Technophobia across age groups

Cross-generation examination on fear and future beliefs on technology

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Abstract

- A brief summary of the research paper, typically between 150–250 words.
- Include the research topic, research questions, methods, results, and conclusions.

Keywords: generational differences, technophobia, risk perception, self-efficacy

Technological advancements like AI, smartphones, and digital banking have created societal shifts requiring adaptation, especially for older adults who face unique challenges in adopting new technologies. This phenomenon, termed "technophobia," refers to fear or anxiety about technology, often rooted in limited early exposure, slower cognitive adaptation, and reduced self-efficacy compared to younger generations (Brosnan, 2002; Khasawneh, 2018).

Older adults frequently struggle with *Technology Awareness (TA)*, making technologies like smartphones and online banking inaccessible without proper support (Khasawneh, 2018). Tomczyk et al. (2023) highlight that digital exclusion, particularly among older adults, has become a significant concern in the digital society, with barriers such as fear of new technologies, lack of access, and resistance to lifelong learning limiting their digital competence. These challenges emphasize the need for targeted interventions to bridge the gap in digital inclusion for older individuals. These barriers highlight the importance of interventions to bridge generational divides and foster technology adoption.

This study found that generational differences significantly influenced support for AI development, with Millennials and post-Millennials expressing more support than Gen Xers and Baby Boomers. Key predictors of support included being male, having a four-year college degree, earning over $100,000 annually, and having computer science experience, while women, those with lower education levels, and lower-income individuals showed more opposition, reflecting broader trends in attitudes toward automation (Zhang, B., & Allan, D. 2019; Morning Consult, 2017). These findings align with Sjöberg's (2002) argument that *Risk Perception (RP) of AI* , particularly fears of job displacement due to automation, can shape attitudes toward new technologies. Additionally, Merenkov et al. (2021) highlight that knowledge gaps, particularly among older adults, increase resistance, emphasizing the need for transparent communication and positive user experiences to boost AI acceptance.

Higher technological self-efficacy—confidence in using technology—strongly predicts adoption rates, yet many older adults struggle due to limited exposure to digital systems (Medici et al., 2023). Structured programs, such as personalized smartphone training, have proven effective in building both confidence and competence, while gradual exposure to technology reduces anxiety and fosters engagement (Smith et al., 2015; Hughes, 2010). Privacy and security concerns, including fears about data usage, further hinder adoption, but clear communication about safeguards and consistent support can help alleviate these barriers (Mitzner et al., 2010; Ghorayeb et al., 2021). By addressing these challenges, older adults can experience the benefits of "technological well-being," such as improved healthcare access, social connection, and independence. Educational efforts designed to reduce technophobia, build self-efficacy, and introduce technology gradually can transform it from a source of fear into a tool for empowerment (Rainie & Anderson, 2018).

Current Study

Technological advancements, including AI and smartphones, present significant challenges for older adults, particularly due to technophobia, limited digital literacy, and reduced exposure to new technologies (Brosnan, 2002; Khasawneh, 2018; Tomczyk et al., 2023). We hypothesize that there will be significant differences between (H1) RP and (H2) TA based on generational membership and education level.

Methodology

Participants

This study analyzed data from Zhang et al. (2019), considering a survey of 2,000 U.S. participants on public opinion regarding AI and technology. The original sample included individuals born from 1927 onwards. However, 3 participants born in 1927 were excluded and the final sample for this analysis included 1,997 participants. Furthermore, after excluding cases with missing data, the sample included 1,047 participants for the *RP* analysis and 1,967 for TA sample. The study also collected demographic data on race, age, educational attainment, employment status and family income. Refer to Table 1 in the Appendix for more insights on demographic information.

Materials & Procedure

Data collection utilized a self-report survey instrument adapted from Zhang et al. (2019), designed to assess public attitudes toward artificial intelligence (AI), automation, and technology adoption. The survey included a range of Likert-scale items measuring constructs such as technological self-efficacy, perceived risks associated with AI, willingness to adopt new technologies, and concerns about data privacy. Demographic questions captured participants' age, educational attainment, gender, generational identity, and income. Data was collected through an online survey conducted by the Center for the Governance of AI at the University of Oxford, utilizing the YouGov survey platform. Participants were recruited via online platforms and completed the survey electronically between June 6th and 14th, 2018.

Data Analysis

Two composite measures were created: *RP*, calculated as the mean of responses to items on AI-related risks, and *TA*, calculated as the mean of responses to items assessing familiarity with technology. Both measures used a 5-point Likert scale. Two-way ANOVAs were conducted to test the effects of generation and education, as well as their interaction, on two previously mentioned dependent variables. Each ANOVA tested whether mean scores of the dependent variables differed significantly across the levels of generation and education, and their interaction. Analyses were performed using R (R Core Team, 2023) and RStudio (Posit, 2023) with the *aov* function, and results were visualized using the *ggplot2* package (Wickham, 2016), with a significance level of $\alpha=0.05$.

Results

A two-way ANOVA was conducted to examine the effects of generation and education on RP. The results showed that the main effect of generation was not statistically significant, $F(4,1047) = 2.05$, $p = .085$, suggesting that RP did not differ meaningfully between generations. Similarly, the main effect of education was not significant, $F(1,1047) = 1.23$, $p = .267$, indicating no evidence of a relationship between education level and RP of AI. The interaction effect between generation and education was also not significant, $F(4,1047) = 0.89$, $p = .470$. Overall, these results suggest no significant differences in RP across generations, education levels, or their interaction. Refer to Figure 1 in Appendix.

For TA , a two-way ANOVA revealed significant effects. The main effect of generation was significant, $F(4,1967) = 7.35$, $p < .001$, indicating that TA differed significantly across generations. The main effect of education was also highly significant, $F(5,1967) = 28.16$, $p < .001$, suggesting strong differences in TA based on education level. However, the interaction effect between generation and education was not significant, $F(20,1967) = 0.67$, $p = .862$, indicating that the relationship between generation and education on TA is not dependent on their interaction. These results indicate that both generation and education independently influence TA, but there is no interaction effect. See Figure 2 in Appendix.

Discussion

This study examined how generational and educational differences influence RP and TA, focusing on RP and TA. Generational and educational differences did not affect RP, suggesting that broader societal or psychological factors play a larger role in shaping attitudes toward RP. This aligns with research emphasizing societal fears, such as concerns over automation and job displacement, as key drivers of risk perception (Sjöberg, 2002; Zhang & Allan, 2019). In contrast, TA varied by generation and education level. Younger individuals and those with higher educational attainment reported greater technological education, consistent with findings that younger generations, particularly Millennials and Generation Z, are more familiar with digital environments (Tomczyk et al., 2023; Zhang & Allan, 2019). The interaction between generation and education highlights how limited TA may exacerbate the digital challenges faced by older adults.

These results contribute to understanding digital exclusion, particularly among older adults. Older generations often face barriers such as technophobia, limited digital literacy, and minimal early exposure to technology (Brosnan, 2002; Khasawneh, 2018). The compounded impact of age and lower education underscores the need for targeted strategies to reduce these disadvantages (Tomczyk et al., 2023). Furthermore, the lack of a clear relationship between technological education and risk perception suggests that while familiarity with technology enhances competence, it may not directly influence perceptions of associated risks. The findings highlight the importance of tailored interventions to promote digital inclusion. Structured, gradual training programs can build confidence and competence among older adults (Smith et al., 2015; Hughes, 2010). For instance, personalized workshops on smartphone use or online banking can help mitigate anxiety and foster engagement. Clear communication about privacy and security measures can also alleviate concerns that often hinder technology adoption (Mitzner et al., 2010; Ghorayeb et al., 2021).Policymakers and educators should develop initiatives tailored to older adults' needs, focusing on reducing technophobia, fostering self-efficacy, and creating accessible learning environments. Bridging the generational digital divide would enable older individuals to benefit from technological advancements, including improved access to healthcare, social connections, and greater independence.

Limitations and Future Directions

This study has several limitations. Self-reported measures may introduce response biases, a common concern in behavioral research. The cross-sectional design restricts causal inferences, highlighting the need for longitudinal studies to better understand how generational and educational factors influence technology-related attitudes over time. Cultural and regional differences, which can shape risk perception and technological education, were not addressed. For instance, digital exclusion among older adults has been linked to societal factors such as fear of new technologies and lack of access (Tomczyk et al., 2023). Future studies should consider these contextual factors to provide a more comprehensive understanding of digital inclusion on a global scale. Additionally, psychological traits such as reduced self-efficacy and slower cognitive adaptation, often cited as barriers to technology adoption among older adults, were not examined (Brosnan, 2002; Khasawneh, 2018). Including these variables in future research could yield deeper insights into individual differences in technology engagement.

This study underscores the complex interplay between generational and educational factors in shaping technological education and risk perception. While risk perception appears stable across demographic groups, variability in technological education outcomes highlights the need for targeted interventions. Addressing barriers to technology adoption can empower older adults to engage with modern technologies, improving their quality of life and fostering greater social inclusion. Future research should further investigate the multifaceted influences on technology-related attitudes to inform strategies for promoting digital equity.

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References

Brosnan, M. J. (2002). *Technophobia: The psychological impact of information technology*. Routledge.

Ghorayeb, A., Comber, R., & Gooberman-Hill, R. (2021). Older adults' perspectives of smart home technology: Are we developing the technology that older people want? *International Journal of Human-Computer Studies, 147,* 102571.

Hughes, J. (2010). *Age, self-efficacy, and the digital divide: Bridging the gap through tailored interventions*. Journal of Digital Engagement, 5(3), 45–59.

Khasawneh, O. Y. (2018). Technophobia: Examining its hidden factors and defining it. *Technology in Society, 54,* 93-100.

Medici, G., Grote, G., Igic, I., & Hirschi, A. (2023). Technological self-efficacy and occupational mobility intentions in the face of technological advancement: a moderated mediation model. European Journal of Work and Organizational Psychology, 32(4), 538–548. https://doi.org/10.1080/1359432X.2023.2197215.

Merenkov, A. V., Campa, R., & Dronishinets, N. P. (2021). Public opinion on artificial intelligence development. *KnE Social Sciences,* 565-574.

Mitzner, T. L., Boron, J. B., Fausset, C. B., Adams, A. E., Charness, N., Czaja, S. J., & Sharit, J. (2010). Older adults talk technology: Technology usage and attitudes. *Computers in Human Behavior, 26*(6), 1710-1721.

Morning Consult. (2017). *National tracking poll 170401* [Survey report]. Morning Consult. https://perma.cc/TBJ9-CB5K.

Rainie, L., & Anderson, J. (2018). The Future of Well-Being in a Tech-Saturated World. *Pew Research Center.*

https://www.pewresearch.org/internet/2018/04/17/the-future-of-well-being-in-a-tech-saturated-world/.

Smith, A., Jones, M., & Clark, P. (2015). The impact of personalized smartphone training programs on older adults. *Journal of Applied Gerontology, 34*(2), 225-243. https://doi.org/10.1177/0733464813494469.

Sjöberg, L. (2002). Attitudes toward technology and risk: Going beyond what is immediately given. *Policy Sciences, 35*(4), 379-400.

Tomczyk, Ł., Mascia, M. L., Gierszewski, D., & Walker, C. (2023). Barriers to digital inclusion among older people: An intergenerational reflection on the need to develop digital competences for the group with the highest level of digital exclusion. *Innoeduca. International Journal of Technology and Educational Innovation, 9*(1), 5–26. https://doi.org/10.24310/innoeduca.2023.v9i1.16433

Zhang, B., & Dafoe, A. (2019). *Replication data for: Artificial intelligence: American attitudes and trends.* Harvard Dataverse. https://doi.org/10.7910/DVN/SGFRYA.

Zhang, B., & Allan, D. (2019). *Artificial intelligence: American attitudes and trends*. Center for the Governance of AI, Future of Humanity Institute, University of Oxford. https://doi.org/10.2139/ssrn.3312874.

Appendix

Table 1

Sociodemographic Information on Participants

Variable	All Participants (*n* = 1,997)	Females (*n* = 1,046)	Males (*n* = 951)
Race	*n (%)*	*n (%)*	*n (%)*
White	1,285 (64.4)	685 (34.3)	602 (30.1)
Black	136 (11.8)	120 (6.0)	116 (5.8)
Hispanic	310 (15.6)	149 (7.5)	161 (8.1)
Asian	75 (3.8)	47 (2.4)	28 (1.4)
Native American	15 (0.8)	6 (0.3)	9 (0.5)
Other	42 (2.2)	27 (1.4)	15 (0.8)
Mixed	26 (1.3)	10 (0.5)	16 (0.8)
Middle Eastern	6 (0.3)	2 (0.1)	4 (0.2)
Generation	*n (%)*	*n (%)*	*n (%)*
Silent Generation (1945 – 1928)	173 (8.7)	99 (5.0)	74 (3.7)
Boomers (1946 – 1964)	616 (30.8)	320 (16.0)	296 (14.8)
Generation X (1965 – 1980)	506 (25.4)	255 (12.8)	251 (12.6)
Millennials (1981 – 1996)	625 (31.3)	336 (16.8)	289 (14.5)
Generation Z (1997 – 2012)	77 (3.9)	36 (1.8)	41 (2.1)
Education	*n (%)*	*n (%)*	*n (%)*
No high school	125 (6.3)	63 (3.2)	62 (3.1)

High school graduate	617 (30.9)	318 (15.9)	299 (15.0)
Some college education	422 (21.2)	225 (11.3)	197 (9.9)
Two-year university graduate	222 (11.1)	126 (6.3)	96 (4.8)
Four-year university graduate	390 (19.6)	197 (9.9)	193 (9.7)
Post-graduate degree	221 (11.1)	117 (5.9)	104 (5.2)
Marital Status	*n (%)*	*n (%)*	*n (%)*
Married	912 (45.6)	468 (23.4)	444 (22.2)
Separated	30 (1.5)	16 (0.8)	14 (0.7)
Divorced	218 (10.9)	140 (7.0)	78 (3.9)
Widowed	90 (4.6)	67 (3.4)	23 (1.2)
Never married	660 (33.0)	306 (15.3)	354 (17.7)
Domestic / civil partnership	87 (4.4)	49 (2.5)	38 (1.9)
Employment Status	*n (%)*	*n (%)*	*n (%)*
Full-time	756 (37.9)	311 (15.6)	445 (22.3)
Part-time	208 (10.5)	121 (6.1)	87 (4.4)
Temporarily laid off	15 (0.8)	9 (0.5)	6 (0.3)
Unemployed	165 (8.3)	90 (4.5)	75 (3.8)
Retired	398 (20)	213 (10.7)	185 (9.3)
Permanently Disabled	154 (7.7)	86 (4.3)	68 (3.4)
Homemaker	154 (7.8)	139 (7.0)	15 (0.8)
Student	119 (6.0)	60 (3.0)	59 (3.0)
Other	28 (1.5)	17 (0.9)	11 (0.6)

Family Income	*n (%)*	*n (%)*	*n (%)*
Less than $10,000	158 (7.9)	106 (5.3)	52 (2.6)
$10,000 - $19,999	172 (8.6)	104 (5.2)	68 (3.4)
$20,000 - $29,999	201 (10.1)	111 (5.6)	90 (4.5)
$30,000 - $39,999	204 (10.2)	116 (5.8)	88 (4.4)
$40,000 - $49,999	141 (7.1)	73 (3.7)	68 (3.4)
$50,000 - $59,999	151 (7.6)	70 (3.5)	81 (4.1)
$60,000 - $69,999	130 (6.6)	71 (3.6)	59 (3.0)
$70,000 - $79,999	115 (5.8)	56 (2.8)	59 (3.0)
$80,000 - $99,999	124 (6.2)	54 (2.7)	70 (3.5)
$100,000 - $119,999	101 (5.1)	44 (2.2)	57 (2.9)
$120,000 - $149,999	84 (4.2)	40 (2.0)	44 (2.2)
$150,000 - $199,999	58 (3.0)	23 (1.2)	35 (1.8)
$200,000 - $249,999	25 (1.5)	11 (0.6)	14 (0.7)
$250,000 - $349,999	16 (0.8)	6 (0.3)	10 (0.5)
$350,000 - $499,999	4 (0.2)	0 (0)	4 (0.2)
$500,000 or more	12 (0.7)	3 (0.2)	9 (0.5)
Undisclosed	301 (15.1)	158 (7.9)	143 (7.2)

Note. Percentages are rounded to one decimal place.

Figure 1

Risk perception of AI by generation and education

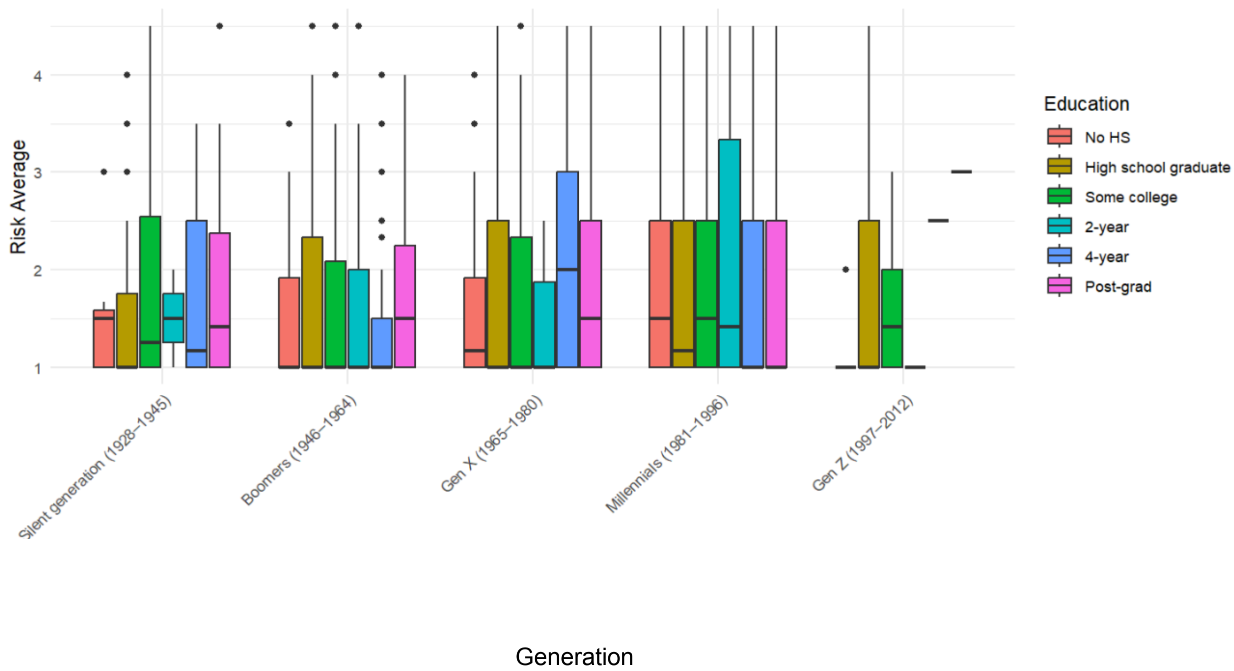
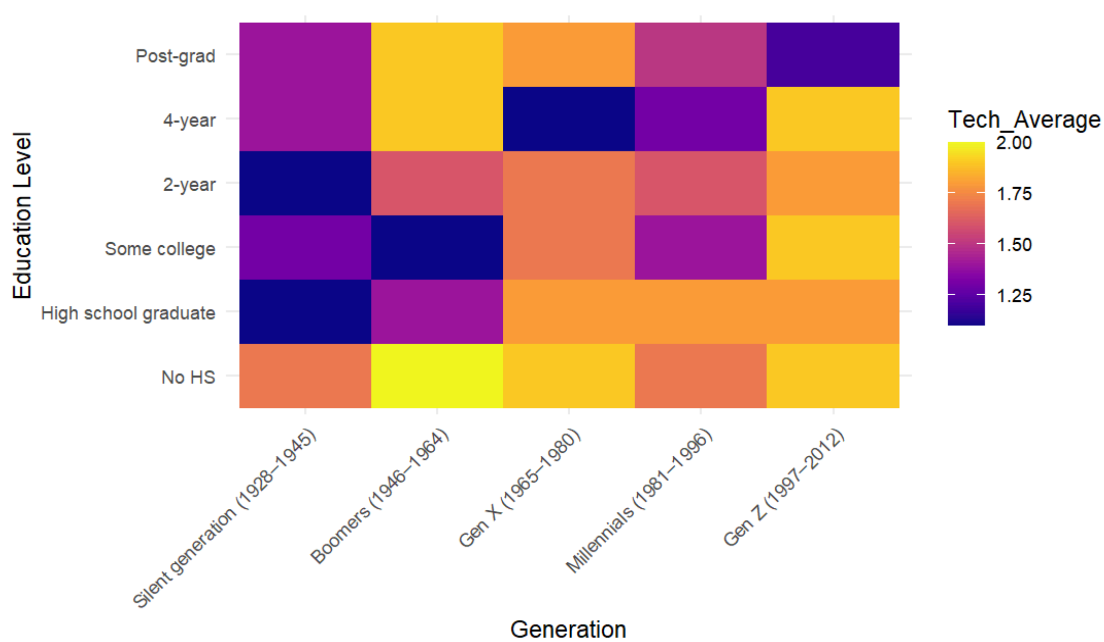


Figure 2

Heatmap: Technological awareness background by generation and education



Codebook

The codebook can be viewed at:
https://docs.google.com/document/d/1vQbBmcUYK3omN1wVSg3V4-q70Jc64vCiJKyNUGSN9hg/edit?usp=sharing

Dataset

The cleaned data sheets can be viewed at:
https://docs.google.com/spreadsheets/d/1lyEP5B3U5KasL9juFVkEUzesfk1XFZe0QpnssTUMx80/edit?usp=sharing