

INFORMATION LITERACY, DATA LITERACY, PRIVACY LITERACY, AND CHATGPT: TECHNOLOGY LITERACIES ALIGN WITH PERSPECTIVES ON EMERGING TECHNOLOGY ADOPTION WITHIN COMMUNITIES

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Abstract: *This research delves into the interplay between three pivotal literacies in the digital age—information literacy, data literacy, and privacy literacy—and the receptivity towards the adoption of emerging technology within communities, with a specific focus on the chatbot ChatGPT. Data was gathered through online surveys conducted among adults residing in a four-county region in northern Texas during a two-week period in late 2022, yielding 130 valid responses. The results of regression analysis indicate a positive association between the inclination to utilize ChatGPT for enhancing one's community and proficiency in information literacy and privacy literacy. However, an unexpected observation emerges as data literacy skills do not exhibit a significant relationship with this inclination, despite ChatGPT's standing as a data science innovation. Moreover, age, gender, educational attainment, and internet usage patterns are identified as influential factors in these associations. These findings hold substantial importance in comprehending the intricate dynamics of how diverse literacies and individual and community-related variables mutually shape each other's development.*

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



INTRODUCTION

The role of both virtual and physical communities is pivotal in individuals' lives. Understanding how beliefs about community adoption of emerging technology relate to an individual's information, data, and privacy literacy is crucial for fostering a communal information society that supports the development of these literacy skills. While research on information literacy, data literacy, and privacy literacy as distinct constructs is abundant, the connections between these literacies remain largely unexplored. Gaining insight into these relationships and the impact of different literacy skills on the community's adoption of emerging technology can help identify and assist individuals with potential literacy gaps.

Information literacy involves a set of skills that empower individuals to efficiently locate and evaluate a variety of information sources, such as books, articles, websites, and databases. It also entails the ability to assess the credibility and reliability of information. The Association for College and Research Libraries (2022) offers an extensive definition of information literacy, emphasizing its multifaceted nature. This includes the skills needed for reflective discovery, comprehension, and appreciation of information's creation and significance, as well as its ethical use within learning communities.

In our information-rich era, where information is abundant, the capacity to distinguish credible and reliable sources is crucial. Jones-Jang et al. (2019) conducted a study showing that individuals with higher information literacy skills are better at identifying false news. This underscores that existing studies on information literacy largely focus on the identification, retrieval, evaluation, and utilization of information. It also highlights the role of information literacy in recognizing and combating misinformation.

Pennycook et al. (2021) conducted an extensive investigation demonstrating that information literacy not only aids in identifying misinformation but also promotes the identification of accurate information, resulting in a significant decrease in the dissemination of misinformation. Afassinou (2014) explored the correlation between educational attainment and the spread of rumors using the SIR (Susceptible, Infected, Recovered) rumor spreading model. The study found that educated individuals in a population tend to have smaller final rumor sizes, underscoring the impact of education in curbing rumor spread. In a study by Bartol et al. (2018) involving first and second-year students, it was found that students' information literacy levels improved as they progressed in their education. This suggests that education has a positive influence on the development of information literacy skills. Similarly, Dolničar et al. (2020) identified a significant association between education and information literacy, indicating that individuals' information literacy skills improve with higher levels of education.

Data literacy, which falls 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 types, 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) defines data literacy as the proficient understanding and effective utilization of data for decision-making processes. This encompasses the ability to access, retrieve, manage, critically evaluate, and ethically use data (Calzada Prado & Marzal, 2013). The Association of College Research and Research Libraries (2013) emphasizes data literacy competencies such as locating and

evaluating data, working with different versions of datasets, identifying data sources and custodians, and adhering to ethical guidelines.

Johnson (2012) extends data literacy to include the skills required for sorting, processing, and filtering vast data, involving 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) found that organizations face challenges in transitioning to data-centric infrastructures due to a lack of individuals equipped with data literacy skills. Given the ongoing expansion of data and the limited pool of individuals proficient in handling it, the urgency and significance of nurturing data literacy cannot be underestimated (Haendel et al., 2012).

Privacy, as defined by Trepte (2020), involves selective control over information sharing. Sindermann et al. (2021) identified a moderate yet positive relationship between online privacy literacy and information behavior. Notably, teenagers may willingly disclose personal information to join online social networks. Privacy literacy seeks to empower individuals in their interactions with technology, as highlighted by Hagendorff (2020). Bartsch and Dienlin (2016) found that individuals with higher 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 gain a limited form of negative privacy but also the ability to engage in a deliberative process regarding privacy, allowing them to exercise agency over the information they choose to disclose, as explained by Masur (2020).

Recent research by Prince et al. (2022) used a survey-based empirical approach to examine the relationship between privacy literacy and privacy concerns among internet users. The study found that individuals with higher privacy literacy expressed heightened concerns regarding their privacy. Interestingly, it noted 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 involving high school and college students who were members of Facebook to explore the predictive role of privacy concerns in their membership decisions. The study revealed that privacy concerns only weakly predicted membership decisions, as individuals with privacy concerns often disclosed substantial amounts of personal information upon joining the network. It was also observed that a significant portion of respondents expressed high levels of privacy concerns yet lacked the necessary information to make privacy-sensitive decisions (Acquisiti & Grossklags, 2005).

In a survey study using a standard multivariate clustering technique (SAS' partitional clustering), Ackerman et al. (1999) found 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. Baruh et al. (2017) conducted a meta-analysis encompassing 166 studies from 34 countries, with a total sample size of 75,269 participants, 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 simultaneously displaying an increased likelihood of utilizing privacy-enhancing measures.

Information literacy has been shown to enhance the detection of fake news and reduce the dissemination of misinformation (Jones-Jang et al., 2019; Pennycook et al., 2021). Privacy literacy education assists users of social media sites in assessing the risks of sharing personal

information online (Correia and Compeau, 2017). Research by Burtle et al. (2018) and Dolnicar et al. (2020) revealed that students' information literacy improved as their educational attainment increased. Afassinou (2014) found that educated individuals in a population tend to have smaller final rumor sizes, indicating the positive role of education. Technology adoption research investigates the processes by which individuals, groups, and organizations embrace and utilize new technologies (Venkatesh et al., 2007). Factors affecting technology adoption include perceived benefits, costs, compatibility, innovation level, risk, complexity, ease of use, and social influence (Hansen et al., 2018). This study focuses on ChatGPT, an emerging chatbot technology developed by OpenAI, designed to facilitate human-like conversation and hold potential for various applications.

Research Question

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

METHODS

This study focuses on four primary scale variables, or "constructs": information literacy, data literacy, privacy literacy, and the eagerness of community adoption of emerging technologies. Each construct is based on the mean score from a five-point Likert scale comprising ten questions, ranging from 1 (least ideal response) to 5 (most ideal response). Additionally, several demographic variables are examined in relation to these constructs using ANOVA and regression analyses. These demographic variables include age (open response), gender (categorized from open responses), educational attainment (ranging from high school or less to advanced degrees), political leaning (conservative, moderate, liberal), type of community (rural, suburban, urban), and Internet usage (multiple hours per day, one hour or less per day, a few hours per week, one hour or less per week).

Data was collected through a survey instrument created within Qualtrics and delivered electronically. A paper version was also made available to accommodate participants with varying levels of internet access and comfort. The survey consisted of 50 questions, with the final 40 questions used to construct the four variables related to eagerness to adopt emerging technology (in this case, ChatGPT, a novel AI chatbot), information literacy, data literacy, and privacy literacy (each construct composed of 10 questions). The remaining ten questions gathered demographic information as described earlier. The survey questions were based on previous studies conducted by the researchers in this field, and a copy of the survey instrument is included in the appendix.

The survey was distributed within a four-county area surrounding the researchers' university, selected for its diversity. One county contained a top-fifteen city by population, part of a top-ten U.S. metropolitan area, with a population that's about 30% Hispanic and known for its liberal politics. Another county included a minority-serving, Hispanic-serving institution with over 40,000 students. The third and fourth counties were rural, with populations of 60,000 and 10,000, and heavily supported the Republican Presidential candidate in 2020. These counties have aging, predominantly White populations. Distribution occurred through social

media and flyers posted at local public libraries. Participants had the option to access an online survey or request a mailed version.

After a four-week data collection period, the survey was closed, and the data was analyzed using SPSS. Due to the Likert scales used, non-parametric analyses were employed. Kruskal-Wallis H tests (non-parametric ANOVA) and Spearman rank correlation tests were used to evaluate relationships among variables. ANOVA tests examined variance in the four connectedness/literacy constructs based on categorical demographic variables (ethnicity, gender, educational attainment, political leaning, type of community, and Internet usage). Correlation tests assessed the strength of relationships among the four constructs and the continuous variable of age.

Ordinary least squares regression was used to explore the impact of various variables on each of the four primary scale variables in the study. In each regression analysis, four separate models were computed. The first model included all potential explanatory variables, encompassing demographic variables and the three remaining scale variables. The second model only considered the demographic variables. The third model retained only the demographic variables shown to potentially contribute statistically significantly in the second model. The final model focused exclusively on 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 provides a comprehensive view of the average scores for emerging technology interest and literacy across different demographic groups. Kruskal-Wallis H tests were employed to detect statistically significant variations among these population segments, denoted by asterisks (*) in the table. Notable findings from this analysis are as follows:

- **Ethnicity:** White respondents showed significantly lower interest in adopting emerging technology, while Asian respondents exhibited notably higher data literacy. However, ethnicity was excluded from subsequent regression analyses due to the limited representation of Asian and Black respondents.
- **Gender:** Female respondents demonstrated significantly stronger privacy literacy scores compared to their male counterparts, although both groups scored similarly on other measures.
- **Education:** Educational attainment emerged as the most influential differentiator among groups. Those with a high school education or less had substantially lower scores for interest in emerging technology. Conversely, individuals with advanced degrees (masters, professional, doctoral) scored significantly higher on the data literacy and privacy literacy scales.
- **Political Leaning:** Political leaning did not yield significant differences on any of the scales.
- **Type of Community:** Minor differences were observed in terms of the type of community. Rural respondents had significantly lower interest in emerging technology, whereas suburban residents had higher scores for privacy literacy. Urban respondents exhibited moderate scores across the board.
- **Internet Usage:** Those with limited internet use tended to score lower in data literacy, whereas individuals with extensive internet usage demonstrated higher 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

This study sought to explore the relationship between demographic factors and individuals' attitudes and competencies in adopting emerging technology for community use. The findings offer valuable insights into how demographics influence these aspects. Notably, the sample was primarily composed of Hispanic, male, and highly educated participants. This sample composition might be attributed to the study's recruitment methods, potentially favoring these particular groups. It's essential to recognize that the generalizability of these findings to other populations may be limited due to the sample's composition.

The age distribution of respondents was fairly even across three categories: 18-29, 30-59, and 60 or older. An interesting observation was that age exhibited a negative correlation with interest in adopting emerging technology but positive correlation with information literacy. In other words, as individuals grew older, their interest in technology adoption decreased, while their scores in literacy increased. This suggests that older individuals may have lower enthusiasm for adopting emerging technologies but possess higher levels of information literacy compared to their younger counterparts. This finding underscores the importance of tailoring technology interventions and educational programs to cater to the distinct needs and preferences of various age groups.

The limited representation of Asian and Black individuals in the sample led to their exclusion from subsequent regression analyses. Nevertheless, it's noteworthy that Asian respondents displayed significantly higher data literacy compared to other ethnic groups, while White respondents exhibited significantly lower interest in adopting emerging technology. These disparities suggest potential variations in technology-related attitudes and competencies among different ethnic groups, warranting further exploration in future research with more diverse samples.

Gender differences were apparent in privacy literacy, with female respondents outperforming their male counterparts. However, no significant gender disparities were observed in other measures. This finding indicates that females may possess a relatively stronger understanding of privacy concepts in the context of emerging technology. Further investigations are needed to delve into the factors contributing to this gender difference, which can inform targeted interventions for enhancing privacy literacy.

Educational attainment emerged as a prominent factor in differentiation among respondents. Individuals with higher educational levels, including advanced degrees, demonstrated significantly better scores in data literacy and privacy literacy. Moreover, those with lower educational attainment, particularly high school or less, exhibited notably lower interest in adopting emerging technology. These results underscore the pivotal role of education in shaping individuals' engagement with technology and their competency levels. Efforts should be made to offer accessible educational opportunities to individuals with lower educational attainment to bridge the digital divide and promote inclusive technology adoption.

While political leaning and type of community showed limited differences in the measures of interest and literacy, respondents from rural areas expressed lower interest in adopting emerging technology compared to those from suburban and urban areas. Additionally, individuals with limited internet usage tended to score lower in data literacy, while those with extensive internet usage fared better in privacy literacy. These findings indicate that an

individual's residential context and access to technology infrastructure can impact their technological engagement and competencies.

The correlation analysis unveiled weak-to-moderate relationships among the variables. The positive correlations observed among interest in emerging technology adoption, information literacy, data literacy, and privacy literacy highlight the interconnectedness of these constructs. However, older adults appeared to defy this pattern, displaying a lower level of interest in technology adoption despite having higher literacy levels. These findings underscore the need to consider multiple dimensions when examining individuals' engagement with emerging technologies.

The regression analyses provided further insights into the factors influencing interest in adopting emerging technology. The models indicated that age and education significantly contributed to the variance in emerging tech interest. Older age was associated with reduced interest in emerging technology adoption, while higher educational attainment predicted increased interest in this domain. This finding about age aligns with the existing literature, which often cites reluctance among older adults to adopt emerging technology. However, the discovery of conflicting findings regarding literacy and aging underscores the need for tailored interventions and educational programs that consider age and educational background to foster interest and engagement in emerging technologies.

It's crucial to acknowledge the limitations of the study. The sample's predominant composition of Hispanic, male, and highly educated individuals restricts the generalizability of the findings to other populations. Additionally, the study relied on self-reported survey data, which can be subject to response biases and social desirability effects. Future research should aim to incorporate more diverse samples and employ mixed-methods approaches to gain a comprehensive understanding of the complex factors influencing individuals' attitudes and competencies in adopting emerging technology.

CONCLUSIONS

This study delves into the intricate relationship among four key constructs: information literacy, data literacy, privacy literacy, and the interest in adopting emerging technologies within communities. The findings illuminate a multifaceted interplay between these variables, influenced by an individual's age, gender, level of education, and internet usage. The model suggests that young, highly educated females who frequently use the internet are most likely to exhibit high levels in all four constructs. However, it also demonstrates that an individual can possess high levels of interest or literacy in one or two areas while having comparatively lower levels in others. This study's results provide valuable insights, highlighting the significance of recognizing various literacy skills required to tailor the appropriate learning plans or curricula for different demographic groups. Practically, these findings can be applied to situations where a deep understanding of the necessary literacy skills is vital for adapting to emerging technologies like generative artificial intelligence, such as ChatGPT. Notably, a deficiency in one construct often corresponds to lower achievement in the other three, although individual differences play a role.

IMPLICATIONS FOR RESEARCH, APPLICATION, OR POLICY

The findings highlight the need for tailored educational programs that consider individuals' age, gender, and educational background. To promote inclusive technology adoption, efforts should be made to provide accessible educational opportunities, especially to individuals with lower educational attainment. Policymakers and educators should focus on designing curricula that cater to the specific needs and preferences of different demographic groups.

The positive correlations among interest in emerging technology adoption, information literacy, data literacy, and privacy literacy suggest that these constructs are interrelated. Researchers and educators should consider these interconnections when designing interventions and assessments to comprehensively evaluate individuals' technological engagement and competencies.

The study confirms the commonly observed reluctance among older adults to adopt emerging technologies. Policymakers and technology developers should focus on creating user-friendly interfaces and providing additional support to older individuals to encourage their participation in the digital age. These are all important considerations as the fourth industrial revolution and AI technologies become more ubiquitous in society.

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Appendix

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 private information.