Technophobia across age groups:

Generational and educational disparities in technology awareness and risk perception among older adults

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Abstract

Technological advancements present unique challenges for older adults, including technophobia and limited digital literacy. This study investigated how generational membership and education level influence Risk Perception (RP) and Technology Awareness (TA) regarding artificial intelligence (AI). Data from a survey of 2,000 U.S. adults was analyzed. Results indicated no significant differences in RP across generations or education levels. However, TA varied significantly, with younger generations and higher-educated individuals demonstrating greater familiarity with technology. These findings highlight the need for targeted interventions to address the digital divide, particularly among older adults with lower education levels. Strategies should focus on reducing technophobia, building digital literacy, and creating accessible learning environments to empower older adults to engage with modern technologies and reap their benefits.

Keywords: artificial intelligence, generational differences, technology awareness, technophobia, risk perception, self-efficacy

Technological advancements, including Artificial Intelligence (AI) and smartphones, have driven societal shifts, particularly impacting older adults who face challenges adopting new technologies due to "technophobia," characterized by fear or anxiety often stemming from limited early exposure, slower cognitive adaptation, and reduced self-efficacy. (Brosnan, 2002; Khasawneh, 2018). This often manifests in low Technology Awareness (TA), hindering access to technologies like smartphones and online banking (Khasawneh, 2018). As Tomczyk et al. (2023) emphasize, digital exclusion among older adults is a significant concern, with barriers like technophobia, limited access, and resistance to learning hindering their digital competence.

Studies have found that generational differences significantly influenced AI development support, with younger generations (Millennials and Generation Z) more supportive than older generations (Gen Xers and Baby Boomers) (Zhang & Allan, 2019). Key predictors of support included male gender, a four-year college degree, high income, and computer science experience, while women, those with lower education and income, demonstrated greater opposition, reflecting broader attitudes towards automation (Morning Consult, 2017). These findings align with Sjöberg's (2002) argument that AI Risk Perception (RP), particularly job displacement fears, shapes attitudes. Furthermore, Merenkov et al. (2021) emphasize that knowledge gaps, especially among older adults, increase resistance, highlighting the need for transparent communication and positive user experiences to enhance AI acceptance.

Higher technological self-efficacy—confidence in using technology—strongly predicts technology adoption rates (Medici et al., 2023). However, limited exposure to digital systems hinders many older adults. Structured programs, such as personalized smartphone training, effectively enhance both confidence and competence, while gradual exposure mitigates anxiety and fosters engagement (Smith et al., 2015; Hughes, 2010). Clear communication about safeguards and consistent support can address these concerns (Mitzner et al., 2010; Ghorayeb et al., 2021). By addressing these challenges, older adults can experience catered educational efforts that reduce technophobia, build self-efficacy, and introduce technology gradually can empower older adults, transforming technology from a source of fear into a tool for empowerment (Rainie & Anderson, 2018).

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. Younger, more educated adults are expected to view technology more favorably, emphasizing its empowering potential, while older, less educated adults may perceive technology with greater apprehension, viewing it as risky or inaccessible.

Methodology

Participants

This study analyzed data from Zhang et al. (2019), examining a survey of 2,000 U.S. participants on public opinion regarding AI and technology. After excluding three participants born in 1927, the final sample comprised 1,997 individuals. Further exclusions due to missing data resulted in 1,047 participants for the RP analysis and 1,967 for the TA analysis. Demographic data collected included race, age, education, employment status, and family income. Refer to Table 1 in the Appendix for detailed demographic information.

Materials & Procedure

Data was collected using a self-report survey instrument adapted from Zhang et al. (2019). This survey assessed public attitudes towards artificial intelligence (AI), automation, and technology adoption. Participants responded to Likert-scale items measuring constructs such as technological self-efficacy, perceived AI risks, technology adoption willingness, and data privacy concerns. Demographic information, including age, education, gender, generational identity, and income, was also collected. The online survey was conducted by the Center for the Governance of AI at the University of Oxford utilizing the YouGov survey platform between June 6th and 14th, 2018.

Data Analysis

Two composite measures were created: Risk Perception (RP), calculated as the mean of AI-related risk item responses, and Technology Awareness (TA), calculated as the mean of technology familiarity item responses. Both measures utilized a 5-point Likert scale. Two-way ANOVAs were conducted to examine the effects of generation and education, including their interaction, on RP and TA. Analyses employed R (R Core Team, 2023) and RStudio (Posit, 2023) with the 'aov' function, and results were visualized using the 'ggplot2' package (Wickham & Wickham, 2016), with $\alpha = 0.05$.

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, $F(4,1047) = 2.05$, $p = .085$, $\eta^2 = .01$, 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, $\eta^2 = .00$, demonstrating no evidence of a relationship between education level and RP of AI. The interaction effect between generation and education was also not significant, $F(4,1047) = 0.89$, $p = .470$, $\eta^2 = .02$. Overall, these results suggest no significant differences in RP across generations, education levels, or their interaction. Given the non-significant main effects and interaction effect, post-hoc tests were not conducted. Refer to Figure 1 in Appendix.

For TA , a two-way ANOVA revealed significant effects. The main effect of generation was significant, $F(4,1967) = 7.35$, $p < .001$, $\eta^2 = .01$, indicating that TA differed significantly across generations. Post-hoc comparisons showed that Millennials ($M = 1.59$, $SD = 0.29$) and Gen Z ($M = 1.59$, $SD = 0.27$) reported the highest levels of TA, while the Silent Generation scored the lowest ($M = 1.50$, $SD = 0.27$). The main effect of education was also significant, $F(5,1967) = 28.16$, $p < .001$, $\eta^2 = 0.07$, displaying strong differences in TA based on education level. Participants with no high school education reported the highest levels of TA ($M = 1.68$, $SD = 0.25$), while postgraduates scored the lowest ($M = 1.46$, $SD = 0.28$). However, the interaction effect between generation and education was not significant, $F(20,1967) = 0.67$, $p = .862$, $\eta^2 = 0.01$, suggesting 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 the influence of generational and educational differences on Risk Perception (RP) and Technology Awareness (TA). While RP remained unaffected by these factors, suggesting broader societal or psychological influences, TA varied significantly by generation and education level. Younger individuals and those with higher education exhibited greater TA, consistent with findings that younger generations are more digitally familiar (Tomczyk et al., 2023; Zhang & Allan, 2019). This highlights how limited TA can exacerbate digital challenges for older adults. These findings contribute to our understanding of digital exclusion among older adults, who frequently encounter barriers like technophobia and limited digital literacy (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). While familiarity with technology enhances competence, it may not directly influence risk perception. Tailored interventions, such as structured training programs and accessible learning environments, are crucial to foster digital inclusion, reduce technophobia, and build self-efficacy among older adults, enabling them to bridge the digital divide and benefit from improved healthcare, social connections, and independence.

Limitations include potential response biases in self-reported data (e.g., social desirability, recall bias), a cross-sectional design restricting causal inference, and limited consideration of cultural and regional factors, such as the influence of societal factors on digital exclusion among older adults (Tomczyk et al., 2023). Future research should examine psychological traits such as reduced self-efficacy and slower cognitive adaptation, which are significant barriers to technology adoption among older adults (Brosnan, 2002; Khasawneh, 2018). Including these variables could provide deeper insights into individual differences in technology engagement. Despite these limitations, the study underscores the complex interplay between generational and educational factors, highlighting the need for targeted interventions to address barriers to technology adoption and promote digital equity among older adults.

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Appendix

Table 1

Sociodemographic Information on Participants

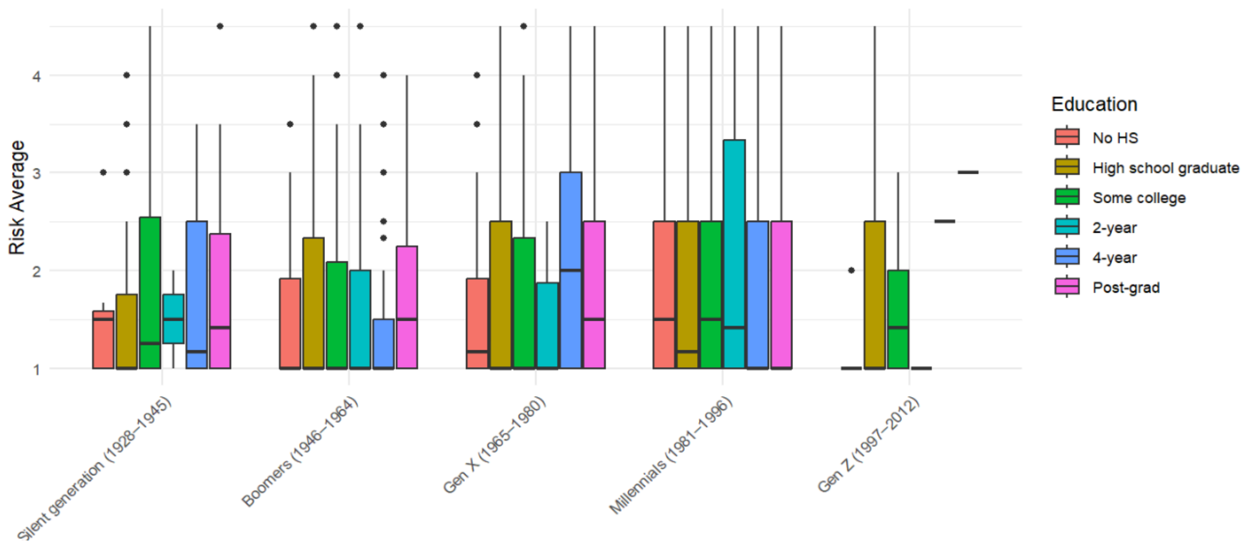
Variable	All Participants (n = 1,997)	Females (n = 1,046)	Males (n = 951)
Race	*n (%)*	*n (%)*	*n (%)*
White	1,285 (64.4)	685 (34.3)	602 (30.1)
Black	136 (11.8)	120 (6.0)	116 (5.8)
Hispanic	310 (15.6)	149 (7.5)	161 (8.1)
Asian	75 (3.8)	47 (2.4)	28 (1.4)
Native American	15 (0.8)	6 (0.3)	9 (0.5)
Other	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)

Note. Percentages are rounded to one decimal place.

Figure 1

Risk perception of AI by generation and education

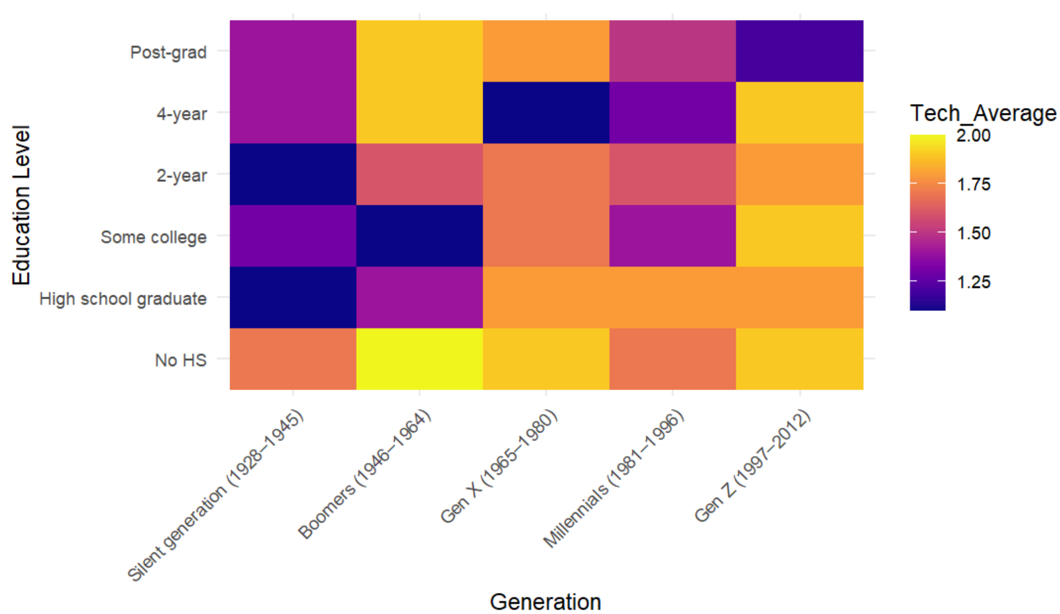


Generation

Note. HS stands for high school.

Figure 2

Heatmap: Technological awareness background by generation and education



Note. Tech Average is short for Technological Awareness (TA) score average

Codebook

The codebook can be viewed at:
https://github.com/fd-col/Research-Methods-for-Cyberspace-Behavior-and-e-Therapy/blob/main/Codebook.pdf

Dataset

The cleaned data sheets can be viewed at:
https://github.com/fd-col/Research-Methods-for-Cyberspace-Behavior-and-e-Therapy/blob/main/YALE0065_OUTPUT_cleaned.xlsx

Original dataset

The original data sheets can be viewed at:
https://doi.org/10.7910/DVN/SGFRYA