Information Literacy, Data Literacy, Privacy Literacy, and ChatGPT: Technology Literacies Align with Perspectives on Emerging Technology Adoption within Communities

Brady D. Lund, Daniel A. Agbaji, Zoë A. Teel

University of North Texas, College of Information

Denton, TX, USA

Brady.Lund@unt.edu

Abstract. This study investigates the relationships between three crucial literacies for the digital world - information literacy, data literacy, and privacy literacy - and positivity towards emerging technology adoption within communities, specifically the chatbot ChatGPT. Data was collected through web-based surveys of adults living in a four-county area in northern Texas over a two-week period in late 2022, resulting in 130 valid responses. Regression analysis shows that interest in using ChatGPT to improve one's community is positively related to information literacy and privacy literacy skills, but not significantly related to data literacy skills, which is unexpected given ChatGPT's status as a data science innovation. Age, gender, educational attainment, and Internet usage are also factors that influence these relationships. These findings are significant for understanding how various literacies and personal and community-based factors influence each other's development.

Keywords: Information Literacy, Data Literacy, Privacy Literacy, ChatGPT, Technology Adoption

Both virtual and physical communities play important roles in the lives of individuals. Understanding the relationship between beliefs about community adoption of emerging technology and an individual's information, data, and privacy literacy is crucial for creating a communal information society that supports the growth and development of these literacy skills. While there is a significant amount of research on information literacy, data literacy, and privacy literacy as separate constructs, the relationships between these literacies are not well understood. Gaining an understanding of these relationships and the effects of various literacy skills on community adoption of emerging technology may help us identify and intervene with individuals who are likely to have deficient literacy skills.

Literature Review

Information literacy encompasses a set of skills that empower individuals to efficiently locate and assess various sources of information, including books, articles, websites, and databases, while also determining the credibility and reliability of that information. The Association for College and Research Libraries (2022) provides an expanded definition of information literacy, highlighting its multifaceted nature. It involves reflective discovery, comprehension, and appreciation of the creation and significance of information, as well as its effective utilization in generating new insights and engaging ethically within learning communities.

In today's information-rich age, where information is readily available and abundant, individuals need to possess the ability to discern credibility and reliability. A study conducted by Jones-Jang et al. (2019) demonstrated that individuals with higher information literacy exhibited improved skills in identifying false news. This research emphasizes that existing studies on information literacy primarily concentrate on the identification, retrieval, evaluation, and utilization of information. Moreover, the findings indicate that information literacy enhances individuals' capacity to recognize fake news, thus emphasizing the importance of cultivating information literacy skills.

Pennycook et al. (2021) conducted a comprehensive investigation comprising four surveys and a field study on Twitter, revealing that information literacy not only aids in identifying misinformation but also promotes the identification of accurate information. As a result, the dissemination of misinformation is significantly reduced. Examining the correlation between educational attainment and the rate of rumor dissemination, Afassinou (2014) employed the SIR (susceptible, infected, and recovered) rumor spreading model. The study demonstrated that individuals with higher levels of education within a population tend to have smaller final rumor sizes, highlighting the substantial role of education in curbing the spread of rumors. In a study by Bartol et al. (2018) involving 310 first and second-year students from diverse academic programs, it was discovered that students' information literacy levels increase as they progress through their educational journey. This finding suggests that education has a positive impact on developing information literacy skills. Similarly, Dolničar et al. (2020) found a significant association between education and information literacy, indicating that individuals' information literacy skills improve with higher levels of education.

The recognition of data literacy's significance within the realm of information literacy is crucial. Data, as defined by the National Science Board (2005), encompasses a wide range of digitally stored information, including text, numbers, images, video, audio, software, algorithms, equations, animations, models, simulations, and more. Borgman (2007) further categorizes data into observational, computational, and experimental types. Mandinach (2013) describes data literacy as the proficient understanding and effective utilization of data to inform decision-making processes. This proficiency encompasses the ability to access, retrieve, manage, critically evaluate, and ethically employ data (Calzada Prado & Marzal, 2013). The Association of College Research and Research Libraries (2013) emphasizes that data literacy includes competencies such as locating and evaluating data, working with different versions of datasets, identifying the data's source and custodian, and adhering to ethical guidelines.

Johnson (2012) asserts that data literacy extends to the skills required for sorting, processing, and filtering vast amounts of data, including search techniques, sorting algorithms, filtering mechanisms, data processing methods, and data synthesis. Similarly, Koltay (2016) suggests that data literacy shares similarities with information literacy and serves similar objectives. Pothier and Condon (2019) discovered that organizations face challenges in transitioning to data-centric infrastructures due to a lack of individuals equipped with data literacy skills. Given the continuous growth of data and the limited pool of individuals proficient in handling it, the urgency and significance of fostering data literacy should not be underestimated (Haendel et al., 2012).

Privacy, as defined by Trepte (2020), is a critical aspect that involves selective control over information sharing. Sindermann et al. (2021) have identified a moderate yet positive relationship between online privacy literacy and information behavior. Notably, teenagers, driven by the desire to join online social networks, may willingly disclose personal information. In this context, privacy literacy seeks to empower individuals in their interaction with technology, as highlighted by Hagendorff (2020). Bartsch and Dienlin (2016) found that individuals with higher levels of online privacy literacy tend to feel more secure on platforms like Facebook and are more inclined to implement social privacy settings. By enhancing online privacy literacy, individuals not only acquire a limited form of negative privacy but also gain the potential to engage in a deliberation process regarding privacy. This transformative process enables individuals to become active agents of positive change, exercising agency over the information they consider necessary to disclose, as expounded by Masur (2020).

Recent research by Prince et al. (2022) employed a survey-based empirical approach to examine the relationship between privacy literacy and privacy concerns among internet users. The study revealed that individuals with higher privacy literacy demonstrated heightened concerns regarding their privacy. Surprisingly, the findings indicated that an increase in knowledge about privacy laws did not necessarily correlate with increased privacy concerns among internet users. Furthermore, Acquisiti and Gross (2005) conducted a survey encompassing high school and college students who were members of Facebook, aiming to explore the predictive role of privacy concerns in determining individuals' membership on social media platforms. Interestingly, the study revealed that privacy concerns only weakly predicted membership decisions, as individuals with privacy concerns still willingly disclosed substantial amounts of personal information upon joining the network. It was noted that over 81% of respondents, comprising both high school and college students, expressed high levels of privacy concerns yet often lacked the necessary information to make privacy-sensitive decisions (Acquisiti & Grossklags, 2005).

In a survey study utilizing a standard multivariate clustering technique (SAS' partitional clustering), Ackerman et al. (1999) discovered that 56% of the 381 U.S. internet users fell into the pragmatic majority category concerning their attitudes toward privacy and their responses to specific privacy-related scenarios. Furthermore, Baruh et al. (2017) conducted a meta-analysis encompassing 166 studies from 34 countries, with a total sample size of 75,269 participants, aiming to investigate the relationship between privacy concerns and privacy literacy. Their analysis revealed that individuals with heightened privacy concerns exhibited a reduced likelihood of using online services and sharing personal information while concurrently displaying an increased likelihood of utilizing privacy-enhancing measures.

Information literacy increases the likelihood of detecting fake news (Jones-Jang et al., 2019), helps identify misinformation, and increases the identification of correct information, resulting in significantly greater sharing of misinformation decrease (Pennycook et al., 2021). Privacy literacy education helps users of social media sites assess the risks of sharing their personal information online (Correia and Compeau, 2017). Burtle et al. (2018) and Dolnicar et al. (2020) found that students' information literacy improved as their educational attainment increased. Afassinou (2014) used the SIR (Vulnerable, Infected, Recovered) rumor diffusion model and found that educated individuals in the population had smaller final rumor sizes.

Technology adoption research has emerged as a crucial field dedicated to investigating the processes by which individuals, groups, and organizations embrace and utilize new technologies (Venkatesh et al., 2007). This area of study provides valuable insights into the various factors that influence the adoption and diffusion of novel technologies and offers guidance on effective promotion strategies. Key determinants affecting technology adoption include the perceived benefits associated with the technology, the perceived costs involved in its adoption, the compatibility of the technology with existing systems and practices, as well as the availability of social and technical support. Factors such as the level of innovation and risk associated with the technology, the complexity and ease of use, the compatibility with established systems and practices, and the influence of social networks and peer pressure have also been identified as influential in the adoption process (Hansen et al., 2018). By examining these factors, researchers strive to enhance our understanding of the dynamics underlying technology adoption and facilitate the successful integration of new technologies into various contexts.

The present study focuses specifically on the emerging technology known as ChatGPT, a chatbot model developed by the OpenAI research team, which builds upon the GPT-3 and GPT-4 language models (Lund et al., 2023; Lund & Wang, 2023). ChatGPT is designed to generate responses that resemble human-like conversation in real-time. Its functionality involves processing chat messages using machine learning algorithms. By leveraging the information within the message and its internal knowledge, ChatGPT generates responses that are contextually relevant and aligned with the intended meaning of the message, mirroring human conversational patterns (Liu et al., 2021). Additionally, it can incorporate knowledge from previous messages within the conversation, enabling it to produce coherent responses. The versatility of ChatGPT offers various potential applications, including assisting in writing tasks such as letter composition and providing concise answers to questions, akin to a more accessible and immediate alternative to traditional search engines like Google. Such capabilities have the potential to benefit individuals across diverse communities. Given the novelty and innovative nature of ChatGPT, it serves as a prominent case study for examining community members' intentions and interests regarding the adoption of this technology.

Research Question:

1. What relationships exist between information literacy, data literacy, privacy literacy, and eagerness to adopt emerging technologies for improving their communities?

Methods

Four main scale variables, or "constructs," are the primary focus of this study: information literacy, data literacy, privacy literacy, and eagerness of community adoption of emerging technologies. Each of these variables is a construct composed of the mean score on a five-point Likert scale across a set of ten questions, where 1 is the "least ideal" response and 5 is the "most ideal" response. Additionally, several demographic variables are examined in relation to the four main constructs and are examined using ANOVA and inclusion in the regression analyses. These demographic variables include age (open response), gender (open response sorted into categories), educational attainment (high school or less, 2-year degree, 4-year degree, advanced degree), political leaning (conservative, moderate, liberal), type of community the respondent lives in (rural, suburban, urban), and Internet usage (multiple hours per day, one hour or less per day, few hours per week, one hour or less per week).

Data were collected using a survey instrument. The survey was created within Qualtrics and was delivered in an electronic format, though a paper version of survey was made available in order to ensure that individuals with different levels of Internet use and comfortability could participate. The survey consists of 50 questions, of which the final forty were used to create the four constructs of eagerness to adopt emerging technology (in this case, the specific technology was ChatGPT, a novel AI chatbot recently released to the public), information literacy, data literacy, and privacy literacy (responses to 10 questions comprise each construct). The remaining ten questions collect the demographic information described in the prior paragraph. The wording of several questions were based on related studies conducted by this study's researchers on this topic. A copy of the survey instrument is provided as an appendix.

The survey was distributed within a four-county area that directly surrounds the researchers' university. This area was selected because of its diversity: one county contains a top-fifteen city by population, which is part of a top-ten metropolitan area within the United States, has a population that is approximately 30% Hispanic, and is known for being a politically liberal county; a second county includes a minority-serving, hispanic-serving institution with a population of over 40,000 students; the third and fourth counties are two rural counties that have populations of 60,000 and 10,000 and that voted in favor of the Republican Presidential candidate in 2020 by margins of 64 and 82 points, respectively, and have an aging and largely White population. The survey was distributed through social media and through flyers posted at local public libraries in the area. Participants could follow a link to the Internet-based survey or contact the researchers to receive a mail version of the survey.

After a period of four weeks, the survey was closed and data was transferred to SPSS for analysis. Due to the use of Likert scales, non-parametric analyses were used to analyze the data. Kruskal-Wallis Htests (non-parametric ANOVA) and Spearman rank correlation tests were determined to be appropriate to evaluate the relationships among variables. The ANOVA tests evaluated variance in the four connectedness/literacy constructs as a function of the categorical demographic variables (ethnicity, gender, educational attainment, political leaning, type of community, and Internet usage). The correlation tests evaluated the strength of relationships among the four constructs as well as the continuous variable of age.

Ordinary least squares regression was used to examine effects on each of the four main scale variables from the other variables included in this study. In each of the regression analyses, four separate models were calculated. The first model includes all possible explanatory variables: the demographic variables as well as the three remaining scale variables. The second model includes only the demographic variables. The third model includes only the demographic variables that were shown in the second model to potentially be statistically significant contributors. The final model looks only at the three remaining scale variables in relation to the dependent variable of interest.

Results

Out of the 136 surveys returned, 130 were complete and able to be included in the analysis. Table 1 shows the demographics of the respondents. The population was predominantly Hispanic, male, and highly educated, which may be due to the recruitment methods used. The age of the respondents was evenly distributed across three ranges: 18-29, 30-59, and 60+. Political leaning was evenly divided, while rural and urban populations were overrepresented. This may be due to the recruitment methods, which focused more on urban and rural areas than suburbs.

Table 1. Demographics of Respondents

Ethnicity	
Asian	4
Black	3
Hispanic	72
White (non-Hispanic)	51
Gender	
Female	45
Male	84
Not Specified	1
Age	
18-29	44
30-59	46
60+	40
Educational Attainment	
High School or Less	13
2-Year Degree	16
4-Year Degree	81
Advanced Degree	20
Political Leaning	
Conservative	54
Liberal	54
Moderate/Neither	22

Type of Community	
Rural	45
Suburban	32
Urban	53
Internet Usage	
Multiple Hours Per Day	66
One Hour or Less Per Day	35
Few Hours Per Week	17
One Hour or Less Per Week	12

Table 2 shows the average scores on the interest in emerging technology for community uses, information literacy, data literacy, and privacy literacy scales overall and based on each demographic group. Statistically significant differences among population groups were identified using Kruskal-Wallis H tests and are signified by an asterisk (* or **) in the table. Within ethnicity, White respondents were found to have significantly lower interest in emerging technology adoption and Asian respondents were found to have significantly higher data literacy. However, ethnicity was omitted from subsequent regression analyses, since the number of respondents that identified as Asian or Black was very small.

Female respondents were found to have significantly better privacy literacy scores compared to their male counterparts, though they scored similarly on all other measures. Education provided the strongest differentiation among groups, where those with high school education or less had substantially lower emerging tech interest scores, and those with advanced degrees (masters, professional, doctoral) scored significantly better on the data literacy and privacy literacy scales. Political leaning showed no difference on any of the scales. Minor differences were found for type of community. Those with limited Internet use tended to score more poorly in terms of data literacy, whereas those with ample use of the Internet scored better in privacy literacy.

Table 2. Average Scores on Emerging Technology Interest and Literacy Scores

Category	Emerging Technology for Community	Information Literacy	Data Literacy	Privacy Literacy
All Respondents	4.1	3.7	3.6	3.7
Asian	4.2	3.8	4.0*	3.8
Black	4.3	3.7	3.7	3.7
Hispanic	4.3	3.7	3.6	3.7
White	3.8**	3.6	3.5	3.6
Female	4.2	3.7	3.6	3.8*
Male	4.1	3.7	3.6	3.6*

High School or Less	3.4**	3.5	3.4	3.5
2 Year Degree	4.2	3.7	3.6	3.7
4 Year Degree	4.2	3.7	3.6	3.7
Advanced Degree	4.2	3.7	3.8**	3.9*
Conservative	4.1	3.7	3.6	3.7
Liberal	4.1	3.7	3.5	3.6
Moderate/Neither	4.2	3.7	3.6	3.7
Rural	3.9*	3.7	3.5	3.6
Suburban	4.3	3.7	3.5	3.8
Urban	4.1	3.6	3.6	3.7
Multiple Hours Per Day	4.0	3.7	3.7	3.8*
One Hour or Less Per Day	4.3	3.7	3.5	3.6
Few Hours Per Week	4.3	3.8	3.5	3.6
One Hour or Less Per Week	4.0	3.5	3.3*	3.5

* Significant difference at $p < .05$
** Significant difference at $p < .01$

Shown in Table 3 is the correlation values for five scale or continuous variables: age, interest in community adoption of emerging technologies, information literacy, data literacy, and privacy literacy. All of the variables have weak-to-moderate correlations with one another, with the exception of age, which only has a significant correlation with data literacy. All other variables are positively correlated with one another. Particularly strong correlations are found between interest in emerging technology adoption for community uses and data literacy and privacy literacy.

Table 3. Correlation Matrix for Scale Variables

Variable	Age	Emerging Tech Interest	Information Literacy	Data Literacy	Privacy Literacy
Age	--	-.131	.127	-.157*	-.089
Emerging Tech Interest	-.131	--	.277**	.565**	.559**
Information Literacy	.127	.277**	--	.273**	.430**
Data Literacy	-.157	.565**	.273**	--	.350**
Privacy Literacy	.089	.559**	.430**	.350**	--

* Significant difference at $p < .05$
** Significant difference at $p < .01$

Table 4 shows the regression findings for the four concepts of emerging tech interest for community use, information literacy, data literacy, and privacy literacy. Model 1 includes all independent variables, Model 2 excludes the scale variables, Model 3 includes only the variables identified as significant in Model 2, and Model 4 looks at only the scale variables. Statistically significant contributors to the models are signified by the asterisks (* for p<.05 and ** for p<.01). The *unstandardized betas* are shown for each variable along with the standard error in parentheses. For instance, in Table 4, Model 3, we see two variables have a significant effect: age and education. With age, each increase in one-year results in an anticipated drop in interest in emerging tech of .009 points; with education, each increase in one level of accomplishment (e.g., going from "high school graduate" to "two-year degree") results in an anticipated increase in emerging tech interest of .231 points.

Table 4. Regression Findings for Dependent Variable of Interest in Emerging Tech for Community Use

	Model 1	Model 2	Model 3	Model 4
Age	-.003 (.003)	-.009 (.003)**	-.009 (.003)**	
Gender (Male = High)	.034 (.105)	-.216 (.112)*	-.195 (.110)	
Education	.166 (.06)**	.241 (.067)**	.231 (.066)**	
Politics (Liberal = High)	-.010 (.066)	-.037 (.075)		
Community (More Urban = High)	-.018 (.056)	-.086 (.060)		
Internet Usage	.066 (.048)	.023 (.052)		
Information Literacy	.643 (.159)**			.707 (.151)**
Data Literacy	-.089 (.156)			-.130 (.144)
Privacy Literacy	.447 (.153)**			.508 (.143)**
Adjusted R^2	0.341	0.181	0.163	.329

* Significant difference at p < .05

** Significant difference at p < .01

Discussion

The present study aimed to investigate the relationship between demographics and various aspects of interest and literacy in emerging technology adoption for community use. The findings revealed important insights regarding the influence of demographic factors on individuals' attitudes and competencies in this domain. Regarding the demographic characteristics of the respondents, the sample was predominantly Hispanic, male, and highly educated. These findings may be attributed to the recruitment methods employed in the study, which potentially favored these particular groups. It is important to note that the generalizability of the findings to other populations may be limited due to the sample composition.

The age distribution of the respondents was relatively even across three ranges: 18-29, 30-59, and 60+. Interestingly, age was found to have a negative correlation with interest in emerging technology adoption, but positive correlations with information literacy, and privacy literacy. As individuals' age increased, their scores on the literacy scales tended to increase, though interest in technology decreased. This suggests that older individuals may exhibit lower interest in adopting emerging technologies but may have higher levels of information, data, and privacy literacy compared to younger individuals. This finding highlights the need for tailored approaches when designing technology interventions and educational programs to address the specific needs and preferences of different age groups.

Ethnicity, specifically Asian and Black identification, showed limited representation in the sample, which led to their omission from subsequent regression analyses. However, it is worth noting that Asian respondents demonstrated significantly higher data literacy compared to other ethnic groups, while White respondents exhibited significantly lower interest in emerging technology adoption. These findings suggest potential differences in technology-related attitudes and competencies among different ethnic groups, which warrant further exploration in future research with more diverse samples.

Gender differences were observed in privacy literacy, with female respondents scoring significantly better than their male counterparts. However, no significant gender differences were found in other measures. This finding suggests that females may have a relatively stronger understanding of privacy-related concepts in the context of emerging technology. It is important to further investigate the underlying factors contributing to this gender difference to inform targeted interventions for promoting privacy literacy.

Educational attainment emerged as a strong differentiating factor among the respondents. Individuals with higher levels of education, such as advanced degrees, exhibited significantly better scores on data literacy and privacy literacy scales. Moreover, respondents with lower educational attainment, specifically high school or less, demonstrated substantially lower interest in emerging technology adoption. These findings emphasize the critical role of education in shaping individuals' technological engagement and competency levels. Efforts should be made to provide accessible educational opportunities to individuals with lower educational attainment to bridge the digital divide and promote inclusive technology adoption.

Political leaning and type of community showed minimal differences in the measures of interest and literacy. Although no significant associations were observed between political leaning and any of the scales, minor differences were found for the type of community. Respondents from rural areas demonstrated lower interest in emerging technology adoption compared to those from suburban and urban areas. Additionally, individuals with limited internet usage tended to score lower in data literacy, while those with ample internet usage scored better in privacy literacy. These findings suggest that the context in which individuals reside and their access to technology infrastructure can influence their technological engagement and competencies.

The correlation analysis revealed weak-to-moderate relationships among the variables. The positive correlations observed among interest in emerging technology adoption, information literacy, data literacy, and privacy literacy indicate the interrelatedness of these constructs. This finding suggests that individuals with higher interest in emerging technologies are likely to possess higher levels of information, data, and privacy literacy. However, those in the older adult group appear to contradict this relationship, by having a lower level of tech interest but higher levels of literacy. These findings underscore the importance of considering multiple dimensions when studying individuals' engagement with emerging technologies.

The regression analyses provided further insights into the factors influencing interest in emerging technology adoption. The models indicated that age and education significantly contributed to the variance in emerging tech interest. Older age was associated with lower interest in emerging technology adoption, while higher educational attainment predicted increased interest in this domain. Some reluctance to the adoption of emerging technology among older adults is a key theme in the literature (Charness & Boot, 2009), however the finding about literacies and aging is more unique, with conflicting findings on literacy and aging being reported in prior studies (Oh et al., 2021; Steelman et al, 2016). These results highlight the need to design targeted interventions and educational programs that consider individuals' age and educational background to foster interest and engagement in emerging technologies.

It is important to acknowledge the limitations of the study. The sample predominantly consisted of Hispanic, male, and highly educated individuals, which limits the generalizability of the findings to other populations. The study also relied on self-reported survey data, which may be subject to response biases and social desirability effects. Future research should aim to include more diverse samples and employ mixed-methods approaches to gain a comprehensive understanding of the complex factors influencing individuals' attitudes and competencies in emerging technology adoption.

Conclusion

This study investigated the relationship between four constructs: information literacy, data literacy, privacy literacy, and interest in adopting emerging technologies in communities. The results reveal a complex connection between these variables that is influenced by an individual's age, gender, education, and internet usage. The model suggests that young, highly educated females who use the internet frequently would most likely have high levels of all four constructs. However, it also shows that an individual can have high levels of tech interest or literacy in one or two areas while having lower levels in others. The result of the study is beneficial where the awareness of different literacy skills is needed to create the right learning plan or curriculum for different demography. Also, it can be practically implemented in situations where the need to understand the right literacy skill needed to adapt an emerging technology like generative artificial intelligence-ChatGPT. The absence of high achievement in one construct is likely to indicate lower achievement in the other three, though there is room for individual variation to play a role.

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Survey Questions

1. What is your age?
2. What is your gender?
3. What is your ethnicity?
4. What is the highest level of education that you have achieved?
5. Which of the following best describes your political beliefs?
6. In what type of community do you currently live?
7. Which of the following best describes the area where you live?
8. Which of the following statements best describes your preferred living situation?
9. Which of the following statements best describes your Internet use?
10. Which of the following statements best describes your online community participation?

For each of the following select the one option that best describes you:

11. I am very interested in using ChatGPT in my community.
12. I have used ChatGPT before.
13. I think ChatGPT would be a useful resource for my community.
14. I think ChatGPT could replace or augment existing community resources.
15. I am concerned about the potential privacy implications of using ChatGPT.
16. I am comfortable with using Chatbot technology in general.
17. I think ChatGPT would be easy to use for members of my community.
18. I would be willing to help promote ChatGPT in my community.
19. I have suggestions for how ChatGPT could be used in my community.
20. I am likely to recommend ChatGPT to others in my community.
21. I can easily find the information I need online.
22. I know how to use a wide range of online search strategies.
23. I find it challenging to decide what keywords to use for online searches.
24. I am not sure whether the information I find online is reliable or not.
25. I am always skeptical of the information I encounter.
26. I look for answers to questions across multiple sources before forming an opinion.
27. I normally look at the top answers to a question on Google.
28. I am more cautious with what I share online compared to in-person.
29. I feel confident in my ability to evaluate the credibility and reliability of information sources.
30. I am able to effectively use library databases and other research tools to find relevant information.
31. I know how to use Microsoft Excel to add, subtract, multiply, and divide a set of numbers.
32. I am not sure how to find vote totals for the most recent county election.
33. I understand what is meant by the phrase "a margin of error of +/- 3 percent"
34. I would prefer to read a summary of findings from a survey and never look at the details myself

35. I find it challenging to decide whether to believe statistics or believe what I am told by people I trust
36. I feel confident in my ability to analyze and interpret data.
37. I often have difficulty understanding data visualizations.
38. I understand how to use data to inform decision making.
39. I know what the abbreviations AI and ML stand for.
40. I am familiar with different sampling methods (e.g., convenience, random, stratified).
41. I know how to access the browsing history on my favorite web browser.
42. I am not sure whether the National Security Agency (NSA) can track the information I am accessing on my computer.
43. I understand what is meant by the phrase "social engineering and phishing pose major threats to the confidentiality of organizational data."
44. I believe that I can request a record of all the personal data that websites have collected about me.
45. I know which web browsers are more secure than others.
46. I always read the privacy policy or statement for the websites that I use.
47. I feel confident that I know how to protect my personal information when using the internet.
48. I am familiar with the privacy settings on the websites and apps that I use.
49. I am aware of the potential risks of sharing personal information online (e.g., identity theft).
50. I regularly review and update my privacy settings on social media platforms.