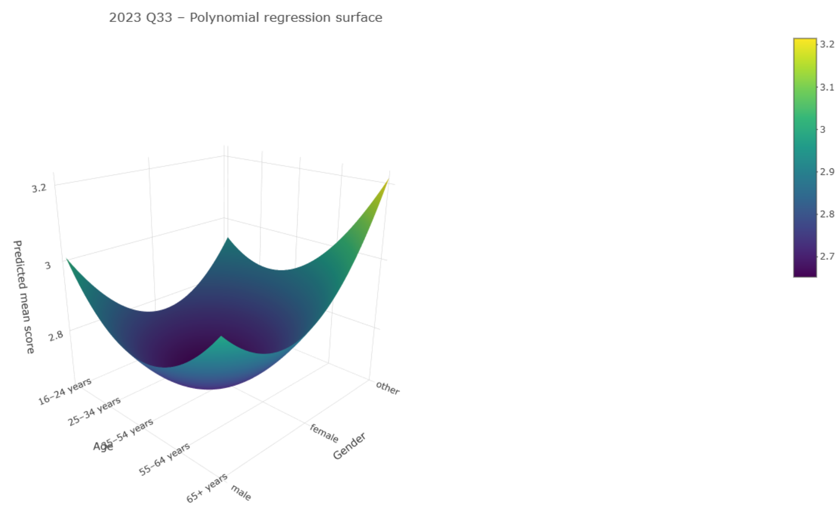
2023 Q32

Comfort with AI used as a tool in healthcare.



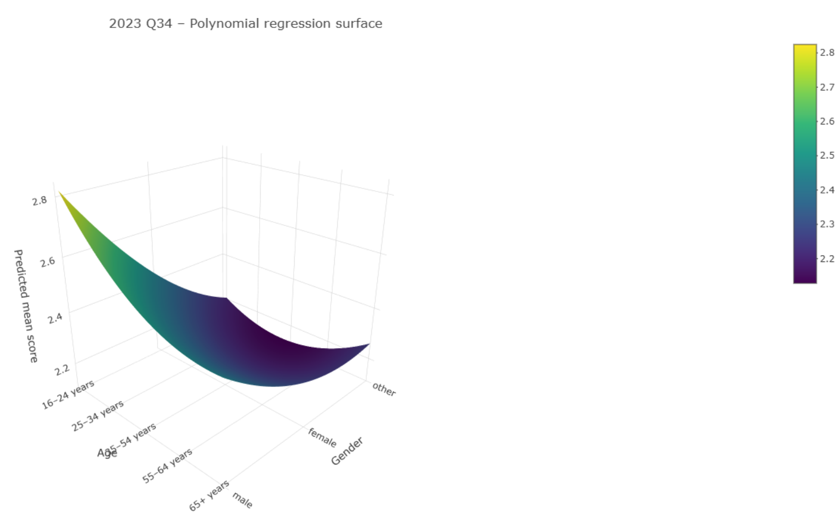
2023 Q33

Comfort with use of personal health data with informed consent.



2023 Q34

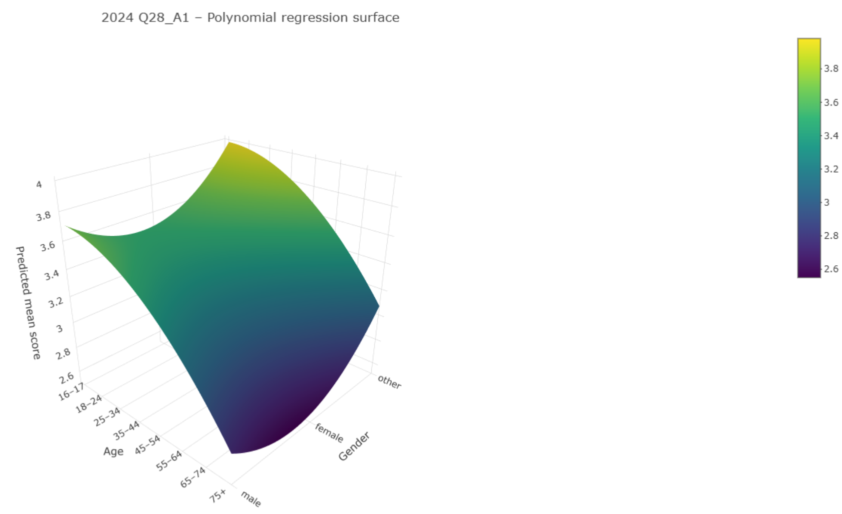
Comfort with use of de-identified personal health data without consent.



3D Surface Plots — 2024

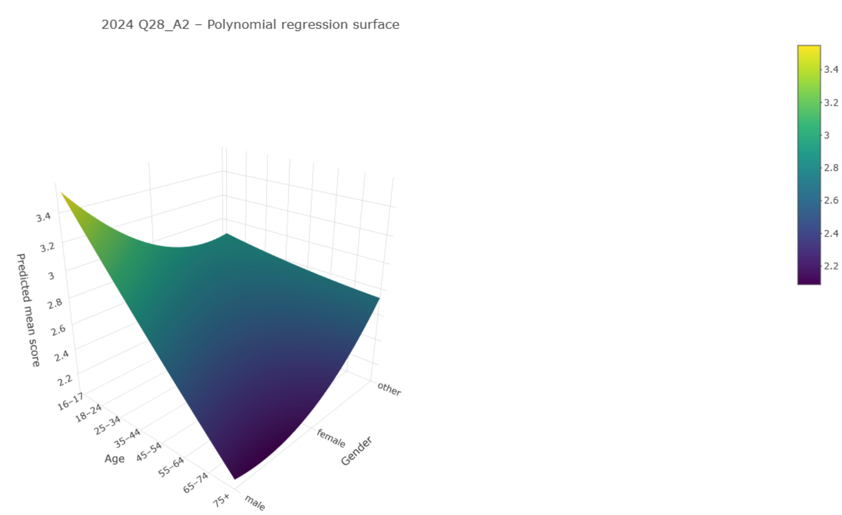
2024 Q28_A1

I am knowledgeable about what artificial intelligence (AI) does.



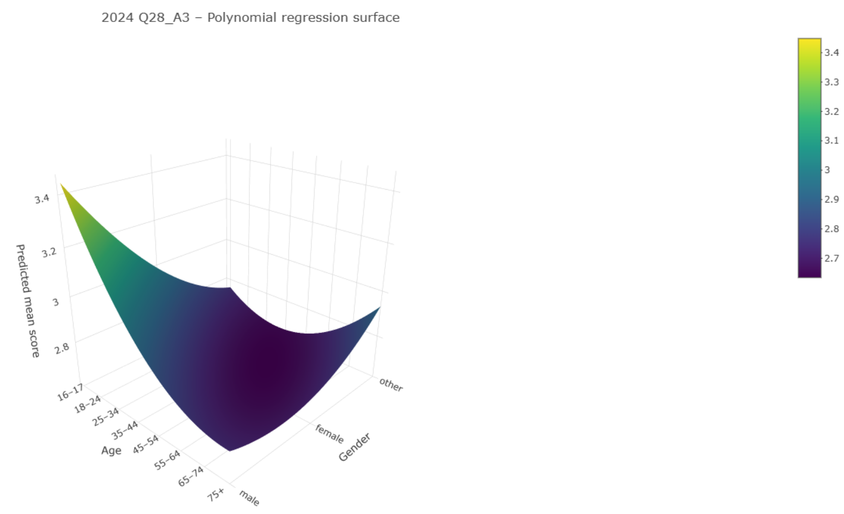
2024 Q28_A2

I am knowledgeable about how AI is used in health care.



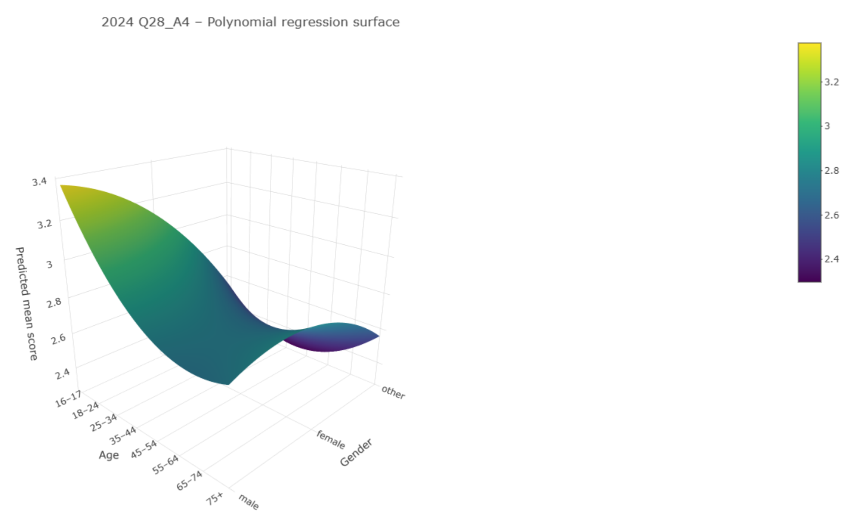
2024 Q28_A3

I am comfortable with AI being used in health care.



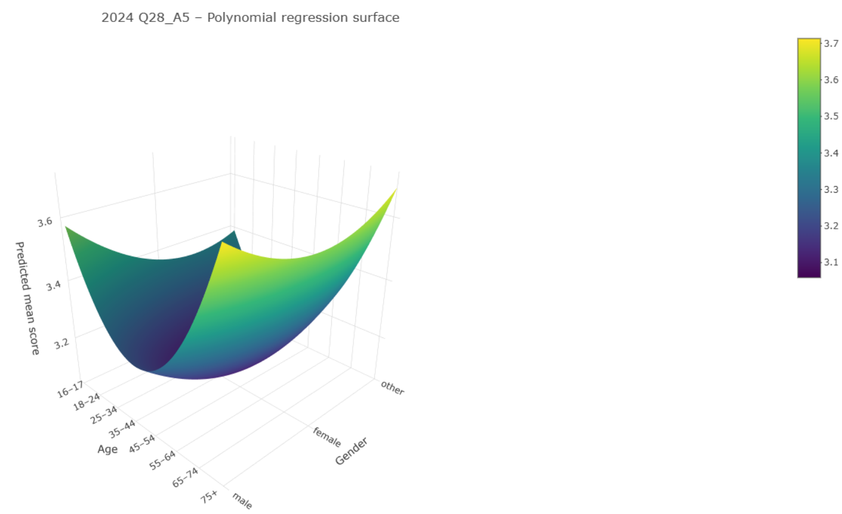
2024 Q28_A4

I trust AI to be unbiased when used in health care.



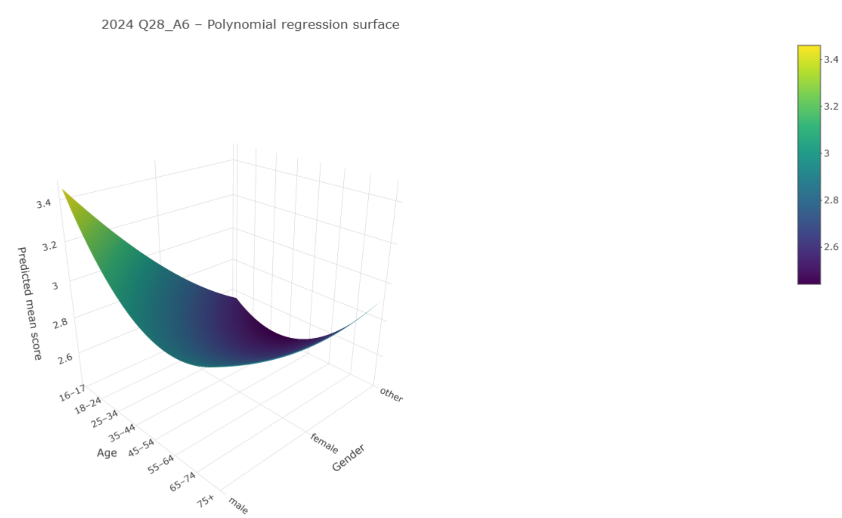
2024 Q28_A5

Scientists can use my de-identified health data for AI research.



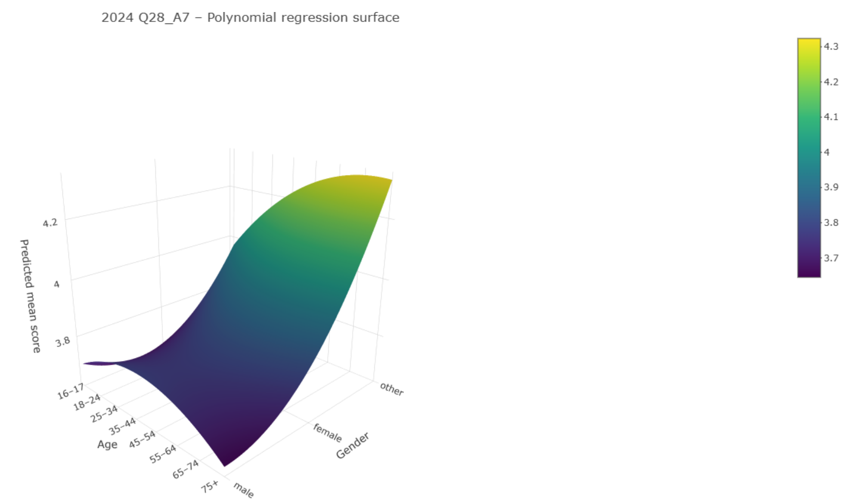
2024 Q28_A6

AI use by health care providers improves my confidence in diagnosis.



2024 Q28_A7

I have privacy concerns regarding AI use in health care.


2024 Q28_A7 – Polynomial regression surface
Predicted mean score
4.2
4
3.8
16–17
18–24
25–34
35–44
45–54
55–64
65–74
75+
Age
male
female
other
Gender
4.3
4.2
4.1
4
3.9
3.8
3.7