

Who Is At Risk? Examining the Prevalence of Digital-Safety Attacks and Contextual Risk Factors in the United States

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Abstract

A growing body of qualitative research has identified *contextual risk factors* that elevate people’s chances of experiencing digital-safety attacks. However, the lack of quantitative data on the population-level distribution of these risk factors prevents policymakers and tech companies from developing targeted, evidence-based interventions to improve digital safety. To address this gap, we surveyed 5,001 adults in the United States to analyze: (1) the frequency of and relationship between digital-safety attacks (e.g., scams, harassment, account hacking), and (2) how these attacks align with 10 contextual risk factors. Nearly half of our respondents identify as resource constrained, which significantly correlates with higher likelihood of experiencing four common attacks. We also present qualitative insights to expand our understanding of the factors beyond the existing literature (e.g., “prominence” included high-visibility roles in local communities). This study provides the first large-scale quantitative analysis correlating digital-safety attacks with contextual risk factors and demographics.

CCS Concepts

• Security and privacy → Human and societal aspects of security and privacy; • Human-centered computing → Empirical studies in HCI.

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1 Introduction

Designing internet experiences that proactively mitigate people’s risk requires a robust understanding of how different digital safety attacks happen, including what circumstances make harms more likely or more intense [12]. Scholarship demonstrates that the dynamics of digital-safety experiences emerge at the intersections between relational dynamics, social identity, and life circumstances [36, 39, 40, 49, 50, 70]. “Digital-safety” attacks can include anything from a bulk phishing attack to being directly targeted with abusive messages or personal images. These attacks can cause financial or emotional harms, and may escalate into physical harm. In scope is any incident pertaining to security, privacy, or online abuse with a digital component, and a negative outcome to individuals or groups [36, 62], which are not experienced equally across the population. Research has outlined the adverse effects of these attacks, demonstrating how some user groups endure heightened forms of unwanted behavior [41], face complex privacy risks [17], and experience greater financial harm from scams and attacks [33].

One hypothesis from the literature, is the disproportionate severity and incidence of digital harms stems from *contextual risk factors*—circumstances rooted in societal, relational, and personal life experiences—that increase a user’s vulnerability to attacks or hinder recovery [36]. Warford et al. [69] synthesized 5 years of research into safety, privacy, and security experiences across settings into a framework identifying ten risk factors, encompassing *societal* (e.g., stigmatization, relationship factors), *relational* (e.g., reliance on a third party), and *personal circumstances* (e.g., prominence, being resource and time constrained). This framework emphasizes how the mechanisms of digital safety risk include factors that cannot



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solely be captured by standard demographics. For instance, scholars highlight the compounding risks faced by financially precarious unhoused youth [73] and disabled creators encountering ableist harassment due to their visibility [33]. To meaningfully reduce risk, digital safety interventions must account for the social and situational factors that influence technology use [54].

While scholars have provided a rich understanding of the lived experiences of vulnerability, research examining perceptions and distribution of risk at the population level remains limited. Without any baseline, designers of technology and builders of safety systems, can not know how generalizable these experiences are, and may treat “at-risk” users as edge cases, designing systems and safety defaults for a theoretical, but not well-grounded, average user. This article offers an analysis of individual’s *perception* of contextual risk factors, which is essential for understanding the scale of the problem, enabling more targeted, evidence-based interventions [54], and identifying user groups bearing disproportionate risk that may not be currently captured in the literature. We describe findings of a nationally-representative survey of 5,001 U.S. adults across age, gender, education, race, and region designed to: (1) measure the prevalence of ten specific digital-safety attacks; and (2) quantify self-identification with the ten established contextual risk factors. Our research questions include:

- **RQ1:** How many US adults experience digital-safety attacks?
- **RQ2:** How many people self-identify with expert-identified contextual factors that may increase risk of attacks, and why?
- **RQ3:** Who is likely to identify with the contextual risk factors and how might their circumstance increase the likelihood of experiencing digital-safety attacks?

Through a logistic regression analysis of the relationship between risk factors and attacks, supported through descriptive analysis of the qualitative explanations our respondents provided, we find that circumstances elevating digital risk are a normative aspect of U.S. adults’ online experience, with 85% of respondents identifying with at least one risk factor. Our findings also add nuance to existing factors, revealing how respondents interpret these factors in more expansive ways than the current scholarly literature has documented. For example, participants in high-visibility roles—such as a “neighborhood nurse” in a rural community—self-reported feeling prominent. We conclude by discussing the implications of these findings for future digital-safety research, including methodological considerations for studying perceived risk and the need for additional at-risk research to inform evidence-backed, targeted outreach in digital-safety awareness and education.

Finally, this study aligns with broader efforts to shift focus from individual identity characteristics and towards circumstantial determinants [60]. Analogous to the “social determinants of health” framework in public health [61, 74]—which recognizes that social and economic conditions, rather than identity traits alone, shape outcomes—this study highlights the situational conditions that contribute to disparities in digital safety threats. By emphasizing these circumstances, the HCI field can avoid placing responsibility solely on identity and instead address the environmental conditions that exacerbate digital harm.

In summary, this study provides a first step towards building a holistic understanding of how expert-identified, contextual risk factors manifest in the U.S. population, offering:

- An updated distribution of digital-safety attacks in the U.S. population.
- An analysis of the demographics and contextual risk factors that correlate with the likelihood of experiencing various digital-safety attacks.
- Directions for future work by identifying: (1) at-risk populations currently not well captured in the digital-safety literature and (2) specific demographic or situational contexts that shape how different digital-safety attacks are experienced.

2 Related Work

In this section, we first summarize key findings from survey-based research on the prevalence of digital-safety attacks and the demographic differences identified in these experiences. We then review at-risk research in HCI, highlighting qualitative studies that reveal contextual factors and circumstances beyond demographics that can increase one’s vulnerability. We specifically focus on attacks that were explored in our survey, which include cybersecurity attacks (i.e. scams, account hacking, virus or malware attacks, money stolen), harassment and abuse, (i.e. insulted, discriminated, stalking, and physical threats), exposure to harmful content (i.e. exposed to unwanted or explicit content), and privacy violations (i.e. having photos or information shared without their permission). While HCI research has increasingly examined digital safety in international and non-WEIRD contexts [26, 71], this review focuses on prior work situated in the United States aligning with the geographic scope of our study.

2.1 Digital-safety attacks in the United States

Numerous organizations conduct large-scale surveys to measure the prevalence of varying digital safety-attacks, with cybersecurity-related incidents among the most frequently reported. Scams and financial fraud, for instance, have long been documented: in 2013, Pew Research found that 6% of internet users had been victims of an online scam resulting in financial loss [45]. Since then, such attacks have become more common. A 2021 U.S. Department of Justice report [7] estimated that 1 in 5 people (22%) had experienced identity theft in their lifetime, with victims losing an average of \$880. More recent U.S. national surveys echo this trend. The 2023 Ipsos Cybersecurity Survey [24] reported that 31% of Americans had been victims of online financial fraud or cybercrime, and a 2025 Pew Research report [44] found that 73% of U.S. adults had experienced incidents such as credit card fraud, ransomware, or online shopping scams.

Surveys have also documented the prevalence of online harassment, abuse, and exposure to harmful content. In 2021, Pew Research [68] reported that 41% of U.S. adults had personally experienced online harassment, and 25% had endured severe forms such as stalking, physical threats, sustained harassment, or sexual harassment, which is up from 12% in earlier Pew Research studies. Emerging work has begun to measure specific types of harmful content. For example, Umbach et al. [66] found that 24.2% of Americans had experienced image-based sexual abuse [66]; Pew Research reported 53% of women ages 18–29 reported receiving unsolicited explicit images [68]; and a U.S. Bureau of Justice Statistics survey [64] reported that 1.5% of people ages 16 and older had been victims of stalking, noting that it was more common for people to be stalked using technology compared to traditional forms of stalking.

Several surveys have documented demographic differences in the likelihood of experiencing various forms of digital attacks. Gender disparities appear consistently, with women reporting higher rates of stalking [64], non-consensual explicit content [68], identity theft [2], and online sexual harassment [68] compared with men. Sexual orientation is also associated with heightened victimization of online abuse: lesbian, gay, or bisexual adults are significantly more likely than straight adults to face both general and severe online harassment [68]. In a large study of 27,000 transgender adults in the United States, participants reported particularly high rates of abuse: 46% had experienced verbal harassment, 47% had been sexually assaulted, and 54% had experienced intimate partner violence.

Differences also emerge across age groups, with younger adults, especially those under 30, encountering online harassment at higher rates than older adults [68], while older and middle-aged adults are more likely to report financial cybercrimes [24]. Additional disparities appear across race, education, and income. Black, Hispanic and Asian adults are more likely than White adults to say they have lost money because of an online scam [44]. Adults with no college education report experiencing scams twice as much as college graduates [48]. Households earning less than \$50,000 per year (12%) are about twice as likely as middle-income (7%) and upper-income adults (6%) to report having been scammed [48]. Conversely in another study, they found people with higher levels of income to report higher rates of identity theft [2]. It is important to note that these demographic differences are based on percentage comparisons. While such descriptive data highlight potential disparities across groups, they do not reveal the magnitude of these relationships or control for other contributing factors. To address this limitation, our work employs logistic regression to assess the significance of associations between individual circumstances, demographic characteristics, and the likelihood of experiencing digital-safety attacks.

While large-scale polls are valuable for confirming that certain types of digital-safety attacks are common, they often lack the granularity to identify the underlying contexts that elevate a user's risk. A richer understanding of what makes users *vulnerable* to digital-safety attacks requires a deeper look at contextual factors, allowing us to connect RQ1 and RQ2.

2.2 At-Risk research

At-risk users are those who face an increased likelihood of, or disproportionate harm from, digital-safety attacks. Synthesizing five years of qualitative HCI research, Warford et al. [69] identified ten contextual *risk factors* which, when present, could increase the risk profile of a user or community:

- (1) **Societal risk factors**, which include people who have increased risk due to legal, political, or societal wide forms of marginalization, for example activists [10], journalists [35], or refugees [56];
- (2) **Relationship-based risk factors**, which include people who have increased risk based on who they know, for example people in abusive relationships [14, 30, 37, 38] or who rely on others, like children [13, 20, 29] or older adults [15]; and

- (3) **Personal risk factors**, which include people who have increased risk due to their own circumstances, for example people who are prominent [9, 51, 63], financial insecure [57], or who have specific technology or accessibility needs. [1, 23, 34, 47]

Research into at-risk users does not just explore a single factor in isolation, but has also explored populations' experiences at the intersection of these contextual risk factors. For example, Heung et al.'s [22] work with disabled creators found they experience high rates of ableist harassment due to their public prominence [22], and Woelfer et al.'s [73] study of unhoused youth highlighted the risks stemming from their financial precarity. However, Warford et al.'s [69] framework shows the large number of possible combinations of factors, and motivates quantitative approaches to understanding more about the prevalence of groups with shared factors.

To quantify the prevalence of contextual risk factors at a population scale, survey methodology is required. Standard demographic polling questions (e.g., age, gender, race, disability) can capture some factors, in part, but are not well suited towards measuring the full range of circumstances that matter for digital safety. Additionally, no survey has measured the prevalence of the full set of contextual risk factors [69]. This approach to capturing the prevalence of digital-safety experiences has precedent (e.g., [53, 66]) within the HCI community for tackling similar sociotechnical questions.

In summary, the extant literature establishes the prevalence of certain digital-safety attacks and provides a rich, qualitative framework for understanding contextual user risk. However, no study has yet measured the distribution of these non-demographic risk factors across a representative population. This study begins to address this gap by providing the first quantitative map of contextual risk factors and their relationship to digital-safety attacks and experienced harm.

3 Methods

The research team conducted a nationally-representative survey of 5,001 U.S. adults regarding their digital-safety experiences and self-identified risk factors. This section details our participant recruitment and demographics, survey design, analysis methods, and limitations.

3.1 Respondents

The survey was fielded between December 15, 2023–January 3, 2024. In total, 5,001 adult respondents were recruited for the study via online panels managed by Morning Consult, a global public opinion polling company. To build a nationally representative sample, respondents were asked to report their age, gender, education, race, and region, which were used to meet pre-determined quotas to sample 5,000 participants matching national demographics on those characteristics. Instead of a standard sample of 1,000 participants the polling company quintupled the sample to provide us a smaller margin of error (1.4% not the standard 3%), to allow us additional precision for less common risk factors and attacks. A summary of respondents' demographic data are shown in Table 1.

Demographic	Group	<i>n</i>	%	Demographic	Group	<i>n</i>	%
Gender	Man	2,314	46.3	Political Party	Republican	1,504	30.1
	Woman	2,657	53.1		Democrat	1,878	37.6
	Nonbinary	20	0.4		Independent	1,346	26.9
	Self-describe	8	0.2				
	Prefer not to say	9	0.2				
Race	White	3,510	70.2	Urbanicity	Suburban	2,189	43.8
	Hispanic/Latino	442	8.8		Urban	1,552	31.0
	Black/African Am.	942	18.8		Rural	1,260	25.2
	Asian	206	4.1	Parentage	With kids	2,703	54.0
	Am. Indian/Alaska	109	2.2		Without kids	2,298	45.9
	Middle Eastern/NA	18	0.4	Sexuality	LGBTQ	432	8.6
	NH/PI	9	0.2		Non-LGBTQ	4,502	90.0
	Another race	33	0.7				
Prefer not to say	27	0.5					
Age Group	18–24 years of age	474	9.5	Generation	Gen Z	616	12.3
	25–34	818	16.4		Millennials	1,305	26.1
	35–44	779	15.6		Gen X	1,320	26.4
	45–54	828	16.6		Baby Boomers	1,595	31.9
	55–64	868	17.4		Silent	165	3.3
	65+	1,234	24.7				
Work Status	Full-time	1,856	37.1	Education	Grade 1–8	24	0.5
	Part-time	589	11.8		HS incomplete	194	3.9
	Unemployed / Not working	763	15.3		HS diploma	1,333	26.7
	Student	144	2.9		Some college	979	19.6
	Stay-at-home parent	209	4.2		Associate’s degree	498	10.0
	Retired	1,378	27.6		4-yr college	1,082	21.6
	Prefer not to say	62	1.2		Technical school	197	3.9
			Grad school, no degree		129	2.6	
			Grad/prof. degree		565	11.3	
Disability	Disabled	1,165	23.3		Non-disabled	3,693	73.8

Table 1: Demographic summary of our nationally representative sample of 5,001 adult respondents in the U.S.

3.2 Survey design

The 20-minute survey started with a consent form and asked respondents about their general experience with digital-safety attacks, whether they self-identified with any of the expert-identified factors that might put them at higher risk, and about their demographic information. This work was led by Google, which does not have an Institutional Review Board, but we adhered to equivalent ethical standards, including required internal ethics trainings, enforced data retention limits, standard Google consent forms for research, and internal review processes for sensitive topics and data collection. Additionally, our survey was reviewed by our Morning Consult through their standard review processes. We describe the core modules of the survey below; see the Appendix for additional details.

Digital-safety attacks. Building on existing surveys of digital-safety attacks (described in Section 2), respondents self-reported whether they had, at any point, experienced any of ten possible digital-safety attacks such as being the target of a scam, having an account hacked, being discriminated against or harassed online, or having their private information leaked (see Table 3). These ten attacks span privacy, safety, and security. Attacks for the survey were adapted from previous work, including [62] and [8]. Language

for the attack descriptions was iterated and confirmed with privacy, safety, and security experts outside the author team to be legible to non-expert audiences. For each experience, respondents selected *Yes*, *No*, or that they *Don’t know* whether the attack applied.

Contextual risk factors. Building on a framework that identified 10 *contextual risk factors* that put people at higher risk [69] (e.g., marginalization, prominence), respondents were asked 18 statements to assess whether they felt any contextual risk factors might apply to themselves. These questions distilled the contextual risk factors into simple statements, designed to be easy for respondents to interpret compared to the academic definitions. The questions and their mapping to each contextual risk factor are presented in Table 2. For each statement, respondents were asked to select from a Likert scale ranging from 1 (*Does not describe you at all*) to 10 (*Describes you very well*), also allowing for respondents to indicate they *Don’t know*. For their top three agreed statements (highest Likert scale ratings), respondents could optionally explain their reasoning in an open-ended survey response.

The statements were designed through an iterative process with security, privacy, and safety experts outside of the authorship team. Expert feedback helped ensure that the statements accurately reflect established definitions of the contextual risk factors and the

Contextual risk factor	Survey item
<i>Legal or political</i>	I feel targeted by governments or political groups
<i>Marginalization</i>	Things are harder for me online because parts of my identity aren't widely accepted Things are harder for me online because the experiences I've had in my life aren't common
<i>Social norms</i>	I feel like technology generally works well for me (reverse keyed) I feel like technology was not designed with people like me in mind
<i>Relationship with attacker</i>	I have had personal relationships with people who have tried to harm me
<i>Reliance on 3rd party</i>	I depend a lot on others for assistance (e.g. to set up or use technology) I feel like I can achieve my goals online without help (reverse keyed)
<i>Access to other at-risk users</i>	I am a person who takes care of or works with people who are vulnerable I am close to a person who is often targeted online
<i>Prominence</i>	I have a higher profile because of my job I have a higher profile because of other people I am close to I have a higher profile because of other aspects of my life
<i>Resource / time-constrained</i>	I don't have the time or money to be safer online I don't have the time or money to recover if something bad happens to me online
<i>Underserved accessibility needs</i>	It is difficult for me to use many technologies Technologies often aren't designed for my needs and this makes me feel less safe online
<i>Access to a sensitive resource</i>	I have access to sensitive resources, such as information or money, that most others do not

Table 2: Survey items used to assess whether respondents felt they may experience a contextual risk factor (as defined by Warford et al. [69]). Prior work has shown ways these factors augment or amplify digital-safety risks and their resulting harms. Respondents were asked: “For each of the statements, think about how well they describe you on a scale of 1 - 10. 1 means the statement doesn't fit you at all, 10 means it describes you very well.”

readability of the statements. This expert review helped confirm that the items appropriately represent and measure the intended risk factors. While this process strengthened the survey's content validity, we acknowledge that the statements may not capture the full range of content or experiences represented by each contextual risk factor. Furthermore, the authors used the open-ended responses to check for any significant confusion or misinterpretation, which we did not find. Future work is needed to further validate the survey items, including conducting cognitive testing with participants.

Demographics. Respondents self-reported their demographic information including their gender, age, education, urbanicity, parental status, race, political attitudes, religion, sexuality, and occupation. Respondents could respond with *Prefer not to say* for all categories. For each model, respondents who responded *Prefer not to say* were excluded from the analyses.

3.3 Analysis

This paper primarily relies on quantitative analysis, but we add qualitative depth based on open-ended details provided by respondents.

Quantitative Analysis. We determine if a respondent is experiencing a risk factor based on how well each of the 18 statements in Table 2 described them. For contextual risk factors represented by a single statement (i.e., legal or political, relationship with attacker, and access to a sensitive resource), we determine that a respondent is experiencing the risk factor if they selected 7–10 on a scale of 1 to 10,¹ and that they are *not* experiencing it if they

selected 1–4. For two of the contextual risk factor statements, they are reverse-keyed, meaning a high level of agreement (7–10) with a survey item indicates a low level of experiencing the risk factor. If a respondent selected 5, 6, or reported that they did not know how well the statement fit them, we do not consider them to be in either group. For risk factors with multiple statements, if a respondent selected 7–10 for at least one of the related statements, we determine that they are experiencing that factor, and that they are 'not' experiencing that factor only if they selected 1–4 for *all* of the related statements. That is, we consider a respondent *prominent* if they selected 7–10 for any of the three prominence statements and *not prominent* only if they selected 1–4 for all three prominence statements. This statement calculation allowed us to use a binary variable, determining whether they are or are not experiencing each risk factor. This calculation was used for our quantitative modeling described below.

Our primary analysis task was to understand the prevalence of digital-safety attacks and contextual risk factors, and ultimately whether those factors and a respondent's demographics influenced the likelihood of experiencing attacks according to logistic regression models. When modeling, we relied on Python and the `statsmodels` library. We treat digital safety attacks as a binary variable and all demographics as categorical variables. When modeling, if all statements for the risk factor are *Don't know*, then we group that response as someone who is not experiencing the risk factor. We also omit results in the findings for demographic categories with fewer than 50 responses due to a lack of statistical power. We report statistically significant ($p < 0.05$) odds ratios in

¹We select 7–10 for agreement – while we could have selected 6+ we felt selections near the middle of the scale did not strongly confirm agreement. The results would have

varied slightly if we selected 6+ or 8+, but we leave exact measures of risk agreement to future work.

the paper. Aligning with best practices outlined by [59], we provide full model details in our Appendix, including p-value, confidence intervals, t-statistics, and β (log2).

Qualitative analysis. We conducted qualitative coding [6] on the open-ended survey responses, where respondents explained why they strongly identified with a contextual risk factor. Respondents were only prompted to submit a short response on their top 3 agreed statements, and this survey item was optional. In line with Braun and Clarke [5], we used a deductive coding approach, since each statement is designed to address one characteristic of a risk factor, and developed semantic codes (codes that are descriptive rather than interpretative). Two authors collaboratively open-coded 20% of the responses ($n = 2,200$) for each statement and wrote memos, noting recurring topics and taking note of responses that were particularly surprising. Then the coders individually coded the rest of the responses. Throughout the coding process, the coders met with the broader authorship team to discuss the codebook. In the end, the codebook contained 9 categories (e.g. demographics, perception, concern) with 179 codes (e.g. woman, not tech-savvy, concern:hacked) (see Appendix B). Many codes aligned with each contextual risk factor, which informed the organization of our findings, where qualitative insights are presented by contextual risk factor. See the appendix for more detailed examples of our codes.

3.4 Limitations

This study carries the standard limitations of public opinion polling and survey methodologies, including self-selection bias and social desirability bias [3]. The findings are based on self-reported data, which may be prone to recall inaccuracies. Additionally, while the sample is large and representative of adults in the U.S., the results are not necessarily generalizable to other countries.

The instrument used to measure contextual risk factors is novel and has not been validated—thus, it is possible that respondents interpreted the survey statements in ways that we did not intend. Although the qualitative analysis of open-ended responses provided a preliminary check for respondents' comprehension of the risk factor survey items, formal cognitive testing is still needed across a representative population cross-section to confirm they assess the intended risk factors. The design of the survey instrument, which used a varying number of statements for different risk factors, may also have led to an underestimation of circumstances that were assessed with fewer questions.

Finally, our analysis does not capture the temporal dynamics of harm. The survey asked whether respondents had ever experienced an attack, not about the frequency, recency, or potential escalation of such incidents. The study did not collect data on all potentially relevant factors, such as income, specific protective behaviors, or other types of online attacks, which may provide a more comprehensive understanding of user circumstances and digital-safety experiences.

4 Results

We begin by reporting the prevalence of digital-safety attacks broadly across U.S. adults (Section 4.1). We then look how many U.S. adults self-identify with contextual risk factors, modeling which demographic groups identify more often with each factor and exploring potential reasons through an analysis of open-ended responses (Section 4.2). It's important to note that this analysis maps

respondents' perceived alignment with the contextual risk factors. We report odds ratio results from logistic regression models and all quoted responses are from a different participant. Finally, we examine how well demographics and contextual risk factors predict the digital-safety attacks explored in our survey (Section 4.3).

4.1 Digital-safety attacks are widely experienced by U.S. adults

Our findings indicate that 74.0% of respondents experienced at least one type of digital-safety attack while online, as detailed in Table 3. The most common attacks were scams and phishing (49.7%), account hacking (41.3%), and exposure to unwanted explicit content (32.8%). Less common but still significant were experiences of being stalked (16.2%) or physically threatened (15.7%). On average, respondents reported experiencing 2.8 distinct attacks. While the survey asked respondents if they had *ever* experienced these attacks, we lack data on their frequency or recency. Nevertheless, these findings illustrate that digital-safety attacks are a common life experience and serve as the dependent variable for our modeling of how digital-safety attacks correlate with contextual risk factors and other demographics.

4.2 Many U.S. adults self-identify as being at elevated risk

Overall, 85% of respondents indicated high agreement with at least one contextual risk factor statement corresponding to a contextual risk factor (correcting for reverse keyed statements). As detailed in Table 4, 38.6% of respondents felt they did not have the time or money to recover if something bad happened online; 26.5% reported taking care or working with people who were vulnerable; and 24.0% said they have had a personal relationship with someone who had tried to harm them. Conversely, only 13.7% of respondents felt they faced obstacles online due to their identities not being widely accepted, and 14.3% that they were close to someone who often was targeted online.

Figure 1 shows the aggregate prevalence for each of the 10 contextual risk factor. The top three self-identified contextual risk factor included being resource and time constrained (47.9%), reliant on a third party (38.0%), and having access to other at-risk users (34.4%). On average, respondents identified highly with 3 contextual risk factors (see a detailed breakdown in Table 5). To understand which demographic groups identified with each contextual risk factor, we modeled the relationship between reporting high agreement and respondents' demographics. A summary of the model results can be found in Table 6. See the Appendix for complete model details.

4.2.1 Resource & Time Constrained. Nearly half of respondents (48%) reported being resource and time constrained, feeling like they could not afford to be safer online and/or they would not be able to recover if something bad happened to them online. Having a disability was associated with higher odds of reporting such constraints than those who are non-disabled (OR = 1.68, CI = 1.44, 1.96). In contrast, male respondents had lower odds of being resource and time constrained than female respondents (OR = 0.77, CI = 0.68, 0.88). Compared to Independents, both Republicans (OR = 1.22, CI = 1.03, 1.42) and Democrats (OR = 1.21, CI = 1.04, 1.41) showed elevated odds of being resource and time constrained. Additionally, respondents whose highest education level was high school or some

Digital-Safety Attack Statement	Yes	No	Don't Know
Been the target of a scam or phishing attack	49.7%	43.7%	6.6%
Had an account hacked	41.3%	51.7%	7.0%
Been exposed to unwanted explicit content	32.8%	61.8%	5.4%
Been the target of a virus or malware attack	31.6%	58.4%	10.0%
Been insulted or treated badly online	29.1%	66.5%	4.4%
Had money stolen	26.6%	68.6%	4.8%
Been discriminated or harassed based on your identity	17.4%	76.6%	6.0%
Had your private photos or information shared without your permission	16.3%	73.2%	10.6%
Been stalked	16.2%	76.1%	7.7%
Physical threats	15.7%	79.7%	4.6%
Any digital-safety attack listed above	74.0%	23.9%	2.2%

Table 3: Self-reported prevalence of digital-safety attacks that occurred online across U.S. adults (% of total, $n = 5,001$).

Contextual Risk Factor Statement	Low	Medium	High	Don't Know
I don't have the time or money to recover if something bad happens to me online	35.3%	21.0%	38.6%	5.2%
I am a person who takes care of or works with people who are vulnerable	51.1%	18.4%	26.5%	4.0%
I have had personal relationships with people who have tried to harm me	57.6%	14.9%	24.0%	3.5%
I don't have the time or money to be safer online	50.4%	21.8%	22.9%	4.9%
I depend a lot on others for assistance (e.g. to set up or use technology)	57.0%	18.1%	22.0%	2.8%
It is difficult for me to use many technologies	58.4%	18.2%	20.7%	2.8%
I feel like I can achieve my goals online without help (reverse keyed)	20.3%	22.9%	53.6%	3.2%
I feel like technology was not designed with people like me in mind	54.9%	20.5%	20.2%	4.4%
I have a higher profile because of other aspects of my life	57.0%	18.9%	19.1%	5.1%
I have access to sensitive resources, such as information or money, that most others do not	59.7%	17.1%	18.9%	4.4%
Technologies often aren't designed for my needs and this makes me feel less safe online	55.1%	22.3%	17.8%	4.8%
I have a higher profile because of other people I am close to	60.0%	17.5%	17.3%	5.2%
I have a higher profile because of my job	63.3%	15.4%	17.0%	4.3%
I feel targeted by governments or political groups	64.0%	15.7%	15.9%	4.4%
Things are harder for me online because the experiences I've had in my life aren't common	63.3%	16.9%	15.7%	4.1%
I feel like technology generally works well for me (reverse keyed)	14.9%	23.6%	58.9%	2.6%
I am close to a person who is often targeted online	69.5%	11.9%	14.3%	4.3%
Things are harder for me online because parts of my identity aren't widely accepted	67.9%	13.7%	13.7%	4.7%

Table 4: Self-reported prevalence of contextual risk factors across U.S. adults, according to the terminology presented to respondents (% of total, $n = 5,001$). High indicates strong agreement that a statement applies (e.g., Likert score of 7–10), Medium that a statement somewhat applies (e.g., 5–6), and Low that a statement does not apply (e.g., 1–4). When sorting, we select the Low value for reverse keyed statements (e.g., strong disagreement with the positive statement).

college had 1.30 times greater odds (CI = 1.07, 1.55) of reporting being resource constrained compared to those with college degrees.

Qualitative Insights. In open-ended survey response, respondents cited financial instability, such as being unemployed, working part-time, or receiving a limited, fixed income (e.g., on disability or

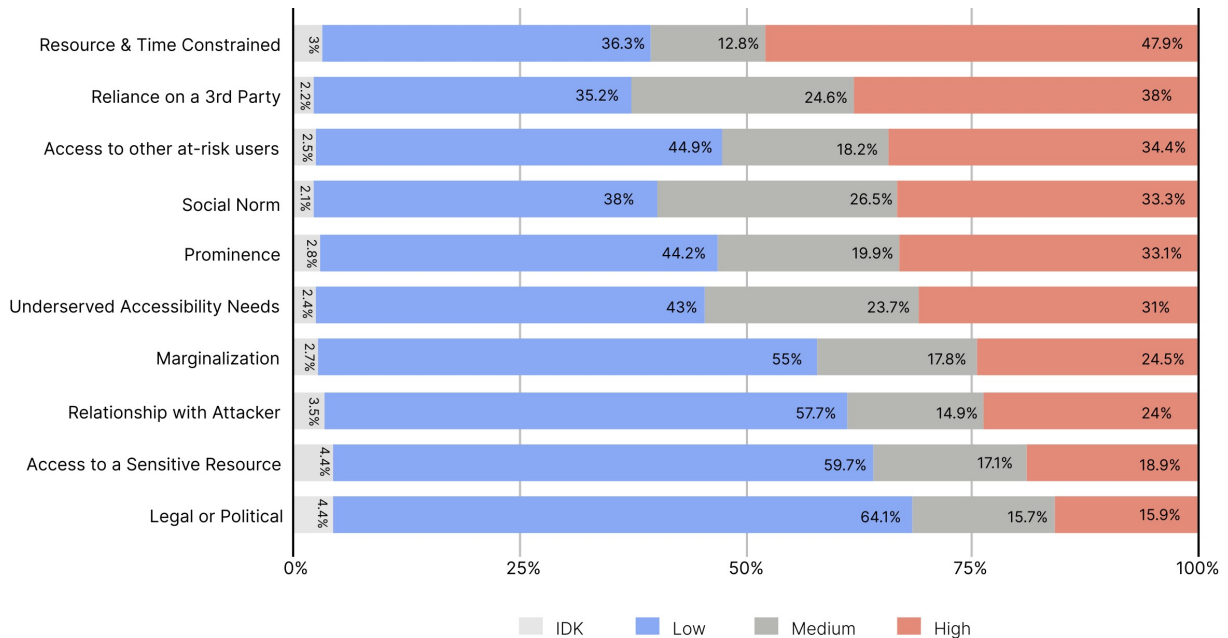


Figure 1: Self-reported prevalence of each contextual risk factor across U.S. adults, after aggregating each of our 18 survey questions per factor.

Number of Risk Factors	0	1	2	3	4	5	6	7	8	9	10
Percentage of respondents	17.4%	18.5%	19.8%	12.7%	10.1%	6.8%	4.4%	3.0%	2.5%	1.7%	3.0%

Table 5: Breakdown of respondents who reported high agreement with 0, 1, or multiple contextual risk factors. On average, respondents self-identified with 3 factors.

on social security) as reasons for resource and time constraints. Respondents also recognized the price of staying safe and secure, noting that VPNs, security software, and anti-virus software is expensive. Some expressed uncertainty about how effective these technologies were relative to the cost, especially when they already had limited savings and financial constraints. For example, one respondent noted that being safer “*means that you’re buying things like VPNs or additional security, all things [they] don’t have a lot of extra money to spend on.*”

4.2.2 Reliance on a 3rd Party. 38% of respondents reported feeling dependent on others for technology assistance and/or feeling like they could not achieve their goals without help. Disabled respondents (OR = 1.43, CI = 1.22, 1.67) and respondents with children (OR = 1.22, CI = 1.07, 1.39) had higher odds of reporting this risk factor compared to non-disabled and non-parental respondents, respectively. Our models suggest a correlation with race: compared to white respondents, Asian (OR = 1.44, CI = 1.02, 2.04), Black / African American (OR = 1.30, CI = 1.09, 1.56), and Hispanic / Latino / Spanish (OR = 1.30, CI = 1.04, 1.64) respondents had higher odds of reporting this risk factor. We also found an association with education: respondents whose highest level of education is “some or no high school” (OR = 2.42, CI = 1.71, 3.41) or “all of high school”

(OR = 1.61, CI = 1.33, 1.95) have higher odds of reporting reliance on a third party than those with college degrees. The only statistically significant result regarding age is that 45-54 years old respondents are less likely to report being reliant on a third party compared to respondents ages 65+ (OR = 0.68, CI = 0.53, 0.87).

Qualitative Insights. Respondents that identified as being reliant on third parties commonly described feeling inadequate at using technology, describing themselves as not “*tech-literate*” or not “*tech-savvy*”. Some respondents described their older age or health circumstances (e.g., head injury, long COVID, and dementia) that required them to rely on others. With technology changing rapidly, respondents explained they rely on other people who are more tech-educated or up-to-date, especially close friends, family members, or professionals (e.g. workers at Best Buy).

Conversely, respondents who did feel like they could achieve their goals online without help, acknowledged they were tech-savvy, had formal education or work experience in IT or tech, and, more generally, felt self-sufficient to teach or figure it out themselves. For example, one respondent explained if a technology issue arises they “*can Google it and then that gives [them] even more information*” to problem solve. Other respondents clarified that their goals using technology were simple, and therefore did not feel like they had to rely on others. For example, one respondent said “*I can*

Risk Factor	Treatment	Odds	Risk Factor	Treatment	Odds
Age <i>Baseline: 65</i>			Education <i>Baseline: College Degree</i>		
Relationship	18–24	3.89	Underserved	Some or no HS	1.74
Legal	18–24	3.37	Marginalization	Some or no HS	1.66
Prominence	18–24	3.31	Reliance	Some or no HS	2.42
Marginalization	18–24	3.14	Social	Some or no HS	1.74
Access	18–24	3.13	Resource	High school	1.30
Sensitive	18–24	2.86	Underserved	High school	1.45
Relationship	25–34	4.12	Reliance	High school	1.61
Legal	25–34	3.88	Social	High school	1.83
Prominence	25–34	3.32	Legal	High school	1.40
Marginalization	25–34	2.99	Access	Prof. schooling	1.34
Access	25–34	2.82	Prominence	Prof. schooling	1.46
Sensitive	25–34	2.83	Resource	Some college...	1.30
Relationship	35–44	4.39	Prominence	Some college...	0.80
Legal	35–44	3.21	Sensitive	Some college...	0.70
Prominence	35–44	3.03	Political Party <i>Baseline: Independent</i>		
Marginalization	35–44	2.60	Resource	Republican	1.22
Access	35–44	2.56	Underserved	Republican	1.22
Sensitive	35–44	2.50	Prominence	Republican	1.50
Relationship	45–54	2.63	Reliance	Republican	1.20
Legal	45–54	2.43	Sensitive	Republican	1.30
Prominence	45–54	1.81	Resource	Democrat	1.21
Access	45–54	1.80	Underserved	Democrat	1.30
Sensitive	45–54	1.76	Prominence	Democrat	1.48
Marginalization	45–54	1.75	Reliance	Democrat	1.19
Reliance	45–54	0.68	Sensitive	Democrat	1.27
Relationship	55–64	2.12	Race <i>Baseline: White</i>		
Legal	55–64	1.72	Underserved	Asian	1.81
Marginalization	55–64	1.54	Reliance	Asian	1.44
Prominence	55–64	1.39	Prominence	Black / African American	1.32
Access	55–64	1.34	Reliance	Black / African American	1.30
Gender <i>Baseline: Female</i>			Reliance	Hispanic / Latino / Spanish	1.30
Resource	Male	0.77	Sexuality <i>Baseline: Non-LGBTQ+</i>		
Prominence	Male	1.57	Underserved	LGBTQ+	0.76
Marginalization	Male	1.40	Prominence	LGBTQ+	0.77
Sensitive	Male	1.57	Relationship	LGBTQ+	1.44
Legal	Male	1.53	Parentage <i>Baseline: No Kids</i>		
Disability <i>Baseline: non-Disability</i>			Reliance	Has kids	1.22
Resource	Disability	1.68	Social	Has kids	1.16
Access	Disability	1.37	Urbancity <i>Baseline: Suburban</i>		
Underserved	Disability	1.49	Underserved	Rural	1.24
Prominence	Disability	1.39	Social	Rural	1.22
Marginalization	Disability	1.91	Legal	Rural	1.27
Reliance	Disability	1.43	Access	Urban	1.23
Social	Disability	1.28	Underserved	Urban	1.21
Sensitive	Disability	1.25	Prominence	Urban	1.41
Legal	Disability	1.61	Marginalization	Urban	1.36
Relationship	Disability	2.11	Social	Urban	1.22
Work Status <i>Baseline: Retired</i>			Sensitive	Urban	1.34
Access	Full-time	2.14	Relationship	Urban	1.36
Prominence	Full-time	2.00			
Marginalization	Full-time	1.45			
Sensitive	Full-time	2.11			
Legal	Unemployed / Not working	0.63			
Access	Part-time	1.40			

Table 6: Odds that a respondent self-identified with a contextual risk factor according to a logistic regression model over their demographics. We only report odds with $p < 0.05$. See Appendix for our full logistic regression model results.

go in and pay bills” and another respondent said *“my online uses are relatively simple and I rarely need help or assistance in achieving my goals.”* This suggests that some respondents evaluate their technological literacy in relation to their own technology-use needs rather than against an absolute standard of digital competency.

4.2.3 Access to other At-Risk Users. 34% of respondents reported having access to other at-risk users, meaning respondents self-reported taking care of or working with people who are vulnerable and/or being close to a person who is often targeted online. We found a relationship between age and reporting access to other at-risk users: compared to adults aged 65+, those aged 18–24 (OR = 3.13, CI = 2.23, 4.41), 25–34 (OR = 2.81, CI = 2.11, 3.76), 35–44 (OR = 2.56, CI = 1.93, 3.40), 45–54 (OR = 1.80, CI = 1.37, 2.36), and 55–64 (OR = 1.34, CI = 1.04, 1.72) all had significantly higher odds. Disabled respondents were also more likely to report this risk factor (OR = 1.37, CI = 1.15, 1.62). Respondents who worked full-time (OR = 2.14, CI = 1.67, 2.74) and part-time (OR = 1.40, CI = 1.06, 1.85) had higher odds of being near other at-risk users compared to retirees. Other elevated odds were found among respondents living in urban areas versus suburban ones (OR = 1.23, CI = 1.05, 1.44) and those with professional schooling compared to college degrees (OR = 1.34, CI = 1.08, 1.66).

Qualitative Insights. Respondents who felt close to a person often targeted online, shared details like having a family member, friend, or customer being targeted of bullying and harassment, identity theft, scams, or account hacking. Many respondents shared details explaining how they care for others. For some, it was a familial responsibility such as being a parent or taking care of their spouse who has a disability. For example, one respondent shared:

“I am a mother of two young people and I also help my parents. My dad has gotten his credit card information stolen several times.”

For other respondents, caring and proximity to at-risk users is an essential responsibility for their profession. For example, one respondent works with “addicts and homeless people” and another is a “school psychologist... [their] job centers on advocating for marginalized groups.” One respondent also shared their experience being a caregiver for older adults who had gotten scammed.

“I have worked as a caregiver for the past 10 years, and I work with the elderly... and they are vulnerable to internet scams. One of my clients lost most of her data online because of a scam. [They were] trying to convince her that her computer had a virus and it needed to be cleaned [then]... they just scrubbed everything off of her computer.”

Respondents also highlighted time bound care-taking, like babysitting and volunteering. For example, one respondent said: *“I babysit my 11 year old granddaughter who’s on her phone all the time.”* Furthermore, respondents noted having a caring personality by educating (e.g., *“I try and warn people about any scams I’m aware of so they don’t get harmed.”*) and advocating for others (e.g., *“If I see someone who’s being bullied, I will definitely help to get justice.”*).

4.2.4 Social Norms. 33% of respondents reported feeling like technology does not work well for them or was not designed with them in mind. Compared to those with college degrees, respondents who

completed some or no high school (OR = 1.74, CI = 1.22, 2.47) and those who finished high school (OR = 1.83, CI = 1.50, 2.23) had higher odds of reporting this risk factor. Having a disability was associated with elevated odds (OR = 1.28, CI = 1.09, 1.50), as was being a parent (OR = 1.16, CI = 1.01, 1.33) and living in an urban (OR = 1.22, CI = 1.04, 1.42) or rural (OR = 1.22, CI = 1.04, 1.44), compared to respondents without a disability, without kids, and living in a suburban areas, respectively.

Qualitative Insights. Respondents who felt like technology was not designed for them cited feeling a disconnect between their experiences and what they saw online. For example, one respondent said: *“I’m old and private. Social media is designed for people who like to flaunt everything about their life.”* As another example, one respondent felt excluded online because of their disability: *“half of us deaf people don’t fit in [on] social media.”* Similar to the qualitative sentiment from Reliance on a 3rd Party (Section 4.2.2), another set of respondents explained it was difficult to learn technology if they were not *“raised on the internet”*, especially at the pace that technology changes. For instance, one respondent said *“I want the basics, nothing complicated, stop changing things when they already work.”* Another respondent explained *“I don’t have the patience or desire to keep up with constant upgrades.”*

4.2.5 Prominence. 33% of respondents felt prominent because of their job, people they are close to, and/or for other aspects of their life. Male respondents had greater odds (OR = 1.57, CI = 1.37, 1.81) of feeling prominent compared to female respondents. Younger age groups showed particularly high odds of experiencing this factor: those aged 18–24 (OR = 3.31, CI = 2.32, 4.73), aged 25–34 (OR = 3.32, CI = 2.46, 4.50), and aged 35–44 (OR = 3.03, CI = 2.25, 4.07) all had over threefold higher odds relative to the 65+ reference group. In addition, respondents ages 45–54 (OR = 1.81, CI = 1.36, 2.42) and 55–64 (OR = 1.39, CI = 1.06, 1.81) age groups also had elevated odds of feeling prominent. Respondents with a disability had higher odds (OR = 1.39, CI = 1.16, 1.67), as did full-time workers (OR = 2.00, CI = 1.55, 2.60) compared to retirees. Urban residents had increased odds (OR = 1.41, CI = 1.20, 1.66) compared to those in suburban areas. With respect to race and party affiliation, Black/African American respondents (OR = 1.32, CI = 1.09, 1.60), Democrats (OR = 1.48, CI = 1.24, 1.76), and Republicans (OR = 1.50, CI = 1.25, 1.80) were more likely to report being prominent than White respondents or Independents, respectively. Conversely, LGBTQ+ respondents also had lower odds of feeling prominent (OR = 0.77, CI = 0.60, 1.00) than non-LGBTQ+ respondents.

Qualitative Insights. Respondents explained various reasons as to why they feel prominent, straightforwardly some mentioned being a content creator, famous, or wealthy. Most survey respondents feel prominent because of their job, such as being the CEO, working with famous, high profile clients, or working with criminals (i.e. lawyer). For example, one respondent said: *“I own my own business. As a woman that makes me stand out.”* Her sense of prominence stemmed partly because women remain underrepresented among business owners.

Other respondents noted how they had high visibility in a local or small community. For example, one survey respondent described herself as *“the one and only neighborhood nurse who is a certain kinda famous in a small town.”* Other jobs that respondents felt

had this higher end of visibility ranged from being a mailman, to small business owner, to being a police officer. Furthermore, some respondents explained that because of their profession they were handling sensitive data (similar to a sentiment in Section 4.2.9 on access to sensitive resource). For example one respondent explained “*I was a fire inspector and had a lot of private information I was responsible for.*” Other reasons why people felt prominent included their older age, being an athlete, being a parent, because of their political views, and their involvement in community organizing.

4.2.6 Underserved Accessibility Needs. 31% of survey respondents reported feeling like it’s difficult for them to use technology and/or technology was not designed for them to be safer. Respondents with a disability (OR = 1.49, CI = 2.7, 1.75) and living in rural areas (OR = 1.24, CI = 1.05, 1.46) or urban areas (OR = 1.21, CI = 1.04, 1.42) have a higher odds compared to respondents without disability and living in suburban areas. Political affiliation was significant: Republicans (OR = 1.22, CI = 1.02, 1.45) and Democrats (OR = 1.30, CI = 1.10, 1.53) both had higher odds compared to Independents. Respondents who have completed high school (OR = 1.45, CI = 1.18, 1.77) or some/no high school (OR = 1.74, CI = 1.22, 2.48) had greater odds relative to those with college degrees or higher. In contrast, individuals identifying as LGBTQ+ had lower odds (OR = 0.76, CI = 0.6, 1.0) than non-LGBTQ+ respondents.

Qualitative Insights. In the qualitative open-ends, respondents noted their disability as a reason why technology was difficult to use. Some respondents mentioned their age or being an older adult as their reasoning. For example, one respondent explained, “*Having to learn on your own increases the difficulties with the ever evolving area of technology so that’s where the difficulty comes in for me.*”

Respondents also explained why unmet needs made them feel unsafe online. They mentioned how being safe is time-intensive and expensive (e.g., “*security software is not cheap.*”) and being safe online is not guaranteed. One respondent said “*I need the internet to be 100% foolproof and unhackable or unspammable.*” Another respondent explained that “*the private policy for most tech is confusing and not sure what I need to do to make sure I’m safe 100% of the time.*” Other respondents mentioned not having the time to learn how to be safer or having limited internet access.

4.2.7 Marginalization. 24% of respondents reported feeling things are harder for them online because their identity is not widely accepted and/or because the experiences they have had in their life are not common. We found disabled respondents to have almost double the odds (OR = 1.91, CI = 1.59, 2.30) of feeling marginalized compared to non-disabled respondents. There was also a strong association between feeling marginalized and age group. Compared to adults 65+, respondents ages 18-24 (OR = 3.14, CI = 2.13, 4.61) and 25-34 (OR = 2.99, CI = 2.14, 4.17) have tripled the odds of feeling marginalized, with other age groups also exhibiting elevated odds. Notably, respondents who identified as male reported a higher odds of marginalization (OR = 1.40, CI = 1.20, 1.63). Additionally, respondents working full-time (OR = 1.45, CI = 1.09, 1.93) were more likely to report feeling marginalized than those retired. Respondents with some or no high school education (OR = 1.66, CI = 1.12, 2.43) and living in urban areas (OR = 1.36, CI = 1.14, 1.61) had higher odds compared to those with college and living in suburban areas, respectively. Interestingly, our model had no statistically significant

results in regards to race; however, some respondents did mention their race in the qualitative responses discussed below.

Qualitative Insight. Respondents shared varied reasons as to why they feel marginalized. Some respondents shared health-related conditions, such as having depression, anxiety, and PTSD. One respondent explained “*I’m still isolating due to being high-risk for COVID-19, which doesn’t go over well with many people.*” Respondents did mention feeling marginalized because of identifying as LGBTQ+. One respondent explained, “*I’m trans and disabled and there’s a lot of false info, misinformation, and harassment online for trans people and disabled people.*”

Respondents also attributed feeling marginalized because they feel unpopular or isolated. For example, one respondent explained why he felt marginalized: “*Heterosexual, Christian Conservative, White Male so none of those are popular.*” This qualitative insight aligns with our quantitative finding that male respondents feel marginalized. Another respondent explained, “*I can’t find many people who relate to my situation as a black, agnostic, African teenager.*”

While we did not have statistically significant results regarding the respondents’ political party, qualitatively respondents did cite feeling marginalized because of politics, such as for their political orientation (e.g., “*I’m republican*”) or being attacked by a political party (e.g., “*conservatives hate queer people and you feel that through harassment, slurs and general behavior online.*”). Respondents also shared feeling marginalized because of their religion. One respondent wrote, “*I am Jewish, a feminist and growing older, and it is hard to express myself without being shouted down*”; another respondent wrote, “*I’m a Christian and I get made fun of often.*”; and another respondent wrote, “*my faith isn’t widely accepted, and I also have Schizoaffective Disorder and I am poor.*” Others also mentioned being marginalized because they are poor, homeless, unemployed, have been to prison, or had prior felony convictions.

Other respondents felt marginalized because of their unique upbringing such as having parents pass away at an early age, being homeschooled, or being a military child. Respondents shared how circumstances change the ways they use or don’t use social media. One respondent said:

“I had a bad childhood with parents and a sibling who are violent criminals, in and out jail and were very abusive to me. They will never stop looking for me, even though I cut off contact a decade ago. Finding me and getting revenge for me turning them in is still on their agenda. That means I can’t use any social media... It is only one of the ways I protect myself, but I still get weird responses when I tell others I don’t have social media. I can’t even have LinkedIn, which has kept me from finding better jobs. It really limits me, but it’s what I have to do.”

4.2.8 Relationship with Attacker. 24% of respondents have had personal relationships with people who have tried to harm them. Respondents with a disability had double the odds (OR = 2.11, CI = 1.76, 2.52) of having a relationship with their attacker compared to those without a disability. Age exhibited a strong association. Compared to those 65+, odds were quadrupled for the youngest groups—18-24 (OR = 3.89, CI = 2.65, 5.72), 25-34 (OR = 4.12, CI = 2.97, 5.73), and 35-44 (OR = 4.39, CI = 3.19, 6.06)—while the 45-54 (OR

= 2.63, CI = 1.92, 3.59) and 55-65 (OR = 2.11, CI = 1.59, 2.81) had double the odds. Respondents who are LGBTQ+ (OR = 1.44, CI = 1.13, 1.84) and live in urban areas (OR = 1.36, CI = 1.15, 1.61) also had increased odds of identifying with this factor.

Qualitative Insights. Respondents shared various forms of harm their attacker imposed, such as sexual abuse, harassment, false rumors and accusations, stalking, personal images and information shared without their permission, and account hacking. Respondents shared their attacker to be friends or family members. For example, one disabled respondent explained that “*people closest to me like to take advantage often because I’m in a [wheelchair-emoji] and cannot walk.*” Another respondent explained that their “*ex best friend leaked personal photos*” of them and another respondents’ “*aunt always gets involved in online schemes and would try and get my information.*”

4.2.9 Access to Sensitive Resource. 19% of respondents reported having access to sensitive resources, such as information or money, that most others do not. Those who are 18-24 (OR = 2.86, CI = 1.89, 4.34), 25-34 (OR = 2.83, CI = 1.99, 4.03), 35-44 (OR = 2.49, CI = 1.76, 3.53) have more than two times the odds of reporting having access to sensitive resources compare to adults 65+. Male respondents had greater odds than females (OR = 1.57, CI = 1.33, 1.84), and respondents with a disability also had higher odds (OR = 1.25, CI = 1.01, 1.54). Being employed full-time was associated with higher odds (OR = 2.11, CI = 1.55, 2.87) compared to retired respondents, as was living in urban areas (OR = 1.34, CI = 1.12, 1.61) compared to suburban areas. On the other hand, having some college (but no degree) was associated with lower odds (OR = 0.70, CI = 0.56, 0.86) compared to those with college degrees.

Qualitative Insights. Respondents who have access to sensitive resources, referred to their personal wealth and financial inheritance. Alternatively a few respondents explained that having their money in online banking is automatically a sensitive resource. Other respondents referenced a variety of jobs where they were handling sensitive information and money such as working at a bank, working in human resources, being a cop, therapist, and lawyer. For example, one respondent explained:

“I work at a law firm and I have access to my employer’s business and personal bank accounts and information, I have all of his username and passwords, I check his email, we handle a lot of client personal information. It’s scary to think that I could be the reason that someone’s information is jeopardized.”

4.2.10 Legal or Political. 16% of respondents feel targeted by governments or political groups. Compared to those aged 65 and older, respondents aged 18-24 (OR = 3.37, CI = 2.17, 5.25), 25-34 (OR = 3.88, CI = 2.65, 5.67), and 35-44 (OR = 3.22, CI = 2.21, 4.69) had over three-fold higher odds of reporting feeling targeted, with elevated odds also existing for other age groups. Respondents with disabilities (OR = 1.61, CI = 1.31, 1.98), who are male (OR = 1.53, CI = 1.29, 1.82), and whose highest level of education was high school (OR = 1.40, CI = 1.09, 1.81) all had higher odds of reporting feeling legally or politically attacked compared to respondents without disabilities, are female, and whose highest education was college, respectively. Conversely, being unemployed was associated with lower odds (OR

= 0.63, CI = 0.44, 0.90) of reporting this factor compared to retired adults.

Qualitative Insights. While we did not find a statistically significant relationship between political party, respondents shared being legally or politically targeted related to their reported identification with various conservative political viewpoints. One respondent clarified that “*since the Biden administration everyone should feel targeted especially republican.*” Other related quotes from respondents include:

“The fact that I’m more conservative and pro gun makes me a target for liberal groups. I often get treated much harsher online than others who do worse than me.”

“I am a conservative white woman and fall outside groups which seem very protected and promoted by mainstream media.”

More broadly, many respondents shared opinions or discontentment about the government that makes them feel targeted. Some have had negative interactions with the government (e.g., FBI). While others explained they feel targeted because of misinformation, censorship, polarization, political ad, and government surveillance. One respondent explained, “*everyone is being targeted by some government or political group due to a serious political divide right now.*”

4.3 Predictive power of demographics & contextual risk factors for digital-safety attacks

Given the diverse interpretations that respondents had towards contextual risk factors, we examine whether self-identifying with a factor also correlates with a higher risk of digital-safety attacks. Here, we report the results of modeling each digital-safety attacks as a function of each respondent’s self-reported demographics and contextual risk factors simultaneously—resulting in 10 total models.

For clarity, we visualize the odds ratio results of all 10 models using two heatmaps, one for contextual risk factors (see Figure 2) and the other for demographics (see Figure 3), even though both types of variables were modeled at the same time. Missing values in each figure indicate the odds ratios were not statistically significant ($p \geq 0.05$). We caution comparing the odds between digital-safety attacks (e.g., between different rows); the difference between odds is only valid within the context of a single model.

4.3.1 Contextual risk factors. Of contextual risk factors, Relationship with an Attacker, Marginalization, and Resource and time constrained correlated with a higher odds of experiencing 4+ types of digital-safety attacks. In particular, having a Relationship with an attacker increased the odds of experiencing every type of digital-safety attack. Other factors exhibit an intuitive affinity with certain types of attacks. For example, Prominence correlated with stalking (OR = 1.40, CI = 1.11, 1.75); Access to a sensitive resource correlated with being targeted by scams and phishing (OR = 1.18, CI = 1.01, 1.38); and Legal or Political correlated with being harassed based on your identity (OR = 1.65, CI = 1.29, 2.10), potentially due to U.S. political polarization.

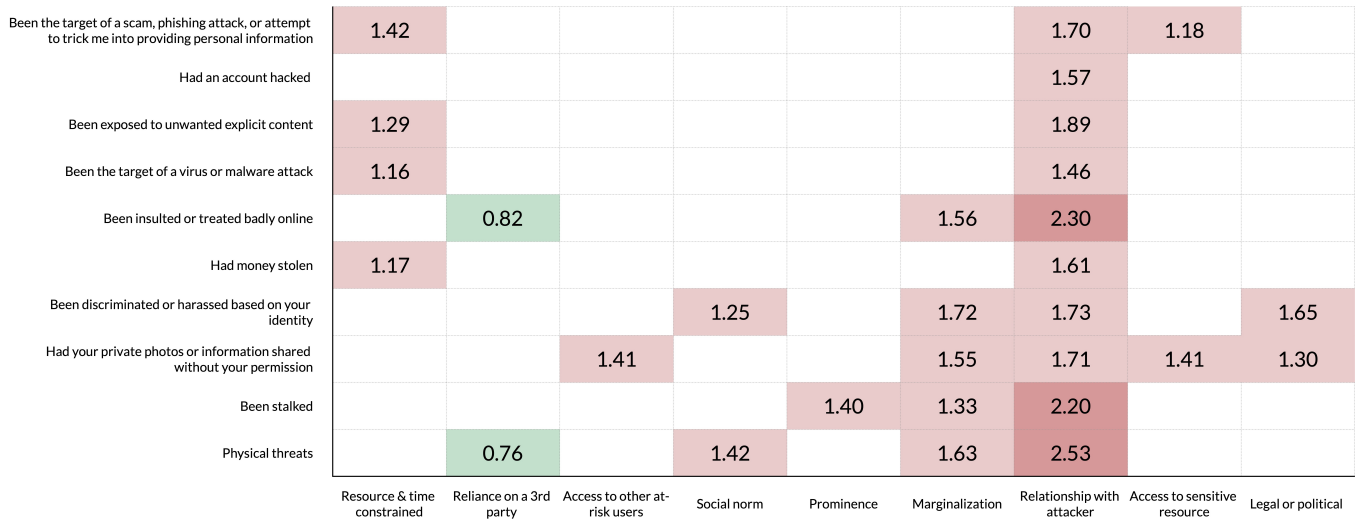


Figure 2: Odds ratio heatmap of experiencing digital-safety attacks per contextual risk factor. Each cell represents the odds ratio (OR) of experiencing an attack if a respondent self-identified with a factor compared to those who did not. Cells are shaded red for OR > 1 and green for OR < 1. Red intensity increases with OR magnitude; darkest red indicates OR > 2. Only statistically significant (p value < 0.05) OR are shown. Complete logistic regression models results are in the Appendix.

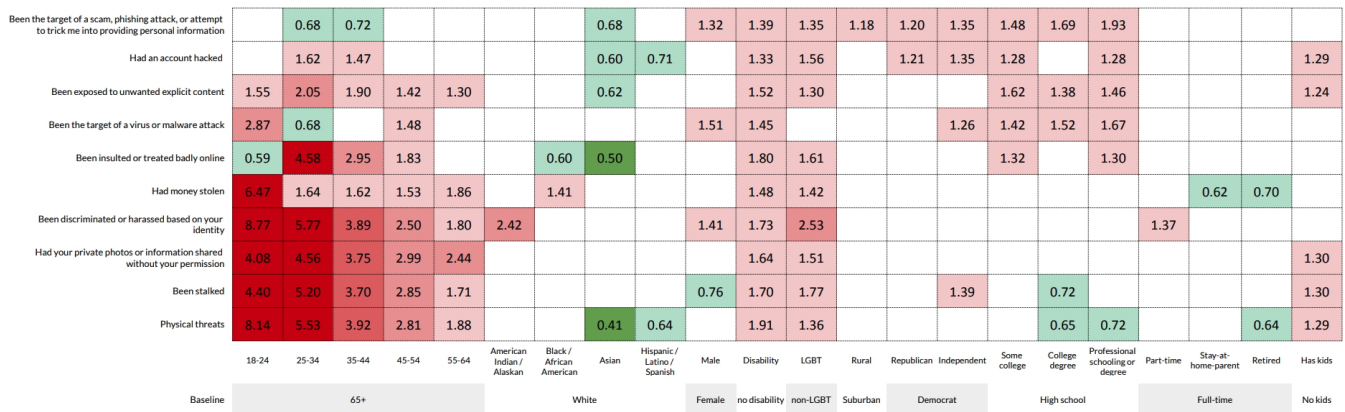


Figure 3: Odds ratio heatmap of experiencing digital-safety attacks per demographic. Each cell represents the odds ratio (OR) of experiencing a digital-safety attack. Cells are shaded red for OR > 1 and green for OR < 1. Red and green intensity increases with OR magnitude; darkest red indicates OR > 4 and darkest green represents OR < 0.5. Only statistically significant (p value < 0.05) OR are shown. Complete logistic regression models results are in the Appendix.

4.3.2 *Demographics.* Apart from contextual risk factors, demographics also provide statistical power to a model. For example, being 45–54, being disabled, or identifying as LGBTQ+ correlated with a higher odds of 8+ different types of digital-safety attacks. Age in particular correlated with a higher risk of attack for multiple age groups (compared to people 65+), with 18–24 year olds experiencing the highest odds of attack. Conversely, being Asian or Hispanic generally correlated with a lower risk of 2–5 different digital-safety attacks (compared to people who identified as White or Non-Hispanic).

5 Discussion

We asked a nationally representative sample of adult respondents in the U.S. about contextual risk factors that put people at elevated risk and their personal experiences with digital-safety attacks. Our findings challenge the prevailing paradigm of the “at-risk” user as a marginal case, presenting evidence that circumstances elevating digital risk are a normative aspect of users’ experience.

5.1 Digital-safety attacks are a common experience

Our findings demonstrate that digital-safety attacks and their underlying contextual risk factors are commonly occurring for the majority of U.S. adults.

5.1.1 Distribution of risk. 74% of respondents have experienced at least one digital-safety attacks and 85% identified with one or more contextual risk factor. This aligns with and extends a growing body of national survey data on digital-safety attacks (e.g., [27, 44]). For example, Pew Research [44] conducted a survey with 9,397 Americans in April 2025 and found 73% had experienced an online scam or attack, with 29% reporting that a personal online account was hacked, such as a social media, email or bank.² Our respondents report experiencing an average of 2.8 distinct digital-safety attacks and identifying with 3 contextual risk factors on average. Our data suggests that digital safety is an ongoing process of navigating dynamic, overlapping threats for the majority of people online.

While being “at-risk” is a normative experience, some demographic groups are disproportionately represented. That is, although most Americans have experienced a digital-safety attacks, some are more at-risk than others. Being disabled, LGBTQ+, or a young adult were strong demographic predictors of being more likely to experience attacks. Further, demographics and contextual risk factors exhibit statistically significant correlations. For example, disabled adults are more likely to experience all digital-safety attacks we surveyed and also are more likely to self-identify with all 10 contextual risk factors.

This correlation between disability and elevated risk is consistent with broader socioeconomic data: nearly one-third of disabled individuals in the United States live below the poverty line [16]. Furthermore, according to 2021 Census data, people with disabilities are 1.7 times more likely to live in poverty compared to those without disabilities, with 20.1% reporting incomes below the federal poverty threshold and three times less likely to be employed [42]. These structural inequalities may contribute to the heightened risk landscape faced by disabled individuals, particularly regarding being resource and time constrained. Furthermore, prior work has also shown that socioeconomic factors shape the adoption of security best-practices; for example, [46] found that individuals with higher socioeconomic status had the resources and skills to learn from a negative security-related experience. Future work should continue to cross-examine contextual, socioeconomic factors that could contribute to one’s likelihood of experiencing a contextual risk factor.

While this survey builds on our understanding of who is experiencing risk of digital-safety attack, it also draws our attention to whose experiences are not captured in existing research. Conducting a survey that asks about contextual risk factors, rather than directly asking people if they believe they are at risk or relying on demographics, may provide a less-charged way to find users and groups who are experiencing disproportionate risks of harms. For example, prominence may go beyond people with vast audiences,

such as politicians, content creators, or activists, as studied in previous work [9, 51, 69]. In our study, respondents self-identified with this contextual risk factor if they had high profiles within their communities, such as nurses in small towns and mailmen. Similarly, respondents who identified with being targeted for their legal or political stance included broad swaths of men and conservatives, not just activists or politicians. Both of these contextual risk factors correlated with elevated risk for some digital-safety attacks. As much of the digital-safety literature is qualitative—building robust understandings of the experiences of specific populations—this approach likely overlooks other at-risk people affected by the same contextual risk factor. By pairing the insights from the existing literature with the measurement-based approach provided by survey data, we can provide a more holistic view of who is actually experiencing digital-safety attacks to better target interventions and guide future research.

5.1.2 Distribution of harm. Digital-safety attacks entail different harms, with variable short-, medium-, and long-term effects. digital-safety attacks may cause emotional harm (i.e. elicit an emotional response such as annoyance, stress, or anxiety) or relational harms (i.e. damage to one’s relationships with others), and some can cause financial and physical harms [52]. Although financial or physical harms were not the most commonly reported in this study, they were not rare: 26% of respondents had their money stolen, 15% received physical threats, and 16% were stalked. The prevalence of stalking is notably higher than the previously reported 1.6% of individuals who experienced stalking in 2016.

Our results also suggest that experiencing certain contextual risk factors—such as being resource constrained or having access to sensitive information—are correlated with attacks that can be more difficult to manage. For example, adults who are resource constrained have higher odds having money stolen, potentially exacerbating their preexisting circumstances of being financially constrained. Similarly, those who have access to sensitive resources and information are correlated with higher odds of being the target of a scam or phishing attack and having private photos or information shared without their permission. These correlations may suggest that individuals facing certain contextual risk factors might be both less equipped to defend against attacks and more likely to be targeted in the first place. Future work should investigate the relationship between experiencing a risk factor and being targeted by attacks that exacerbate a related at-risk circumstance.

Identifying which groups are more likely to experience specific harms can enable more targeted and effective interventions. By understanding **who** is most at risk for **what** kinds of attack and **what** types of harms, we can better tailor interventions to reduce both the likelihood of experiencing the harm and the barriers to recovery. For example, Uber [43] collaborated with the National Network to End Domestic Violence to create safety guides for survivors of intimate partner abuse. Such advocacy and awareness efforts aim to support at-risk groups by access to safety features. Our findings can similarly support the development of targeted safety interventions. Matthews et al. [36] maps design principles that are especially beneficial for users experiencing certain contextual risk factor. For example, providing digital education and

²We find a lower overall evidence of scams, likely due how they additively asked about multiple scam types, or possibly due to an escalating scam landscape.

making digital-safety options easy to find are crucial design principles for preventative measures. A person who is prominent would especially benefit from both; and our work indicates how not only would this be beneficial for conventional “high profile” individuals such as journalists, politicians, and celebrities but also individuals in rural towns where they feel prominent within their local community. There is a design opportunity for targeted outreach in educating people on security preventions that is personalized and evidence-backed. For example, growing evidence shows that individuals with technical backgrounds may actually be more prone to believing misconceptions about HTTPS, VPNs, passwords, device security, and malware [21] – a surprising finding that debunks the assumption that technical expertise inherently offers stronger digital-safety awareness. This finding underscores the need for continuously reassessing who is at risk in order to design personalized, evidence-backed security-prevention outreach. Furthermore, insights like these can guide the design of educational materials, red-teaming exercises, persona development [25], and the advocacy work of tech clinics.

5.2 Conducting future research on understanding risk

We now highlight key considerations for researchers when building samples that reflect the range of users who are more likely to experience digital-safety attack in order to improve intervention design and increase overall digital safety. We also provide recommendations for future work, emphasizing the importance of continuing to identify and understand the unique, and often underrepresented in research, conditions that shape individuals’ risk for digital-safety attacks.

5.2.1 Methodological considerations for participant selection. A digital-safety ecosystem that works for all users requires testing safety features and interventions across the full spectrum of circumstances that place people at risk *and* ensuring that designs are validated with populations that are actually experiencing harm. Our findings point to a methodological imperative for safety researchers to reflect on what the right sample population(s) are for a given research question.

For qualitative, in-depth work: recruiting specific populations based on a single feature (a demographic attribute, a single profession) may answer some questions, but these features alone may not provide a deeper profile of the ways risk and harm manifest. We encourage researchers to consider recruiting based on contextual risk factors, and exploring what other contextual risk factors participants in a study have to more deeply consider the intersectionality of multiple risk factors with demographics.

For quantitative, large-scale digital-safety work: we encourage the collection of demographics and contextual risk factors. As we have shown that both demographics and contextual risk factors are predictors of digital-safety attacks, measuring them is essential for determining the representativeness of the sample and the efficacy of a safety intervention. We note that LGBTQ+, disability, and being resource/time-constrained were three factors that increased the odds for the digital-safety attacks we studied, but research into other attacks, or safety practices may be more aligned with other demographic attributes or contextual risk factors. The exclusion of

demographic or risk groups from a study sample may thus reflect critical omissions that prevents a full understanding of how safety or harm manifests.

5.2.2 Methodological considerations for studying perceived risk. We offer several recommendations for how researchers can refine and expand upon our survey instrument to more accurately capture users’ self-understandings of digital risk. A methodological challenge in digital-safety research lies in effectively capturing users’ subjective experiences of risk [28, 55, 58, 72], which often diverge from expert-defined classifications. Risk perception is a “multidimensional phenomenon” [11, p. 14].

Our study further demonstrates that to more meaningfully understand user behavior, we also have to understand their mental models of harm, which are shaped by their lived experiences and affective perceptions. For instance, some respondents interpreted personalized political ads as a form of government surveillance rather than a function of platform algorithms. While technically distinct, these perceptions meaningfully shape their feelings of safety and trust online, in line with arguments of how risk is shaped by “feelings” [32]. Ignoring these subjective realities because they do not align with expert knowledge or other data on systemic marginalization would be a mistake, as they are drivers of behavior [18]. Men reporting higher rates of perceived discriminated and political targeting compared to women illustrates this point. Although this gendered perception of risk contradicts data on actual risk [53, 67], this perception nonetheless influences how men interpret their online experiences, engage with digital platforms, and seek support.

This gap between expert and user perceptions has direct implications for intervention design, particularly when viewed through Matthews et al.’s [36] User States Framework of prevention, monitoring, active event, and recovery. The information, tools, and skills a user needs in each state are predicated on their personal understanding of the threat. A user who believes they are preventing state surveillance will adopt different strategies than one trying to avoid targeted advertising. Likewise, the support needed to recover from the emotional distress of perceived government targeting is likely different from the support needed to manage algorithmic content. Consequently, future research should adopt methods that deliberately elicit these self-understandings. Qualitative research, in particular, can be useful in eliciting subjective and contextual operationalizations of “risks” or “threats.”

5.2.3 Recommendations for Future Work. This study lays groundwork for several critical lines of inquiry. First, future research should continue to validate this instrument as a tool for measuring contextual risk factors. Further refinement of the existing items, particularly those for which we noticed qualitative concerns (e.g., prominence for other aspects) and inclusion of additional items should be tested. Studying the instrument as a tool to help users assess their own contextual risk factors, and reflecting those factors back to users to help them manage their risk and respond to potential digital-safety attacks may also be productive.

Second, research should validate and expand this framework beyond the context of the United States, particularly in non-WEIRD settings (Western, Educated, Industrialized, Rich, and Democratic) where self-reported contextual risk factors may differ dramatically [31]. Usable security and safety research has historically

focused on WEIRD populations [19]. As a result, the survey instrument used in this study may omit contextual risk factors that are unique to non-WEIRD settings. Because digital safety threats, their prevalence, and their consequences are shaped by local infrastructures, norms, and sociopolitical conditions, the distribution and severity of risks experienced by individuals in other countries may differ from those reflected in our findings. Future work that examines perceptions of risk and experiences with digital safety attacks in non-WEIRD contexts is essential for developing a complete understanding of the safety landscape, which in turn can inform product designs and educational interventions that are accessible, contextualized, and responsive to diverse risk environments.

Third, a recurring theme was the tension between a user's self-perceived "tech savviness" and their actual vulnerability. Research should investigate this gap, exploring the efficacy of digital literacy interventions versus the development of structural support systems, such as clinical models for digital safety (e.g., [65]), which can provide expert, tailored support to those most in need. Our findings also point to contextual risk factors that are narrowly framed in the current literature and the need for a broader exploration of whom contextual risk factors might apply to. Finally, longitudinal studies are necessary to understand how an individual's risk profile changes over their lifetime and in response to major life events—and how digital-safety attacks and contextual risk factors do or do not align throughout a user's life—moving from a static point-in-time snapshot to a dynamic understanding of digital safety.

As Matthews et al. [36] note, "progress on solutions for inclusive digital safety is formative; the field is not ready to create best practices." We similarly view this domain as being in an early stage, lacking consistent or validated approaches for understanding population-level risk, circumstances, and prevalence over time. The field must work toward stronger measure validation and more systematic inquiry, while conducting digital-safety research ethically and responsibly, especially with at-risk users [4].

6 Conclusion

Making the internet safe for everyone requires attending to who is experiencing increased harm and what circumstances contribute to increased risk to better tailor inventions and lower barriers to recovery. This study presents a first-of-its-kind, quantitative perspective on the distribution of contextual risk factors in a US population, an analysis of the relationships between demographic characteristics, risk factors, and experiences of digital-safety attacks. These results can be used to demonstrate the urgency of addressing digital-safety attacks, as well as guiding future digital-safety research to more accurately reflect the distribution of risk overall, including previously unstudied dynamics.

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References

- [1] Tousif Ahmed, Patrick Shaffer, Kay Connelly, David Crandall, and Apu Kapadia. 2016. Addressing Physical Safety, Security, and Privacy for People with Visual Impairments. In *Twelfth Symposium on Usable Privacy and Security (SOUPS 2016)*. USENIX Association, Denver, CO, 341–354. <https://www.usenix.org/conference/soups2016/technical-sessions/presentation/ahmed>
- [2] Keith B. Anderson. 2005. Identity Theft: Does the Risk Vary with Demographics? <https://www.ftc.gov/reports/identity-theft-does-risk-vary-demographics> Accessed: 2025-12-03.
- [3] Chittaranjan Andrade. 2020. The Limitations of Online Surveys. *Indian Journal of Psychological Medicine* 42, 6 (2020), 575–576. arXiv:<https://doi.org/10.1177/0253717620957496> doi:10.1177/0253717620957496 PMID: 33354086.
- [4] Rosanna Bellini, Emily Tseng, Noel Warford, Alaa Daffalla, Tara Matthews, Sunny Consolvo, Jill Palzkill Woelfer, et al. 2024. SoK: Safer Digital-Safety Research Involving At-Risk Users. In *Proceedings of the 2024 IEEE Symposium on Security and Privacy (SP)*. IEEE, 635–654.
- [5] Virginia Braun and Victoria Clarke. 2021. One size fits all? What counts as quality practice in (reflexive) thematic analysis? *Qualitative Research in Psychology* 18, 3 (2021), 328–352. arXiv:<https://doi.org/10.1080/14780887.2020.1769238> doi:10.1080/14780887.2020.1769238
- [6] Virginia Braun and Victoria Clarke. 2022. Conceptual and Design Thinking for Thematic Analysis. *Qualitative psychology* 9, 1 (2022), 3.
- [7] Bureau of Justice Statistics. 2023. Press release: Victims of Identity Theft, 2021. https://bjs.ojp.gov/document/vit21_pr.pdf Accessed: 2025-12-03.
- [8] Pew Research Center. 2017. *Online Harassment 2017*. Technical Report.
- [9] Sunny Consolvo, Patrick Gage Kelley, Tara Matthews, Kurt Thomas, Lee Dunn, and Elie Bursztein. 2021. "Why wouldn't someone think of democracy as a target?": Security practices & challenges of people involved with U.S. political campaigns. In *30th USENIX Security Symposium (USENIX Security 21)*. USENIX Association, 1181–1198. <https://www.usenix.org/conference/usenixsecurity21/presentation/consolvo>
- [10] Alaa Daffalla, Lucy Simko, Tadayoshi Kohno, and Alexandru G Bardas. 2021. Defensive technology use by political activists during the Sudanese revolution. In *2021 IEEE symposium on security and privacy (SP)*. IEEE, 372–390.
- [11] Sharon Dunwoody and Kurt Newirth. 1991. Coming to terms with the impact of communication on scientific and technological risk judgments. *Risky business: Communicating issues of science, risk, and public policy* (1991), 11–30.
- [12] eSafety Commissioner. 2019. *Safety by Design: Overview*. Technical Report. Australian Government.
- [13] Diana Freed, Natalie N. Bazarova, Sunny Consolvo, Eunice J Han, Patrick Gage Kelley, Kurt Thomas, and Dan Cosley. 2023. Understanding Digital-Safety Experiences of Youth in the U.S.. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (Hamburg, Germany) (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 191, 15 pages. doi:10.1145/3544548.3581128
- [14] Diana Freed, Jackeline Palmer, Diana Minchala, Karen Levy, Thomas Ristenpart, and Nicola Dell. 2018. "A Stalker's Paradise": How Intimate Partner Abusers Exploit Technology. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (Montreal QC, Canada) (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3173574.3174241
- [15] Alisa Frik, Leysan Nurgalieva, Julia Bernd, Joyce Lee, Florian Schaub, and Serge Egelman. 2019. Privacy and security threat models and mitigation strategies of older adults. In *Fifteenth symposium on usable privacy and security (SOUPS 2019)*. 21–40.
- [16] Nanette Goodman, Michael Morris, and Kelvin Boston. 2019. Financial Inequality: Disability, Race and Poverty in America. <https://www.nationaldisabilityinstitute.org/wp-content/uploads/2019/02/disability-race-poverty-in-america.pdf> Accessed: 2025-09-11.
- [17] Tamy Guberek, Allison McDonald, Sylvia Simioni, Abraham H. Mhaidli, Kentaro Toyama, and Florian Schaub. 2018. Keeping a Low Profile? Technology, Risk and Privacy among Undocumented Immigrants. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems (Montreal QC, Canada) (CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–15. doi:10.1145/3173574.3173688
- [18] Bonnie L Halpern-Felsher, Susan G Millstein, Jonathan M Ellen, Nancy E Adler, Jeanne M Tschann, and Michael Biehler. 2001. The role of behavioral experience in judging risks. *Health Psychology* 20, 2 (2001), 120.
- [19] Ayako A. Hasegawa, Daisuke Inoue, and Mitsuaki Akiyama. 2024. How WEIRD is Usable Privacy and Security Research?. In *33rd USENIX Security Symposium (USENIX Security 24)*. USENIX Association, Philadelphia, PA, 3241–3258. <https://www.usenix.org/conference/usenixsecurity24/presentation/hasegawa>
- [20] Amelia Hassoun, Ian Beacock, Sunny Consolvo, Beth Goldberg, Patrick Gage Kelley, and Daniel M. Russell. 2023. Practicing Information Sensibility: How Gen Z Engages with Online Information. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (Hamburg, Germany) (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 662, 17 pages. doi:10.

- 1145/3544548.3581328
- [21] Franziska Herbert, Steffen Becker, Leonie Schaewitz, Jonas Hielscher, Marvin Kowalewski, Angela Sasse, Yasemin Acar, and Markus Dürmuth. 2023. A World Full of Privacy and Security (Mis)conceptions? Findings of a Representative Survey in 12 Countries. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 582, 23 pages. doi:10.1145/3544548.3581410
- [22] Sharon Heung, Lucy Jiang, Shiri Azenkot, and Aditya Vashistha. 2024. "Vulnerable, Victimized, and Objectified": Understanding Ableist Hate and Harassment Experienced by Disabled Content Creators on Social Media. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 744, 19 pages. doi:10.1145/3613904.3641949
- [23] Sharon Heung, Mahika Phutane, Shiri Azenkot, Megh Marathe, and Aditya Vashistha. 2022. Nothing Micro About It: Examining Ableist Microaggressions on Social Media. In *Proceedings of the 24th International ACM SIGACCESS Conference on Computers and Accessibility* (Athens, Greece) (ASSETS '22). Association for Computing Machinery, New York, NY, USA, Article 27, 14 pages. doi:10.1145/3517428.3544801
- [24] Ipsos. 2023. Topline - Wells Fargo Cybersecurity Study. https://www.ipsos.com/sites/default/files/ct/news/documents/2023-12/Topline%20-%20Wells%20Fargo%20-%20Cybersecurity%20Study_0.pdf Accessed: 2025-12-03.
- [25] Madeleine Janickij and Leonie Maria Tanczer. 2025. Tech Abuse Personas: Exploring Help-Seeking Behaviours and Support Needs of Victim/Survivors of Technology-Facilitated Abuse. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* (CHI EA '25). Association for Computing Machinery, New York, NY, USA, Article 509, 11 pages. doi:10.1145/3706599.3719986
- [26] J. A. Jiang, M. K. Scheuerman, C. Fiesler, and J. R. Brubaker. 2021. Understanding International Perceptions of the Severity of Harmful Content Online. *PLOS ONE* 16, 8 (2021), e0256762. doi:10.1371/journal.pone.0256762
- [27] Lisa M Jones, Kimberly J Mitchell, and David Finkelhor. 2013. Online harassment in context: Trends from three youth internet safety surveys (2000, 2005, 2010). *Psychology of violence* 3, 1 (2013), 53.
- [28] Hannah AD Keage and Tobias Loetscher. 2018. Estimating everyday risk: Subjective judgments are related to objective risk, mapping of numerical magnitudes and previous experience. *PLoS One* 13, 12 (2018), e0207356.
- [29] Priya C. Kumar, Marshini Chetty, Tamara L. Clegg, and Jessica Vitak. 2019. Privacy and Security Considerations For Digital Technology Use in Elementary Schools. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (CHI '19). Association for Computing Machinery, New York, NY, USA, 1–13. doi:10.1145/3290605.3300537
- [30] Karen Levy and Bruce Schneier. 2020. Privacy threats in intimate relationships. *Journal of Cybersecurity* 6, 1 (2020). doi:10.1093/cybsec/tyaa006
- [31] Sebastian Linxen, Christian Sturm, Florian Brühlmann, Vincent Cassau, Klaus Opwis, and Katharina Reinecke. 2021. How weird is CHI?. In *Proceedings of the 2021 chi conference on human factors in computing systems*. 1–14.
- [32] George F Loewenstein, Elke U Weber, Christopher K Hsee, and Ned Welch. 2001. Risk as feelings. *Psychological bulletin* 127, 2 (2001), 267.
- [33] Yao Lyu, Jie Cai, Anisa Callis, Kelley Cotter, and John M. Carroll. 2024. "I Got Flagged for Supposed Bullying, Even Though It Was in Response to Someone Harassing Me About My Disability": A Study of Blind TikTokers' Content Moderation Experiences. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI '24). Association for Computing Machinery, New York, NY, USA, Article 741, 15 pages. doi:10.1145/3613904.3642148
- [34] Sonali Tukaram Marne, Mahdi Nasrullah Al-Ameen, and Matthew Wright. 2017. Learning System-assigned Passwords: A Preliminary Study on the People with Learning Disabilities. In *Thirteenth Symposium on Usable Privacy and Security (SOUPS 2017)*. USENIX Association, Santa Clara, CA. <https://www.usenix.org/conference/soups2017/workshop-program/wips2017/marne>
- [35] Fiona Martin. 2018. Tackling gendered violence online: Evaluating digital safety strategies for women journalists. *Australian Journalism Review* 40, 2 (2018), 73–89.
- [36] Tara Matthews, Elie Bursztein, Patrick Gage Kelley, Lea Kissner, Andreas Kramm, Andrew Oplinger, Andreas Schou, Manya Sleeper, Stephan Somogyi, Dalila Szostak, Kurt Thomas, Anna Turner, Jill Palzkill Woelfer, Lawrence L. You, Izzie Zahorian, and Sunny Consolvo. 2025. Supporting the Digital Safety of At-Risk Users: Lessons Learned from 9+ Years of Research and Training. *ACM Trans. Comput.-Hum. Interact.* 32, 3, Article 22 (June 2025), 39 pages. doi:10.1145/3716382
- [37] Tara Matthews, Kathleen O'Leary, Anna Turner, Manya Sleeper, Jill Palzkill Woelfer, Martin Shelton, Cori Manthorne, Elizabeth F. Churchill, and Sunny Consolvo. 2017. Security and Privacy Experiences and Practices of Survivors of Intimate Partner Abuse. *IEEE Security & Privacy* 15, 05 (Sept. 2017), 76–81. doi:10.1109/MSP.2017.3681046
- [38] Tara Matthews, Kathleen O'Leary, Anna Turner, Manya Sleeper, Jill Palzkill Woelfer, Martin Shelton, Cori Manthorne, Elizabeth F. Churchill, and Sunny Consolvo. 2017. Stories from Survivors: Privacy & Security Practices when Coping with Intimate Partner Abuse. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) (CHI '17). Association for Computing Machinery, New York, NY, USA, 2189–2201. doi:10.1145/3025453.3025875
- [39] Nora McDonald, Karla Badillo-Urquiola, Morgan G. Ames, Nicola Dell, Elizabeth Keneski, Manya Sleeper, and Pamela J. Wisniewski. 2020. Privacy and Power: Acknowledging the Importance of Privacy Research and Design for Vulnerable Populations. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) (CHI EA '20). Association for Computing Machinery, New York, NY, USA, 1–8. doi:10.1145/3334480.3375174
- [40] Brenna McNally, Priya Kumar, Chelsea Hordatt, Matthew Louis Mauriello, Shalmali Naik, Leyla Norooz, Alazandra Shorter, Evan Golub, and Allison Druin. 2018. Co-designing Mobile Online Safety Applications with Children. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) (CHI '18). Association for Computing Machinery, New York, NY, USA, 1–9. doi:10.1145/3173574.3174097
- [41] Tyler Musgrave, Alia Cummings, and Sarita Schoenebeck. 2022. Experiences of Harm, Healing, and Joy among Black Women and Femmes on Social Media. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) (CHI '22). Association for Computing Machinery, New York, NY, USA, Article 240, 17 pages. doi:10.1145/3491102.3517608
- [42] National Council on Disability. 2023. 2023 Progress Report: Toward Economic Security: The Impact of Income and Asset Limits on People with Disabilities. *National Council on Disability Progress Report* (October 2023). <https://www.ncd.gov/report/2023-progress-report-toward-economic-security-the-impact-of-income-and-asset-limits-on-people-with-disabilities/> Accessed: 2025-09-11.
- [43] NNEDV and Uber. 2023. Using Uber: Safety and Privacy Considerations for Survivors. <https://www.techsafety.org/uber-safety-and-privacy-accessed>: 2025-12-04.
- [44] Pew Research Center. 2025. Online Scams and Attacks in America Today. <https://www.pewresearch.org/internet/2025/07/online-scams-and-attacks-in-america-today> Accessed September 8, 2025.
- [45] Lee Rainie, Sara Kiesler, Ruogu Kang, Mary Madden, Maeve Duggan, Stephanie Brown, and Laura Dabbish. 2013. Anonymity, privacy, and security online. *Pew research center* 5 (2013).
- [46] Elissa M Redmiles, Sean Kross, and Michelle L Mazurek. 2016. How i learned to be secure: a census-representative survey of security advice sources and behavior. In *Proceedings of the 2016 ACM SIGSAC conference on computer and communications security*. 666–677.
- [47] Karen Renaud and Lizzie Coles-Kemp. 2022. Accessible and Inclusive Cyber Security: A Nuanced and Complex Challenge. *SN Computer Science* 3 (2022), 346. doi:10.1007/s42979-022-01239-1
- [48] Lydia Saad. 2023. Scams: Relatively Common and Anxiety-Inducing for Americans. Gallup News. <https://news.gallup.com/poll/544643/scams-relatively-common-anxiety-inducing-americans.aspx>
- [49] Nithya Sambasivan, Amna Batool, Nova Ahmed, Tara Matthews, Kurt Thomas, Laura Sanely Gaytán-Lugo, David Nemer, Elie Bursztein, Elizabeth Churchill, and Sunny Consolvo. 2019. "They Don't Leave Us Alone Anywhere We Go": Gender and Digital Abuse in South Asia. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) (CHI '19). Association for Computing Machinery, New York, NY, USA, 1–14. doi:10.1145/3290605.3300232
- [50] Nithya Sambasivan, Garek Checkley, Amna Batool, Nova Ahmed, David Nemer, Laura Sanely Gaytán-Lugo, Tara Matthews, Sunny Consolvo, and Elizabeth Churchill. 2018. "Privacy is not for me, it's for those rich women": performative privacy practices on mobile phones by women in South Asia. In *Proceedings of the Fourteenth USENIX Conference on Usable Privacy and Security* (Baltimore, MD, USA) (SOUPS '18). USENIX Association, USA, 127–142.
- [51] Patrawat Samermit, Anna Turner, Patrick Gage Kelley, Tara Matthews, Vanessa Wu, Sunny Consolvo, and Kurt Thomas. 2023. "Millions of people are watching you": Understanding the Digital-Safety Needs and Practices of Creators. In *32nd USENIX Security Symposium (USENIX Security 23)*. USENIX Association, Anaheim, CA, 5629–5645. <https://www.usenix.org/conference/usenixsecurity23/presentation/samermit>
- [52] Morgan Klaus Scheuerman, Jialun Aaron Jiang, Casey Fiesler, and Jed R. Brubaker. 2021. A Framework of Severity for Harmful Content Online. 5, CSCW2, Article 368 (Oct. 2021), 33 pages. doi:10.1145/3479512
- [53] Sarita Schoenebeck, Amna Batool, Giang Do, Sylvia Darling, Gabriel Grill, Daricia Wilkinson, Mehtab Khan, Kentaro Toyama, and Louise Ashwell. 2023. Online Harassment in Majority Contexts: Examining Harms and Remedies across Countries. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) (CHI '23). Association for Computing Machinery, New York, NY, USA, Article 485, 16 pages. doi:10.1145/3544548.3581020
- [54] Louise Shaxson. 2005. Is your evidence robust enough? Questions for policy makers and practitioners. *Evidence & Policy* 1, 1 (2005), 101–111.

- [55] Michael Siegrist and Joseph Árvai. 2020. Risk perception: Reflections on 40 years of research. *Risk analysis* 40, S1 (2020), 2191–2206.
- [56] Lucy Simko, Ada Lerner, Samia Ibtasam, Franziska Roesner, and Tadayoshi Kohno. 2018. Computer Security and Privacy for Refugees in the United States. In *2018 IEEE Symposium on Security and Privacy (SP)*, 409–423. doi:10.1109/SP.2018.00023
- [57] Manya Sleeper, Tara Matthews, Kathleen O’Leary, Anna Turner, Jill Palzkill Woelfer, Martin Shelton, Andrew Oplinger, Andreas Schou, and Sunny Consolvo. 2019. Tough Times at Transitional Homeless Shelters: Considering the Impact of Financial Insecurity on Digital Security and Privacy. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland UK) (*CHI ’19*). Association for Computing Machinery, New York, NY, USA, 1–12. doi:10.1145/3290605.3300319
- [58] Paul Slovic. 2016. Understanding Perceived Risk: 1978–2015. *Environment: Science and Policy for Sustainable Development* 58, 1 (2016), 25–29. arXiv:https://doi.org/10.1080/00139157.2016.1112169 doi:10.1080/00139157.2016.1112169
- [59] Jenny Tang, Lujo Bauer, and Nicolas Christin. 2025. Misuse, Misreporting, Misinterpretation of Statistical Methods in Usable Privacy and Security Papers. In *Proceedings of the Twenty-First Symposium on Usable Privacy and Security (SOUPS 2025)*. USENIX Association, Seattle, WA, USA. <https://www.usenix.org/conference/soups2025/presentation/tang>
- [60] Xinru Tang, Gabriel Lima, Jiang Jiang, Li, Lucy Simko, and Yixin Zou. 2025. Beyond "Vulnerable Populations": A Unified Understanding of Vulnerability From A Socio-Ecological Perspective. *Proc. ACM Hum.-Comput. Interact.* 9, 2, Article CSCW037 (May 2025), 30 pages. doi:10.1145/3710935
- [61] Marco Thimm-Kaiser, Adam Benzekri, and Vincent Guilamo-Ramos. 2023. Conceptualizing the mechanisms of social determinants of health: a heuristic framework to inform future directions for mitigation. *The Milbank Quarterly* 101, 2 (2023), 486–526.
- [62] Kurt Thomas, Devdatta Akhawe, Michael Bailey, Dan Boneh, Elie Bursztein, Sunny Consolvo, Nicola Dell, Zakir Durumeric, Patrick Gage Kelley, Deepak Kumar, Damon McCoy, Sarah Meiklejohn, Thomas Ristenpart, and Gianluca Stringhini. 2021. SoK: Hate, Harassment, and the Changing Landscape of Online Abuse. In *2021 IEEE Symposium on Security and Privacy (SP)*, 247–267. doi:10.1109/SP40001.2021.00028
- [63] Kurt Thomas, Patrick Gage Kelley, Sunny Consolvo, Patrawat Samermit, and Elie Bursztein. 2022. "It’s common and a part of being a content creator": Understanding How Creators Experience and Cope with Hate and Harassment Online. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) (*CHI ’22*). Association for Computing Machinery, New York, NY, USA, Article 121, 15 pages. doi:10.1145/3491102.3501879
- [64] Jennifer L. Truman and Rachel E. Morgan. 2021. Stalking Victimization, 2016. <https://bjs.ojp.gov/library/publications/stalking-victimization-2016> Accessed: 2025-12-03.
- [65] Emily Tseng, Rosanna Bellini, Yeuk-Yu Lee, Alana Ramjit, Thomas Ristenpart, and Nicola Dell. 2024. Data Stewardship in Clinical Computer Security: Balancing Benefit and Burden in Participatory Systems. *Proc. ACM Hum.-Comput. Interact.* 8, CSCW1, Article 39 (April 2024), 29 pages. doi:10.1145/3637316
- [66] Rebecca Umbach, Nicola Henry, and Gemma Beard. 2025. Prevalence and Impacts of Image-Based Sexual Abuse Victimization: A Multinational Study. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI ’25)*. Association for Computing Machinery, New York, NY, USA, Article 517, 20 pages. doi:10.1145/3706598.3713545
- [67] Rebecca Umbach, Nicola Henry, and Gemma Beard. 2025. Prevalence and Impacts of Image-Based Sexual Abuse Victimization: A Multinational Study. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems (CHI ’25)*. Association for Computing Machinery, New York, NY, USA, Article 517, 20 pages. doi:10.1145/3706598.3713545
- [68] Emilyya Vogels. 2021. Online harassment occurs most often on social media, but strikes in other places, too. *Pew Research Center* (2021).
- [69] Noel Warford, Tara Matthews, Kaitlyn Yang, Omer Akgul, Sunny Consolvo, Patrick Gage Kelley, Nathan Malkin, Michelle L Mazurek, Manya Sleeper, and Kurt Thomas. 2022. Sok: A framework for unifying at-risk user research. In *2022 IEEE Symposium on Security and Privacy (SP)*. IEEE, 2344–2360.
- [70] Miranda Wei, Sunny Consolvo, Patrick Gage Kelley, Tadayoshi Kohno, Tara Matthews, Sarah Meiklejohn, Franziska Roesner, Renee Shelby, Kurt Thomas, and Rebecca Umbach. 2024. Understanding Help-Seeking and Help-Giving on Social Media for Image-Based Sexual Abuse. In *33rd USENIX Security Symposium (USENIX Security 24)*. USENIX Association, Philadelphia, PA, 4391–4408. <https://www.usenix.org/conference/usenixsecurity24/presentation/wei-miranda-understanding>
- [71] Darcia Wilkinson and Bart Knijnenburg. 2022. Many Islands, Many Problems: An Empirical Examination of Online Safety Behaviors in the Caribbean. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) (*CHI ’22*). Association for Computing Machinery, New York, NY, USA, Article 102, 25 pages. doi:10.1145/3491102.3517643
- [72] Robyn S Wilson, Adam Zwickle, and Hugh Walpole. 2019. Developing a broadly applicable measure of risk perception. *Risk Analysis* 39, 4 (2019), 777–791.
- [73] Jill Palzkill Woelfer and David G. Hendry. 2010. Homeless Young People’s Experiences with Information Systems: Life and Work in a Community Technology Center. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI ’10)*. ACM, New York, NY, 1291–1300. doi:10.1145/1753326.1753520
- [74] World Health Organization. 2025. Social determinants of health. <https://www.who.int/health-topics/social-determinants-of-health> Accessed: 2025-12-04.

A Survey Questions

A.1 Demographics

- (1) What is your gender? Select all that apply. [SELECT ALL]
 - Man
 - Woman
 - Non-binary
 - Prefer to self-describe [OPEN END]
 - Prefer not to answer [EXCLUSIVE]
- (2) In what year were you born? [OPEN END][FORCE NUMERIC 0-100]
- (3) What is the last grade or class you completed in school?
 - None, or grade 1-8
 - High school incomplete (grades 9-11)
 - High school diploma or equivalent, no further schooling
 - Technical or vocational school after high school
 - Some college, no degree
 - Associate's or two-year college degree
 - Four-year college degree
 - Graduate or professional school after college, no degree
 - Graduate or professional degree
- (4) Would you consider where you live to be...
 - An urban area
 - A suburban area
 - A rural area
- (5) Do you have any children?
 - Yes
 - No
- (6) Do you have any children under the age of 18 living in your home?
 - Yes, I have one or more child under the age of 13
 - Yes, I have one or more child aged 13 -18
 - No
- (7) In which state do you currently reside? [DROP DOWN]
- (8) With which racial or ethnic groups do you identify? Select all that apply. [SELECT ALL]
 - White
 - Hispanic, Latino, or Spanish origin
 - Black or African American
 - Asian
 - American Indian or Alaska Native
 - Middle Eastern or North African
 - Native Hawaiian or other Pacific Islander
 - Another race or ethnicity not listed [OPEN END]
 - Prefer not to answer [EXCLUSIVE]
- (9) What is your preferred language to read?
 - English
 - Spanish
 - Chinese
 - French
 - Tagalog
 - German
 - Vietnamese
 - Korean
 - Other languages (please specify) [OPEN END]
- (10) Generally speaking, do you think of yourself as...
 - Republican

- Democrat
 - Independent
 - Something else
- (11) Do you identify as LGBTQ+ (Lesbian, Gay, Bisexual, Transgender, Queer, and/or Questioning)?
 - Yes
 - No
 - I prefer not to say
 - (12) Do you identify as a person with a disability?
 - Yes
 - No
 - I prefer not to say
 - (13) Do you use any assistive technology?

Assistive technology is anything a person might use to perform activities which might otherwise be inaccessible to them. Assistive technologies are often used by individuals with disabilities but they can be helpful to anyone. Examples include screen readers, text-to-speech, power wheelchairs, using a magnifying glass used to read small print, or using a cane to get around.

 - Yes
 - No
 - I'm not sure
 - I prefer not to answer
 - (14) What is your current working status?
 - Full time
 - Part time
 - Stay at home parent
 - Student
 - Unemployed / Non-working
 - Retired
 - Prefer not to answer

A.2 Risk

- (1) For each of the statements, think about how well they describe you on a scale of 1 - 10. 1 means the statement doesn't fit you at all, 10 means it describes you very well. [MATRIX RANDOMIZE ALL]
 - I feel targeted by governments or political groups.
 - Things are harder for me online because parts of my identity aren't widely accepted.
 - Things are harder for me online because the experiences I've had in my life aren't common.
 - I feel like technology generally works well for me.
 - I feel like technology was not designed with people like me in mind.
 - I have had personal relationships with people who have tried to harm me.
 - I depend a lot on others for assistance (e.g. to set up or use technology).
 - I feel like I can achieve my goals online without help.
 - I am a person who takes care of or works with people who are vulnerable.
 - I am close to a person who is often targeted online.
 - I have a higher profile because of my job.
 - I have a higher profile because of other people I am close to.

- I have a higher profile because of other aspects of my life.
 - I don't have the time or money to be safer online.
 - I don't have the time or money to recover if something bad happens to me online.
 - It is difficult for me to use many technologies.
 - Technologies often aren't designed for my needs and this makes me feel less safe online.
 - I have access to sensitive resources, such as information or money, that most others do not.
- (2) You rated these statements as those that most describe you. For each statement, give us more details on why you feel this statement describes you well. [OPEN END]
- (3) Have you ever experienced any of the following online? [MATRIX][Responses: Yes, No, Don't know]

- Physical threats
- Had your private photos or information shared without your permission
- Been stalked
- Been discriminated or harassed based on your identity
- Had an account hacked
- Had money stolen
- Been the target of a virus or malware attack
- Been the target of a scam, phishing attack, or attempt to trick me into providing personal information
- Been insulted or treated badly online
- Been exposed to unwanted explicit content

B Codebook

Category	Codes (examples)	Brief description	Originated from this statement
Demographics / Circumstance	blue collar; disabled; retired; parent; student; low income	Self-described social, economic, or work circumstances	I don't have the time or money to be safer online.
Caregivers / Helping roles	takes care of parents; social worker; educator; therapist	Roles involving caring for or supporting vulnerable others	I am a person who takes care of or works with people who are vulnerable.
General reactions	agrees; disagrees; worried; not that important; depends	High-level stance or affective reaction to the statement	I don't have the time or money to be safer online.
Cost and resource concerns	security not worth price; money constraint; time constrained; safety should be affordable	Concerns about money, time, or other resources for safety	I don't have the time or money to be safer online.
Prior negative experiences	exp:scammed; exp:hacked; exp:identity theft; exp:abuse	Past harmful online or offline experiences	I don't have the time or money to recover if something bad happens to me online.
Safety worries	concern:identity theft; concern:scammed; feels unsafe paying online; limit being online	Anticipated or ongoing worries about online safety	I don't have the time or money to be safer online.
Tech orientation	tech satisfies goals; not tech-savvy; tech is harmful; prefer ppl over tech	How people see and use technology in everyday life	I feel like technology generally works well for me.
Targets and perpetrators	target:women; target:lgbtq; p:partner; p:friend	Who is seen as targeted or as a perpetrator of harm	I am close to a person who is often targeted online.

Table 7: Condensed codebook used for qualitative coding of survey responses.

C Modeling Results

C.1 Model 1 is a logistic regression model with contextual risk factors x demographics

- Table 8: Dependent variables: Resource / time-constrained, Access to other at-risk users, and Underserved accessibility needs
- Table 9: Dependent variables: Prominence, Marginalization, Reliance on 3rd party
- Table 10: Dependent variables: Social norm, Access to a sensitive resource, Legal or political
- Table 11: Dependent variable: Relationship with attacker

C.2 Model 2 is logistic regression model with contextual risk factors + demographics x digital-safety attacks

- Table 12: Dependent variables: Physical threats and Had your private photos or information shared without your permission
- Table 13: Dependent variables: Been stalked and Been discriminated or harassed based on your identity
- Table 14: Dependent variables: Had an account hacked and Had money stolen
- Table 15: Dependent variables: Been the target of a virus or malware attack and Been the target of a scam or phishing attack
- Table 16: Dependent variables: Been insulted or treated badly online and Been exposed to unwanted explicit content

Dependent Variable	Indep. Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Resource	gender	Male	Female	-0.3687	-0.2556	-4.0458	0.0001	0.7745	0.6843	0.8765
Resource	gender	Non-binary	Female	-0.7700	-0.5338	-1.0401	0.2983	0.5864	0.2145	1.6032
Resource	race	American Indian...	White	0.5856	0.4059	1.3144	0.1887	1.5006	0.8193	2.7488
Resource	race	Asian	White	0.1683	0.1166	0.6720	0.5016	1.1237	0.7997	1.5791
Resource	race	Black or African American	White	-0.0317	-0.0220	-0.2432	0.8079	0.9783	0.8194	1.1679
Resource	race	Hispanic, Latino, or Spanish	White	0.0713	0.0494	0.4316	0.6660	1.0507	0.8394	1.3150
Resource	race	Middle Eastern...	White	0.6953	0.4820	0.7505	0.4530	1.6193	0.4599	5.7010
Resource	race	Native Hawaiian...	White	-0.5459	-0.3784	-0.4061	0.6847	0.6850	0.1103	4.2540
Resource	sexuality	LGBT	non-LGBT	0.1806	0.1252	1.0767	0.2816	1.1334	0.9024	1.4235
Resource	disability	Disability	non-Disability	0.7480	0.5185	6.6549	0.0000	1.6795	1.4417	1.9566
Resource	political_party	Democrat	Independent	0.2771	0.1921	2.4748	0.0133	1.2118	1.0408	1.4109
Resource	political_party	Republican	Independent	0.2839	0.1968	2.4447	0.0145	1.2175	1.0398	1.4256
Resource	urbanicity	Rural	Suburban	0.1647	0.1142	1.4557	0.1455	1.1210	0.9612	1.3073
Resource	urbanicity	Urban	Suburban	0.1233	0.0855	1.1671	0.2432	1.0893	0.9436	1.2574
Resource	age	18-24	65	-0.1363	-0.0945	-0.5955	0.5515	0.9099	0.6667	1.2416
Resource	age	25-34	65	0.0291	0.0202	0.1545	0.8772	1.0204	0.7902	1.3176
Resource	age	35-44	65	0.1363	0.0945	0.7393	0.4597	1.0991	0.8555	1.4120
Resource	age	45-54	65	-0.1272	-0.0882	-0.7269	0.4673	0.9156	0.7218	1.1614
Resource	age	55-64	65	-0.0190	-0.0132	-0.1239	0.9014	0.9869	0.8011	1.2158
Resource	parentage	Has kids	Does not have kids	0.0758	0.0525	0.8061	0.4202	1.0539	0.9275	1.1976
Resource	work_status	Full-time	Retired	0.2040	0.1414	1.2882	0.1977	1.1519	0.9289	1.4283
Resource	work_status	Part-time	Retired	0.1315	0.0912	0.7513	0.4525	1.0954	0.8636	1.3895
Resource	work_status	Stay-at-home parent	Retired	-0.3792	-0.2629	-1.3995	0.1617	0.7688	0.5321	1.1110
Resource	work_status	Student	Retired	-0.2504	-0.1736	-0.7631	0.4454	0.8407	0.5383	1.3129
Resource	work_status	Unemployed / Not working	Retired	0.2328	0.1613	1.3195	0.1870	1.1751	0.9247	1.4933
Resource	education	High school	College degree	0.3688	0.2557	2.7167	0.0066	1.2913	1.0738	1.5529
Resource	education	Professional schooling...	College degree	0.0625	0.0433	0.4188	0.6753	1.0443	0.8526	1.2791
Resource	education	Some college...	College degree	0.3728	0.2584	3.0161	0.0026	1.2949	1.0947	1.5316
Resource	education	Some or no high school	College degree	0.2519	0.1746	1.0070	0.3139	1.1908	0.8477	1.6726
Access	gender	Male	Female	-0.0105	-0.0073	-0.1037	0.9174	0.9928	0.8656	1.1387
Access	gender	Non-binary	Female	-1.1448	-0.7935	-1.3232	0.1858	0.4523	0.1396	1.4651
Access	race	American Indian...	White	0.3141	0.2177	0.6597	0.5094	1.2432	0.6511	2.3736
Access	race	Asian	White	0.0960	0.0666	0.3661	0.7143	1.0688	0.7484	1.5265
Access	race	Black or African American	White	0.1838	0.1274	1.3253	0.1851	1.1359	0.9408	1.3714
Access	race	Hispanic, Latino, or Spanish	White	0.0278	0.0193	0.1595	0.8733	1.0195	0.8043	1.2922
Access	race	Middle Eastern...	White	-0.2691	-0.1865	-0.2591	0.7956	0.8298	0.2024	3.4025
Access	race	Native Hawaiian...	White	0.2062	0.1429	0.1553	0.8766	1.1536	0.1901	7.0024
Access	sexuality	LGBT	non-LGBT	0.1162	0.0806	0.6558	0.5119	1.0839	0.8520	1.3790
Access	disability	Disability	non-Disability	0.4519	0.3133	3.5439	0.0004	1.3679	1.1503	1.6266
Access	political_party	Democrat	Independent	0.2205	0.1528	1.7822	0.0747	1.1651	0.9849	1.3784
Access	political_party	Republican	Independent	0.2267	0.1571	1.7483	0.0804	1.1701	0.9812	1.3955
Access	urbanicity	Rural	Suburban	-0.1147	-0.0795	-0.8866	0.3753	0.9236	0.7747	1.1011
Access	urbanicity	Urban	Suburban	0.2975	0.2062	2.6013	0.0093	1.2290	1.0522	1.4356
Access	age	18-24	65	1.6483	1.1425	6.5588	0.0000	3.1347	2.2280	4.4103
Access	age	25-34	65	1.4943	1.0358	7.0434	0.0000	2.8174	2.1119	3.7586
Access	age	35-44	65	1.3585	0.9417	6.5356	0.0000	2.5643	1.9334	3.4010
Access	age	45-54	65	0.8470	0.5871	4.2117	0.0000	1.7987	1.3687	2.3638
Access	age	55-64	65	0.4218	0.2924	2.2749	0.0229	1.3396	1.0413	1.7233
Access	parentage	Has kids	Does not have kids	0.1896	0.1314	1.8143	0.0696	1.1404	0.9895	1.3144
Access	work_status	Full-time	Retired	1.0958	0.7596	5.9987	0.0000	2.1373	1.6676	2.7394
Access	work_status	Part-time	Retired	0.4871	0.3376	2.4048	0.0162	1.4016	1.0644	1.8455
Access	work_status	Stay-at-home parent	Retired	-0.2685	-0.1861	-0.8579	0.3909	0.8302	0.5427	1.2700
Access	work_status	Student	Retired	0.2721	0.1886	0.7912	0.4288	1.2076	0.7568	1.9267
Access	work_status	Unemployed / Not working	Retired	-0.0720	-0.0499	-0.3474	0.7283	0.9513	0.7178	1.2607
Access	education	High school	College degree	-0.2340	-0.1622	-1.5563	0.1196	0.8503	0.6932	1.0430
Access	education	Professional schooling...	College degree	0.4223	0.2927	2.6594	0.0078	1.3401	1.0800	1.6627
Access	education	Some college...	College degree	-0.2216	-0.1536	-1.6294	0.1032	0.8576	0.7129	1.0317
Access	education	Some or no high school	College degree	-0.2817	-0.1953	-1.0118	0.3116	0.8226	0.5635	1.2008
Underserved	gender	Male	Female	-0.0308	-0.0213	-0.3104	0.7563	0.9789	0.8555	1.1201
Underserved	gender	Non-binary	Female	-1.3728	-0.9516	-1.2386	0.2155	0.3861	0.0857	1.7406
Underserved	race	American Indian...	White	-0.2087	-0.1447	-0.4092	0.6824	0.8653	0.4327	1.7304
Underserved	race	Asian	White	0.8558	0.5932	3.3190	0.0009	1.8097	1.2749	2.5689
Underserved	race	Black or African American	White	0.1211	0.0839	0.8612	0.3892	1.0875	0.8985	1.3164
Underserved	race	Hispanic, Latino, or Spanish	White	0.2416	0.1674	1.3683	0.1712	1.1823	0.9302	1.5027
Underserved	race	Middle Eastern...	White	0.0340	0.0236	0.0296	0.9764	1.0239	0.2142	4.8936
Underserved	race	Native Hawaiian...	White	-0.7658	-0.5308	-0.4701	0.6383	0.5881	0.0643	5.3778
Underserved	sexuality	LGBT	non-LGBT	-0.3993	-0.2768	-2.1005	0.0357	0.7582	0.5857	0.9817
Underserved	disability	Disability	non-Disability	0.5759	0.3992	4.7996	0.0000	1.4906	1.2664	1.7546
Underserved	political_party	Democrat	Independent	0.3729	0.2585	3.0223	0.0025	1.2950	1.0951	1.5313
Underserved	political_party	Republican	Independent	0.2864	0.1985	2.2373	0.0253	1.2196	1.0249	1.4513
Underserved	urbanicity	Rural	Suburban	0.3087	0.2140	2.5105	0.0121	1.2386	1.0480	1.4637
Underserved	urbanicity	Urban	Suburban	0.2768	0.1918	2.4056	0.0161	1.2115	1.0362	1.4164
Underserved	age	18-24	65	0.0759	0.0526	0.3055	0.7600	1.0540	0.7521	1.4771
Underserved	age	25-34	65	0.0935	0.0648	0.4566	0.6479	1.0669	0.8079	1.4089
Underserved	age	35-44	65	0.0820	0.0568	0.4100	0.6818	1.0585	0.8067	1.3889
Underserved	age	45-54	65	-0.2295	-0.1591	-1.1957	0.2318	0.8529	0.6571	1.1071
Underserved	age	55-64	65	-0.1664	-0.1153	-0.9897	0.3223	0.8911	0.7091	1.1197
Underserved	parentage	Has kids	Does not have kids	0.1558	0.1080	1.5204	0.1284	1.1140	0.9693	1.2804
Underserved	work_status	Full-time	Retired	0.1534	0.1063	0.8852	0.3761	1.1122	0.8789	1.4074
Underserved	work_status	Part-time	Retired	-0.0027	-0.0019	-0.0143	0.9886	0.9981	0.7692	1.2952
Underserved	work_status	Stay-at-home parent	Retired	-0.2171	-0.1505	-0.7371	0.4611	0.8603	0.5767	1.2835
Underserved	work_status	Student	Retired	-0.4146	-0.2874	-1.1358	0.2561	0.7502	0.4569	1.2319
Underserved	work_status	Unemployed / Not working	Retired	-0.2869	-0.1989	-1.4864	0.1372	0.8197	0.6306	1.0654
Underserved	education	High school	College degree	0.5352	0.3710	3.6054	0.0003	1.4492	1.1845	1.7730
Underserved	education	Professional schooling...	College degree	0.1208	0.0838	0.7300	0.4654	1.0874	0.8684	1.3615
Underserved	education	Some college...	College degree	0.2297	0.1592	1.6668	0.0956	1.1726	0.9724	1.4139
Underserved	education	Some or no high school	College degree	0.7957	0.5515	3.0352	0.0024	1.7359	1.2158	2.4785

Table 8: Model 1: contextual risk factors x demographics. Part 1 of 4 tables includes dependent variables: Resource / time-constrained, Access to other at-risk users, and Underserved accessibility needs

Dependent Variable	Indep. Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Prominence	gender	Male	Female	0.6548	0.4539	6.2636	0.0000	1.5744	1.3660	1.8147
Prominence	gender	Non-binary	Female	-0.7156	-0.4960	-0.7392	0.4598	0.6089	0.1635	2.2686
Prominence	race	American Indian...	White	-0.1568	-0.1087	-0.2974	0.7662	0.8970	0.4383	1.8359
Prominence	race	Asian	White	0.2845	0.1972	1.0599	0.2892	1.2180	0.8458	1.7538
Prominence	race	Black or African American	White	0.4026	0.2791	2.8396	0.0045	1.3219	1.0903	1.6027
Prominence	race	Hispanic, Latino, or Spanish	White	0.3099	0.2148	1.7479	0.0805	1.2396	0.9743	1.5773
Prominence	race	Middle Eastern...	White	1.1456	0.7941	1.1824	0.2370	2.2124	0.5932	8.2510
Prominence	race	Native Hawaiian...	White	0.1701	0.1179	0.1275	0.8985	1.1251	0.1838	6.8867
Prominence	sexuality	LGBT	non-LGBT	-0.3793	-0.2629	-2.0164	0.0438	0.7688	0.5954	0.9927
Prominence	disability	Disability	non-Disability	0.4775	0.3310	3.6026	0.0003	1.3923	1.1629	1.6670
Prominence	political_party	Democrat	Independent	0.5624	0.3898	4.3231	0.0000	1.4767	1.2375	1.7622
Prominence	political_party	Republican	Independent	0.5842	0.4049	4.2947	0.0000	1.4992	1.2463	1.8035
Prominence	urbanicity	Rural	Suburban	0.0715	0.0496	0.5308	0.5956	1.0508	0.8751	1.2618
Prominence	urbanicity	Urban	Suburban	0.4992	0.3460	4.2295	0.0000	1.4135	1.2040	1.6593
Prominence	age	18-24	65	1.7270	1.1971	6.5798	0.0000	3.3104	2.3175	4.7286
Prominence	age	25-34	65	1.7317	1.2004	7.7997	0.0000	3.3213	2.4565	4.4906
Prominence	age	35-44	65	1.5997	1.1088	7.3484	0.0000	3.0307	2.2548	4.0737
Prominence	age	45-54	65	0.8574	0.5943	4.0469	0.0001	1.8118	1.3586	2.4161
Prominence	age	55-64	65	0.4731	0.3279	2.4234	0.0154	1.3881	1.0647	1.8097
Prominence	parentage	Has kids	Does not have kids	0.1803	0.1249	1.6671	0.0955	1.1311	0.9783	1.3124
Prominence	work_status	Full-time	Retired	1.0063	0.6975	5.2747	0.0000	2.0088	1.5501	2.6031
Prominence	work_status	Part-time	Retired	0.2524	0.1749	1.1742	0.2403	1.1912	0.8895	1.5950
Prominence	work_status	Stay-at-home parent	Retired	-0.2692	-0.1866	-0.8133	0.4160	0.8298	0.5293	1.3009
Prominence	work_status	Student	Retired	0.2439	0.1691	0.6870	0.4921	1.1842	0.7310	1.9183
Prominence	work_status	Unemployed / Not working	Retired	-0.2571	-0.1782	-1.1840	0.2364	0.8368	0.6230	1.1239
Prominence	education	High school	College degree	0.0105	0.0073	0.0678	0.9460	1.0073	0.8161	1.2434
Prominence	education	Professional schooling...	College degree	0.5415	0.3753	3.2977	0.0010	1.4555	1.1645	1.8192
Prominence	education	Some college...	College degree	-0.3154	-0.2186	-2.2081	0.0272	0.8036	0.6619	0.9757
Prominence	education	Some or no high school	College degree	-0.0628	-0.0435	-0.2196	0.8262	0.9574	0.6492	1.4119
Marginalization	gender	Male	Female	0.4859	0.3368	4.2924	0.0000	1.4005	1.2008	1.6333
Marginalization	gender	Non-binary	Female	0.6384	0.4425	0.8335	0.4046	1.5566	0.5499	4.4065
Marginalization	race	American Indian...	White	-0.2264	-0.1569	-0.3866	0.6991	0.8548	0.3857	1.8941
Marginalization	race	Asian	White	0.2882	0.1998	0.9923	0.3210	1.2211	0.8230	1.8118
Marginalization	race	Black or African American	White	0.1977	0.1370	1.3090	0.1905	1.1468	0.9341	1.4080
Marginalization	race	Hispanic, Latino, or Spanish	White	0.3203	0.2220	1.7199	0.0855	1.2486	0.9695	1.6080
Marginalization	race	Middle Eastern...	White	1.7595	1.2196	1.8261	0.0678	3.3858	0.9145	12.5355
Marginalization	race	Native Hawaiian...	White	0.6294	0.4362	0.4697	0.6386	1.5469	0.2506	9.5503
Marginalization	sexuality	LGBT	non-LGBT	0.3094	0.2145	1.6572	0.0975	1.2392	0.9616	1.5970
Marginalization	disability	Disability	non-Disability	0.9367	0.6493	6.8557	0.0000	1.9142	1.5899	2.3046
Marginalization	political_party	Democrat	Independent	0.2174	0.1507	1.5843	0.1131	1.1626	0.9649	1.4008
Marginalization	political_party	Republican	Independent	0.0649	0.0450	0.4446	0.6566	1.0460	0.8579	1.2754
Marginalization	urbanicity	Rural	Suburban	-0.0412	-0.0285	-0.2794	0.7799	0.9719	0.7956	1.1872
Marginalization	urbanicity	Urban	Suburban	0.4394	0.3046	3.4818	0.0005	1.3561	1.1424	1.6097
Marginalization	age	18-24	65	1.6500	1.1437	5.8076	0.0000	3.1383	2.1334	4.6166
Marginalization	age	25-34	65	1.5804	1.0954	6.4488	0.0000	2.9904	2.1436	4.1718
Marginalization	age	35-44	65	1.3776	0.9549	5.6995	0.0000	2.5983	1.8710	3.6082
Marginalization	age	45-54	65	0.8068	0.5592	3.4137	0.0006	1.7493	1.2689	2.4116
Marginalization	age	55-64	65	0.6202	0.4299	2.8747	0.0040	1.5371	1.1466	2.0607
Marginalization	parentage	Has kids	Does not have kids	0.0102	0.0071	0.0879	0.9300	1.0071	0.8597	1.1798
Marginalization	work_status	Full-time	Retired	0.5349	0.3707	2.5393	0.0111	1.4488	1.0883	1.9288
Marginalization	work_status	Part-time	Retired	-0.0067	-0.0046	-0.0280	0.9776	0.9954	0.7206	1.3751
Marginalization	work_status	Stay-at-home parent	Retired	0.1231	0.0853	0.3608	0.7182	1.0890	0.6852	1.7509
Marginalization	work_status	Student	Retired	-0.1205	-0.0835	-0.3147	0.7530	0.9199	0.5469	1.5473
Marginalization	work_status	Unemployed / Not working	Retired	-0.0996	-0.0690	-0.4392	0.6605	0.9333	0.6859	1.2700
Marginalization	education	High school	College degree	0.3215	0.2228	1.9094	0.0562	1.2496	0.9941	1.5708
Marginalization	education	Professional schooling...	College degree	0.2863	0.1985	1.5592	0.1190	1.2195	0.9503	1.5651
Marginalization	education	Some college...	College degree	-0.0049	-0.0034	-0.0310	0.9753	0.9966	0.8044	1.2347
Marginalization	education	Some or no high school	College degree	0.7269	0.5038	2.5625	0.0104	1.6550	1.1258	2.4331
Reliance	gender	Male	Female	-0.1611	-0.1116	-1.7075	0.0877	0.8944	0.7868	1.0166
Reliance	gender	Non-binary	Female	-0.0398	-0.0276	-0.0523	0.9583	0.9728	0.3458	2.7366
Reliance	race	American Indian...	White	-0.1770	-0.1227	-0.3717	0.7101	0.8845	0.4631	1.6894
Reliance	race	Asian	White	0.5284	0.3663	2.0689	0.0386	1.4423	1.0195	2.0406
Reliance	race	Black or African American	White	0.3816	0.2645	2.8640	0.0042	1.3028	1.0871	1.5613
Reliance	race	Hispanic, Latino, or Spanish	White	0.3843	0.2664	2.2832	0.0224	1.3052	1.0384	1.6406
Reliance	race	Middle Eastern...	White	-0.5329	-0.3694	-0.4615	0.6444	0.6911	0.1440	3.3179
Reliance	race	Native Hawaiian...	White	-26.2016	-18.1616	-0.0034	0.9973	0.0000	0.0000	inf
Reliance	sexuality	LGBT	non-LGBT	-0.1187	-0.0823	-0.6762	0.4989	0.9210	0.7256	1.1690
Reliance	disability	Disability	non-Disability	0.5161	0.3577	4.4904	0.0000	1.4301	1.2234	1.6718
Reliance	political_party	Democrat	Independent	0.2452	0.1700	2.1086	0.0350	1.1853	1.0121	1.3881
Reliance	political_party	Republican	Independent	0.2599	0.1801	2.1525	0.0314	1.1974	1.0162	1.4108
Reliance	urbanicity	Rural	Suburban	0.1042	0.0723	0.8899	0.3735	1.0749	0.9168	1.2604
Reliance	urbanicity	Urban	Suburban	0.2100	0.1456	1.9255	0.0542	1.1567	0.9974	1.3415
Reliance	age	18-24	65	0.0593	0.0411	0.2537	0.7997	1.0420	0.7584	1.4315
Reliance	age	25-34	65	-0.1734	-0.1202	-0.8919	0.3724	0.8868	0.6810	1.1548
Reliance	age	35-44	65	-0.3359	-0.2328	-1.7556	0.0792	0.7923	0.6110	1.0275
Reliance	age	45-54	65	-0.5563	-0.3856	-3.0409	0.0024	0.6801	0.5304	0.8719
Reliance	age	55-64	65	-0.1579	-0.1095	-0.9995	0.3175	0.8963	0.7232	1.1109
Reliance	parentage	Has kids	Does not have kids	0.2899	0.2009	2.9708	0.0030	1.2225	1.0708	1.3958
Reliance	work_status	Full-time	Retired	0.1116	0.0774	0.6821	0.4952	1.0804	0.8651	1.3494
Reliance	work_status	Part-time	Retired	-0.1976	-0.1370	-1.0832	0.2787	0.8720	0.6805	1.1173
Reliance	work_status	Stay-at-home parent	Retired	-0.0069	-0.0048	-0.0252	0.9799	0.9952	0.6844	1.4472
Reliance	work_status	Student	Retired	-0.0481	-0.0334	-0.1449	0.8848	0.9672	0.6159	1.5188
Reliance	work_status	Unemployed / Not working	Retired	-0.1602	-0.1110	-0.8798	0.3790	0.8949	0.6988	1.1461
Reliance	education	High school	College degree	0.6861	0.4756	4.8808	0.0000	1.6089	1.3292	1.9475
Reliance	education	Professional schooling...	College degree	0.2488	0.1724	1.5960	0.1105	1.1882	0.9614	1.4684
Reliance	education	Some college...	College degree	0.1947	0.1350	1.4945	0.1350	1.1445	0.9588	1.3661
Reliance	education	Some or no high school	College degree	1.2753	0.8839	5.0603	0.0000	2.4204	1.7187	3.4086

Table 9: Model 1: contextual risk factors x demographics. Part 2 of 4 tables includes dependent variables: Prominence, Marginalization, Reliance on 3rd party

Dependent Variable	Indep. Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Social	gender	Male	Female	0.0064	0.0044	0.0650	0.9482	1.0045	0.8785	1.1485
Social	gender	Non-binary	Female	-1.1580	-0.8027	-1.2234	0.2212	0.4481	0.1239	1.6214
Social	race	American Indian...	White	0.1411	0.0978	0.2948	0.7681	1.1027	0.5756	2.1127
Social	race	Asian	White	0.0295	0.0205	0.1053	0.9161	1.0207	0.6973	1.4941
Social	race	Black or African American	White	0.1926	0.1335	1.3840	0.1664	1.1428	0.9460	1.3806
Social	race	Hispanic, Latino, or Spanish	White	0.3186	0.2208	1.8307	0.0671	1.2471	0.9845	1.5797
Social	race	Middle Eastern...	White	0.5008	0.3472	0.4955	0.6203	1.4150	0.3584	5.5865
Social	race	Native Hawaiian...	White	1.7238	1.1948	1.2893	0.1973	3.3030	0.5372	20.3098
Social	sexuality	LGBT	non-LGBT	0.0311	0.0216	0.1718	0.8636	1.0218	0.7990	1.3068
Social	disability	Disability	non-Disability	0.3591	0.2489	2.9918	0.0028	1.2826	1.0896	1.5098
Social	political_party	Democrat	Independent	0.0628	0.0435	0.5156	0.6062	1.0445	0.8852	1.2324
Social	political_party	Republican	Independent	0.2179	0.1510	1.7403	0.0818	1.1630	0.9811	1.3787
Social	urbanicity	Rural	Suburban	0.2889	0.2002	2.3717	0.0177	1.2217	1.0354	1.4415
Social	urbanicity	Urban	Suburban	0.2841	0.1970	2.4843	0.0130	1.2177	1.0424	1.4224
Social	age	18-24	65	0.0605	0.0420	0.2462	0.8056	1.0429	0.7467	1.4565
Social	age	25-34	65	0.1840	0.1275	0.9037	0.3662	1.1360	0.8615	1.4979
Social	age	35-44	65	-0.0918	-0.0636	-0.4558	0.6485	0.9384	0.7138	1.2336
Social	age	45-54	65	-0.2927	-0.2029	-1.5202	0.1285	0.8164	0.6285	1.0605
Social	age	55-64	65	-0.2923	-0.2026	-1.7302	0.0836	0.8166	0.6491	1.0273
Social	parentage	Has kids	Does not have kids	0.2149	0.1490	2.1053	0.0353	1.1606	1.0103	1.3333
Social	work_status	Full-time	Retired	0.1232	0.0854	0.7110	0.4771	1.0891	0.8607	1.3782
Social	work_status	Part-time	Retired	-0.3513	-0.2435	-1.7903	0.0734	0.7839	0.6004	1.0233
Social	work_status	Stay-at-home parent	Retired	-0.1121	-0.0777	-0.3865	0.6991	0.9253	0.6240	1.3719
Social	work_status	Student	Retired	0.0429	0.0297	0.1243	0.9010	1.0302	0.6446	1.6464
Social	work_status	Unemployed / Not working	Retired	-0.1852	-0.1284	-0.9669	0.3336	0.8795	0.6780	1.1409
Social	education	High school	College degree	0.8733	0.6054	5.9777	0.0000	1.8319	1.5021	2.2341
Social	education	Professional schooling...	College degree	0.1411	0.0978	0.8521	0.3941	1.1027	0.8806	1.3808
Social	education	Some college...	College degree	0.0914	0.0634	0.6607	0.5088	1.0654	0.8828	1.2857
Social	education	Some or no high school	College degree	0.7957	0.5515	3.0602	0.0022	1.7359	1.2193	2.4713
Sensitive	gender	Male	Female	0.6468	0.4483	5.4098	0.0000	1.5657	1.3310	1.8418
Sensitive	gender	Non-binary	Female	-0.6947	-0.4815	-0.6121	0.5405	0.6178	0.1322	2.8870
Sensitive	race	American Indian...	White	0.0645	0.0447	0.1098	0.9126	1.0457	0.4709	2.3220
Sensitive	race	Asian	White	0.3750	0.2599	1.2897	0.1972	1.2968	0.8736	1.9251
Sensitive	race	Black or African American	White	0.2614	0.1812	1.6306	0.1030	1.1986	0.9641	1.4902
Sensitive	race	Hispanic, Latino, or Spanish	White	0.2450	0.1698	1.2284	0.2193	1.1851	0.9038	1.5538
Sensitive	race	Middle Eastern...	White	1.2852	0.8908	1.2336	0.2173	2.4371	0.5919	10.0353
Sensitive	race	Native Hawaiian...	White	-41.0643	-28.4636	0.0000	1.0000	0.0000	0.0000	inf
Sensitive	sexuality	LGBT	non-LGBT	0.0069	0.0048	0.0334	0.9734	1.0048	0.7591	1.3300
Sensitive	disability	Disability	non-Disability	0.3212	0.2226	2.0685	0.0386	1.2494	1.0118	1.5428
Sensitive	political_party	Democrat	Independent	0.3411	0.2364	2.2994	0.0215	1.2667	1.0355	1.5496
Sensitive	political_party	Republican	Independent	0.3867	0.2680	2.4876	0.0129	1.3074	1.0585	1.6147
Sensitive	urbanicity	Rural	Suburban	0.1038	0.0720	0.6617	0.5081	1.0746	0.8683	1.3299
Sensitive	urbanicity	Urban	Suburban	0.4226	0.2929	3.1651	0.0016	1.3404	1.1180	1.6069
Sensitive	age	18-24	65	1.5175	1.0519	4.9581	0.0000	2.8630	1.8890	4.3392
Sensitive	age	25-34	65	1.5029	1.0417	5.7956	0.0000	2.8341	1.9926	4.0310
Sensitive	age	35-44	65	1.3182	0.9137	5.1711	0.0000	2.4936	1.7637	3.5257
Sensitive	age	45-54	65	0.8175	0.5667	3.2505	0.0012	1.7624	1.2523	2.4803
Sensitive	age	55-64	65	0.4359	0.3022	1.8504	0.0643	1.3528	0.9823	1.8631
Sensitive	parentage	Has kids	Does not have kids	0.2184	0.1514	1.7766	0.0756	1.1634	0.9845	1.3748
Sensitive	work_status	Full-time	Retired	1.0789	0.7478	4.7737	0.0000	2.1124	1.5540	2.8717
Sensitive	work_status	Part-time	Retired	0.1147	0.0795	0.4400	0.6599	1.0827	0.7599	1.5427
Sensitive	work_status	Stay-at-home parent	Retired	-0.2010	-0.1393	-0.5013	0.6161	0.8700	0.5046	1.4997
Sensitive	work_status	Student	Retired	-0.1794	-0.1243	-0.4087	0.6828	0.8831	0.4864	1.6032
Sensitive	work_status	Unemployed / Not working	Retired	-0.3221	-0.2233	-1.2069	0.2275	0.7999	0.5566	1.1495
Sensitive	education	High school	College degree	-0.2797	-0.1939	-1.5949	0.1107	0.8238	0.6492	1.0454
Sensitive	education	Professional schooling...	College degree	0.3375	0.2340	1.9054	0.0567	1.2636	0.9933	1.6074
Sensitive	education	Some college...	College degree	-0.5269	-0.3652	-3.2711	0.0011	0.6940	0.5576	0.8638
Sensitive	education	Some or no high school	College degree	-0.6648	-0.4608	-1.8371	0.0662	0.6308	0.3858	1.0313
Legal	gender	Male	Female	0.6165	0.4273	4.8704	0.0000	1.5331	1.2909	1.8208
Legal	gender	Non-binary	Female	-0.8079	-0.5600	-0.7198	0.4717	0.5712	0.1243	2.6245
Legal	race	American Indian...	White	-0.9787	-0.6784	-1.2635	0.2064	0.5074	0.1772	1.4535
Legal	race	Asian	White	-0.0617	-0.0428	-0.1798	0.8573	0.9581	0.6009	1.5276
Legal	race	Black or African American	White	0.2257	0.1564	1.3555	0.1753	1.1693	0.9326	1.4661
Legal	race	Hispanic, Latino, or Spanish	White	0.0069	0.0048	0.0321	0.9744	1.0048	0.7509	1.3445
Legal	race	Middle Eastern...	White	0.8055	0.5584	0.6893	0.4906	1.7478	0.3573	8.5499
Legal	race	Native Hawaiian...	White	1.2196	0.8453	0.9135	0.3610	2.3288	0.3797	14.2821
Legal	sexuality	LGBT	non-LGBT	0.0515	0.0357	0.2425	0.8084	1.0363	0.7767	1.3828
Legal	disability	Disability	non-Disability	0.6881	0.4769	4.4817	0.0000	1.6111	1.3078	1.9848
Legal	political_party	Democrat	Independent	0.0903	0.0626	0.5880	0.5566	1.0646	0.8642	1.3114
Legal	political_party	Republican	Independent	0.0442	0.0307	0.2750	0.7833	1.0311	0.8288	1.2829
Legal	urbanicity	Rural	Suburban	0.3426	0.2375	2.1508	0.0315	1.2680	1.0213	1.5744
Legal	urbanicity	Urban	Suburban	0.2567	0.1779	1.7846	0.0743	1.1947	0.9827	1.4526
Legal	age	18-24	65	1.7547	1.2163	5.3921	0.0000	3.3747	2.1688	5.2509
Legal	age	25-34	65	1.9547	1.3549	6.9797	0.0000	3.8764	2.6497	5.6711
Legal	age	35-44	65	1.6854	1.1682	6.0752	0.0000	3.2163	2.2064	4.6885
Legal	age	45-54	65	1.2787	0.8864	4.7581	0.0000	2.4263	1.6841	3.4955
Legal	age	55-64	65	0.7820	0.5420	3.1659	0.0015	1.7195	1.2293	2.4052
Legal	parentage	Has kids	Does not have kids	-0.1433	-0.0993	-1.1107	0.2667	0.9054	0.7599	1.0789
Legal	work_status	Full-time	Retired	0.2661	0.1845	1.1288	0.2590	1.2026	0.8730	1.6566
Legal	work_status	Part-time	Retired	-0.1937	-0.1343	-0.7253	0.4683	0.8743	0.6083	1.2568
Legal	work_status	Stay-at-home parent	Retired	-0.6275	-0.4350	-1.5114	0.1307	0.6473	0.3683	1.1378
Legal	work_status	Student	Retired	-0.4955	-0.3435	-1.1353	0.2563	0.7093	0.3920	1.2834
Legal	work_status	Unemployed / Not working	Retired	-0.6665	-0.4620	-2.5597	0.0105	0.6300	0.4423	0.8974
Legal	education	High school	College degree	0.4900	0.3397	2.6166	0.0089	1.4045	1.0890	1.8114
Legal	education	Professional schooling...	College degree	0.3643	0.2525	1.7770	0.0756	1.2873	0.9743	1.7007
Legal	education	Some college...	College degree	0.0700	0.0485	0.3930	0.6943	1.0497	0.8240	1.3373
Legal	education	Some or no high school	College degree	0.1944	0.1348	0.5689	0.5694	1.1443	0.7193	1.8203

Table 10: Model 1: contextual risk factors x demographics. Part 3 of 4 tables includes dependent variables: Social norms, Access to a sensitive resource, Legal or political

Dependent Variable	Indep. Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Relationship	gender	Male	Female	0.0552	0.0382	0.5027	0.6151	1.0390	0.8951	1.2060
Relationship	gender	Non-binary	Female	-1.7533	-1.2153	-1.8357	0.0664	0.2966	0.0810	1.0857
Relationship	race	American Indian...	White	0.5727	0.3970	1.1645	0.2442	1.4873	0.7625	2.9011
Relationship	race	Asian	White	-0.2562	-0.1776	-0.8517	0.3944	0.8373	0.5564	1.2600
Relationship	race	Black or African American	White	0.0644	0.0447	0.4363	0.6626	1.0457	0.8555	1.2781
Relationship	race	Hispanic, Latino, or Spanish	White	-0.2906	-0.2014	-1.5108	0.1309	0.8176	0.6296	1.0617
Relationship	race	Middle Eastern...	White	-1.3781	-0.9552	-0.8929	0.3719	0.3847	0.0473	3.1319
Relationship	race	Native Hawaiian...	White	1.6812	1.1653	1.2581	0.2084	3.2070	0.5220	19.7030
Relationship	sexuality	LGBT	non-LGBT	0.5295	0.3670	2.9437	0.0032	1.4434	1.1305	1.8430
Relationship	disability	Disability	non-Disability	1.0739	0.7444	8.1073	0.0000	2.1052	1.7585	2.5202
Relationship	political_party	Democrat	Independent	0.1607	0.1114	1.2014	0.2296	1.1178	0.9321	1.3406
Relationship	political_party	Republican	Independent	0.0582	0.0404	0.4122	0.6802	1.0412	0.8594	1.2614
Relationship	urbanicity	Rural	Suburban	0.1725	0.1196	1.2317	0.2181	1.1270	0.9317	1.3633
Relationship	urbanicity	Urban	Suburban	0.4420	0.3064	3.5570	0.0004	1.3585	1.1475	1.6084
Relationship	age	18-24	65	1.9598	1.3584	6.9106	0.0000	3.8900	2.6463	5.7184
Relationship	age	25-34	65	2.0440	1.4168	8.4384	0.0000	4.1238	2.9674	5.7307
Relationship	age	35-44	65	2.1352	1.4800	9.0381	0.0000	4.3931	3.1870	6.0556
Relationship	age	45-54	65	1.3938	0.9661	6.0489	0.0000	2.6276	1.9214	3.5934
Relationship	age	55-64	65	1.0778	0.7471	5.1362	0.0000	2.1108	1.5873	2.8072
Relationship	parentage	Has kids	Does not have kids	0.0766	0.0531	0.6772	0.4983	1.0546	0.9043	1.2299
Relationship	work_status	Full-time	Retired	0.3592	0.2489	1.7622	0.0780	1.2827	0.9725	1.6919
Relationship	work_status	Part-time	Retired	0.3078	0.2134	1.3777	0.1683	1.2378	0.9138	1.6769
Relationship	work_status	Stay-at-home parent	Retired	-0.3340	-0.2315	-0.9987	0.3179	0.7933	0.5037	1.2496
Relationship	work_status	Student	Retired	-0.2946	-0.2042	-0.7688	0.4420	0.8153	0.4844	1.3722
Relationship	work_status	Unemployed Not working	Retired	-0.1361	-0.0943	-0.6241	0.5325	0.9100	0.6767	1.2237
Relationship	education	High school	College degree	-0.0987	-0.0684	-0.5976	0.5501	0.9339	0.7461	1.1688
Relationship	education	Professional schooling...	College degree	0.1923	0.1333	1.0833	0.2787	1.1426	0.8977	1.4542
Relationship	education	Some college...	College degree	0.0975	0.0676	0.6523	0.5142	1.0700	0.8733	1.3110
Relationship	education	Some or no high school	College degree	-0.0887	-0.0615	-0.3054	0.7600	0.9404	0.6338	1.3953

Table 11: Model 1: contextual risk factors x demographics. Part 4 of 4 tables includes dependent variable: Relationship with attacker

Dependent Variable	Independent Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Physical threats	gender	Male	Female	0.1911	0.1325	1.3473	0.1779	1.1416	0.9415	1.3842
Physical threats	gender	Non-binary	Female	-1.3011	-0.9019	-1.2948	0.4058	1.0366	0.1036	1.5894
Physical threats	race	American Indian...	White	-1.3648	-0.9460	-1.6712	0.0947	0.3883	0.1280	1.1776
Physical threats	race	Asian	White	-1.2964	-0.8986	-2.7915	0.0052	0.4071	0.2166	0.7652
Physical threats	race	Black or African American	White	-0.3259	-0.2259	-1.7823	0.0747	0.7978	0.6223	1.0228
Physical threats	race	Hispanic, Latino, or Spanish	White	-0.6479	-0.4491	-2.7128	0.0067	0.6382	0.4614	0.8828
Physical threats	race	Middle Eastern...	White	-68.1943	-47.2687	0.0000	1.0000	0.0000	0.0000	inf
Physical threats	race	Native Hawaiian...	White	-1.8965	-1.3146	-1.0561	0.2909	0.2686	0.0234	3.0806
Physical threats	sexuality	LGBT	non-LGBT	0.4436	0.3074	2.0564	0.0397	1.3599	1.0145	1.8230
Physical threats	disability	Disability	non-Disability	0.9314	0.6456	5.5665	0.0000	1.9071	1.5193	2.3938
Physical threats	political_party	Independent	Democrat	0.1746	0.1211	1.0357	0.3003	1.1287	0.8976	1.4193
Physical threats	political_party	Republican	Democrat	-0.0319	-0.0221	-0.1864	0.8521	0.9781	0.7750	1.2344
Physical threats	urbanicity	Rural	Suburban	0.1925	0.1335	1.0904	0.2755	1.1428	0.8990	1.4526
Physical threats	urbanicity	Urban	Suburban	0.2350	0.1629	1.4831	0.1381	1.1769	0.9490	1.4596
Physical threats	age	18-24	65	3.0256	2.0972	8.0759	0.0000	8.1435	4.8951	13.5474
Physical threats	age	25-34	65	2.4665	1.7096	7.1790	0.0000	5.5268	3.4655	8.8142
Physical threats	age	35-44	65	1.9700	1.3655	5.7919	0.0000	3.9176	2.4680	6.2187
Physical threats	age	45-54	65	1.4901	1.0329	4.4906	0.0000	2.8091	1.7897	4.4091
Physical threats	age	55-64	65	0.9114	0.6317	2.8562	0.0043	1.8808	1.2192	2.9014
Physical threats	parentage	Has kids	Does not have kids	0.3660	0.2537	2.5105	0.0121	1.2888	1.0572	1.5711
Physical threats	work_status	Part-time	Full-time	0.1728	0.1198	0.8079	0.4191	1.1273	0.8430	1.5074
Physical threats	work_status	Retired	Full-time	-0.6550	-0.4540	-2.2685	0.0233	0.6351	0.4290	0.9401
Physical threats	work_status	Stay-at-home parent	Full-time	-0.6096	-0.4225	-1.6309	0.1029	0.6554	0.3944	1.0890
Physical threats	work_status	Student	Full-time	-0.0847	-0.0587	-0.2254	0.8217	0.9430	0.5659	1.5712
Physical threats	work_status	Unemployed / Not working	Full-time	-0.1799	-0.1247	-0.8368	0.4027	0.8827	0.6591	1.1822
Physical threats	education	College degree	High school	-0.6165	-0.4273	-2.8734	0.0041	0.6522	0.4873	0.8730
Physical threats	education	Professional schooling or degree	High school	-0.4831	-0.3349	-1.9713	0.0487	0.7154	0.5128	0.9981
Physical threats	education	Some college...	High school	0.0455	0.0315	0.2622	0.7931	1.0320	0.8155	1.3060
Physical threats	education	Some or no high school	High school	0.0966	0.0670	0.2925	0.7699	1.0693	0.6827	1.6746
Physical threats	resource_high	1	0	-0.1081	-0.0750	-0.7337	0.4632	0.9278	0.7594	1.1335
Physical threats	access_high	1	0	0.1427	0.0989	0.8965	0.3700	1.1040	0.8893	1.3705
Physical threats	underserved_high	1	0	-0.0981	-0.0680	-0.5494	0.5827	0.9342	0.7330	1.1908
Physical threats	prominence_high	1	0	0.2350	0.1629	1.3645	0.1724	1.1769	0.9314	1.4872
Physical threats	marginalization_high	1	0	0.7078	0.4906	3.9739	0.0001	1.6333	1.2823	2.0804
Physical threats	reliance_high	1	0	-0.4021	-0.2787	-2.5962	0.0094	0.7568	0.6132	0.9340
Physical threats	social_high	1	0	0.5107	0.3540	3.2542	0.0011	1.4247	1.1512	1.7633
Physical threats	sensitive_high	1	0	0.0244	0.0169	0.1380	0.8903	1.0170	0.8001	1.2928
Physical threats	legal_high	1	0	0.2760	0.1913	1.4781	0.1394	1.2109	0.9395	1.5605
Physical threats	relationship_high	1	0	1.3407	0.9293	8.8478	0.0000	2.5328	2.0615	3.1117
Photos or info shared...	gender	Male	Female	-0.0672	-0.0466	-0.5009	0.6164	0.9545	0.7955	1.1452
Photos or info shared...	gender	Non-binary	Female	-2.6793	-1.8572	-1.7466	0.0807	0.1561	0.0194	1.2547
Photos or info shared...	race	American Indian...	White	0.6188	0.4289	1.1112	0.2665	1.5356	0.7207	3.2722
Photos or info shared...	race	Asian	White	-0.2387	-0.1654	-0.6442	0.5194	0.8475	0.5123	1.4020
Photos or info shared...	race	Black or African American	White	-0.1775	-0.1230	-0.9875	0.3234	0.8842	0.6926	1.1288
Photos or info shared...	race	Hispanic, Latino, or Spanish	White	-0.3266	-0.2264	-1.4326	0.1520	0.7974	0.5850	1.0869
Photos or info shared...	race	Middle Eastern...	White	-0.9668	-0.6701	-0.6030	0.5465	0.5117	0.0579	4.5177
Photos or info shared...	race	Native Hawaiian...	White	2.1006	1.4560	1.4686	0.1419	4.2888	0.6144	29.9401
Photos or info shared...	sexuality	LGBT	non-LGBT	0.5937	0.4115	2.8570	0.0043	1.5091	1.1379	2.0014
Photos or info shared...	disability	Disability	non-Disability	0.7095	0.4918	4.4637	0.0000	1.6352	1.3177	2.0294
Photos or info shared...	political_party	Independent	Democrat	-0.1217	-0.0843	-0.7365	0.4614	0.9191	0.7344	1.1503
Photos or info shared...	political_party	Republican	Democrat	0.1173	0.0813	0.7427	0.4577	1.0847	0.8752	1.3442
Photos or info shared...	urbanicity	Rural	Suburban	0.2357	0.1633	1.4221	0.1550	1.1774	0.9401	1.4747
Photos or info shared...	urbanicity	Urban	Suburban	0.0941	0.0652	0.6196	0.5355	1.0674	0.8684	1.3120
Photos or info shared...	age	18-24	65	2.0273	1.4052	5.7955	0.0000	4.0765	2.5345	6.5567
Photos or info shared...	age	25-34	65	2.1879	1.5165	7.1436	0.0000	4.5564	3.0055	6.9075
Photos or info shared...	age	35-44	65	1.9066	1.3216	6.3082	0.0000	3.7493	2.4867	5.6530
Photos or info shared...	age	45-54	65	1.5809	1.0958	5.4379	0.0000	2.9915	2.0154	4.4403
Photos or info shared...	age	55-64	65	1.2887	0.8933	4.8554	0.0000	2.4431	1.7035	3.5039
Photos or info shared...	parentage	Has kids	Does not have kids	0.3743	0.2595	2.7186	0.0066	1.2962	1.0751	1.5629
Photos or info shared...	work_status	Part-time	Full-time	0.1883	0.1305	0.8925	0.3721	1.1394	0.8554	1.5177
Photos or info shared...	work_status	Retired	Full-time	0.0459	0.0318	0.1823	0.8553	1.0323	0.7335	1.4528
Photos or info shared...	work_status	Stay-at-home parent	Full-time	-0.5651	-0.3917	-1.5793	0.1143	0.6759	0.4157	1.0990
Photos or info shared...	work_status	Student	Full-time	0.1214	0.0841	0.3074	0.7585	1.0878	0.6362	1.8599
Photos or info shared...	work_status	Unemployed / Not working	Full-time	-0.1560	-0.1081	-0.7365	0.4616	0.8975	0.6730	1.1969
Photos or info shared...	education	College degree	High school	-0.3696	-0.2562	-1.8240	0.0682	0.7740	0.5877	1.0193
Photos or info shared...	education	Professional schooling or degree	High school	-0.0742	-0.0514	-0.3302	0.7413	0.9499	0.6999	1.2891
Photos or info shared...	education	Some college...	High school	0.1301	0.0902	0.7726	0.4398	1.0944	0.8705	1.3759
Photos or info shared...	education	Some or no high school	High school	-0.0221	-0.0153	-0.0673	0.9464	0.9848	0.6305	1.5382
Photos or info shared...	resource_high	1	0	0.1473	0.1021	1.0614	0.2885	1.1075	0.9172	1.3373
Photos or info shared...	access_high	1	0	0.4994	0.3461	3.3340	0.0009	1.4136	1.1533	1.7326
Photos or info shared...	underserved_high	1	0	0.0825	0.0572	0.4969	0.6193	1.0589	0.8450	1.3269
Photos or info shared...	prominence_high	1	0	0.1676	0.1161	1.0230	0.3063	1.1232	0.8991	1.4031
Photos or info shared...	marginalization_high	1	0	0.6347	0.4399	3.7301	0.0002	1.5526	1.2322	1.9564
Photos or info shared...	reliance_high	1	0	-0.2026	-0.143	-1.1421	0.8870	0.9858	0.8093	1.2007
Photos or info shared...	social_high	1	0	0.1642	0.1138	1.0862	0.2774	1.1205	0.9125	1.3760
Photos or info shared...	sensitive_high	1	0	0.0416	0.0288	0.2475	0.8045	1.0293	0.8191	1.2933
Photos or info shared...	legal_high	1	0	0.3839	0.2661	2.1659	0.0303	1.3049	1.0256	1.6602
Photos or info shared...	relationship_high	1	0	0.7733	0.5360	5.2354	0.0000	1.7091	1.3984	2.0889

Table 12: Model 2: contextual risk factors + demographics x digital-safety attacks. Part 1 of 5 tables includes dependent variables: Physical threats and Had your private photos or information shared without your permission

Dependent Variable	Independent Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Been stalked	gender	Male	Female	-0.3913	-0.2712	-2.8230	0.0048	0.7624	0.6316	0.9204
Been stalked	gender	Non-binary	Female	-3.1085	-2.1547	-2.0253	0.0428	0.1159	0.0144	0.9328
Been stalked	race	American Indian...	White	0.6638	0.4601	1.1604	0.2459	1.5843	0.7283	3.4465
Been stalked	race	Asian	White	-0.8167	-0.5661	-1.9392	0.0525	0.5677	0.3204	1.0061
Been stalked	race	Black or African American	White	-0.0709	-0.0492	-0.3947	0.6931	0.9520	0.7459	1.2152
Been stalked	race	Hispanic, Latino, or Spanish	White	-0.2582	-0.1790	-1.1235	0.2612	0.8361	0.6119	1.1426
Been stalked	race	Middle Eastern...	White	-1.2126	-0.8405	-0.7442	0.4567	0.4315	0.0472	3.9471
Been stalked	race	Native Hawaiian...	White	0.3979	0.2758	0.2678	0.7888	1.3176	0.1751	9.9156
Been stalked	sexuality	LGBT	non-LGBT	0.8259	0.5725	3.9672	0.0001	1.7727	1.3360	2.3521
Been stalked	disability	Disability	non-Disability	0.7621	0.5282	4.6337	0.0000	1.6959	1.3563	2.1205
Been stalked	political_party	Independent	Democrat	0.4729	0.3278	2.8645	0.0042	1.3879	1.1091	1.7369
Been stalked	political_party	Republican	Democrat	0.2864	0.1985	1.7196	0.0855	1.2196	0.9726	1.5293
Been stalked	urbanicity	Rural	Suburban	0.1345	0.0933	0.7830	0.4337	1.0977	0.8692	1.3864
Been stalked	urbanicity	Urban	Suburban	0.2600	0.1803	1.6890	0.0912	1.1975	0.9715	1.4761
Been stalked	age	18-24	65	2.1383	1.4822	5.8519	0.0000	4.4025	2.6798	7.2327
Been stalked	age	25-34	65	2.3780	1.6483	7.3706	0.0000	5.1983	3.3535	8.0579
Been stalked	age	35-44	65	1.8880	1.3087	5.9107	0.0000	3.7013	2.3982	5.7124
Been stalked	age	45-54	65	1.5085	1.0456	4.8799	0.0000	2.8451	1.8695	4.3300
Been stalked	age	55-64	65	0.7737	0.5363	2.6003	0.0093	1.7096	1.1412	2.5613
Been stalked	parentage	Has kids	Does not have kids	0.3811	0.2641	2.6939	0.0071	1.3023	1.0746	1.5783
Been stalked	work_status	Part-time	Full-time	0.3755	0.2603	1.7781	0.0754	1.2973	0.9737	1.7284
Been stalked	work_status	Retired	Full-time	-0.2570	-0.1782	-0.9335	0.3506	0.8368	0.5757	1.2164
Been stalked	work_status	Stay-at-home parent	Full-time	-0.2667	-0.1848	-0.7696	0.4415	0.8312	0.5191	1.3310
Been stalked	work_status	Student	Full-time	0.2596	0.1800	0.6869	0.4922	1.1972	0.7164	2.0007
Been stalked	work_status	Unemployed / Not working	Full-time	0.1507	0.1045	0.7135	0.4755	1.1101	0.8332	1.4790
Been stalked	education	College degree	High school	-0.4750	-0.3293	-2.2892	0.0221	0.7195	0.5427	0.9538
Been stalked	education	Professional schooling or degree	High school	-0.2065	-0.1431	-0.8839	0.3767	0.8666	0.6310	1.1903
Been stalked	education	Some college...	High school	0.1028	0.0712	0.6021	0.5471	1.0738	0.8516	1.3541
Been stalked	education	Some or no high school	High school	-0.4502	-0.3121	-1.3231	0.1858	0.7319	0.4610	1.1621
Been stalked	resource_high	1	0	0.0301	0.0209	0.2110	0.8329	1.0211	0.8412	1.2394
Been stalked	access_high	1	0	0.2679	0.1857	1.7434	0.0813	1.2040	0.9772	1.4835
Been stalked	underserved_high	1	0	0.1332	0.0923	0.7811	0.4348	1.0967	0.8699	1.3826
Been stalked	prominence_high	1	0	0.4840	0.3355	2.9007	0.0037	1.3986	1.1149	1.7545
Been stalked	marginalization_high	1	0	0.4067	0.2819	2.3316	0.0197	1.3257	1.0460	1.6802
Been stalked	reliance_high	1	0	-0.2432	-0.1686	-1.6254	0.1041	0.8449	0.6895	1.0353
Been stalked	social_high	1	0	0.2805	0.1944	1.8226	0.0684	1.2146	0.9855	1.4970
Been stalked	sensitive_high	1	0	0.0943	0.0654	0.5487	0.5832	1.0675	0.8453	1.3483
Been stalked	legal_high	1	0	0.3230	0.2239	1.7660	0.0774	1.2509	0.9757	1.6038
Been stalked	relationship_high	1	0	1.1396	0.7899	7.7094	0.0000	2.2031	1.8023	2.6931
Discriminated...	gender	Male	Female	0.4959	0.3437	3.6051	0.0003	1.4102	1.1698	1.7000
Discriminated...	gender	Non-binary	Female	1.3900	0.9635	1.4099	0.1586	2.6208	0.6867	10.0032
Discriminated...	race	American Indian...	White	1.2735	0.8827	2.3861	0.0170	2.4175	1.1707	4.9918
Discriminated...	race	Asian	White	-0.2114	-0.1466	-0.5688	0.5695	0.8637	0.5212	1.4311
Discriminated...	race	Black or African American	White	0.2221	0.1539	1.2708	0.2038	1.1664	0.9199	1.4789
Discriminated...	race	Hispanic, Latino, or Spanish	White	0.0247	0.0171	0.1122	0.9106	1.0173	0.7542	1.3721
Discriminated...	race	Middle Eastern...	White	-0.3232	-0.2241	-0.2500	0.8026	0.7993	0.1380	4.6307
Discriminated...	race	Native Hawaiian...	White	0.1527	0.1058	0.1001	0.9203	1.1116	0.1398	8.8371
Discriminated...	sexuality	LGBT	non-LGBT	1.3406	0.9292	6.7126	0.0000	2.5325	1.9307	3.3219
Discriminated...	disability	Disability	non-Disability	0.7934	0.5499	4.8405	0.0000	1.7331	1.3872	2.1654
Discriminated...	political_party	Independent	Democrat	0.0139	0.0096	0.0848	0.9324	1.0097	0.8085	1.2608
Discriminated...	political_party	Republican	Democrat	0.0316	0.0219	0.1911	0.8484	1.0221	0.8167	1.2792
Discriminated...	urbanicity	Rural	Suburban	-0.0364	-0.0253	-0.2089	0.8345	0.9751	0.7694	1.2357
Discriminated...	urbanicity	Urban	Suburban	0.1766	0.1224	1.1654	0.2439	1.1302	0.9199	1.3886
Discriminated...	age	18-24	65	3.1330	2.1716	8.8223	0.0000	8.7723	5.4149	14.2113
Discriminated...	age	25-34	65	2.5274	1.7518	7.7962	0.0000	5.7652	3.7114	8.9553
Discriminated...	age	35-44	65	1.9613	1.3595	6.0391	0.0000	3.8941	2.5049	6.0537
Discriminated...	age	45-54	65	1.3237	0.9175	4.1991	0.0000	2.5030	1.6311	3.8410
Discriminated...	age	55-64	65	0.8456	0.5861	2.8425	0.0045	1.7970	1.1996	2.6918
Discriminated...	parentage	Has kids	Does not have kids	0.2143	0.1485	1.5175	0.1291	1.1601	0.9576	1.4055
Discriminated...	work_status	Part-time	Full-time	0.4531	0.3140	2.1713	0.0299	1.3690	1.0310	1.8176
Discriminated...	work_status	Retired	Full-time	-0.0057	-0.0040	-0.0210	0.9832	0.9960	0.6868	1.4444
Discriminated...	work_status	Stay-at-home parent	Full-time	-0.2733	-0.1894	-0.7322	0.4641	0.8274	0.4983	1.3739
Discriminated...	work_status	Student	Full-time	-0.0020	-0.0014	-0.0054	0.9957	0.9986	0.6129	1.6273
Discriminated...	work_status	Unemployed / Not working	Full-time	0.0873	0.0605	0.4147	0.6784	1.0624	0.7981	1.4142
Discriminated...	education	College degree	High school	-0.0350	-0.0242	-0.1697	0.8653	0.9761	0.7377	1.2914
Discriminated...	education	Professional schooling or degree	High school	-0.1357	-0.0940	-0.5658	0.5715	0.9103	0.6572	1.2607
Discriminated...	education	Some college...	High school	0.3228	0.2237	1.8760	0.0607	1.2507	0.9900	1.5801
Discriminated...	education	Some or no high school	High school	0.3932	0.2725	1.2416	0.2144	1.3133	0.8541	2.0193
Discriminated...	resource_high	1	0	-0.0143	-0.0099	-0.1006	0.9199	0.9901	0.8164	1.2009
Discriminated...	access_high	1	0	0.2163	0.1499	1.4118	0.1580	1.1618	0.9434	1.4306
Discriminated...	underserved_high	1	0	-0.0865	-0.0600	-0.5033	0.6148	0.9418	0.7456	1.1896
Discriminated...	prominence_high	1	0	0.2226	0.1543	1.3458	0.1784	1.1669	0.9320	1.4609
Discriminated...	marginalization_high	1	0	0.7809	0.5413	4.5732	0.0000	1.7183	1.3625	2.1669
Discriminated...	reliance_high	1	0	-0.1842	-0.1277	-1.2405	0.2148	0.8802	0.7194	1.0768
Discriminated...	social_high	1	0	0.3216	0.2229	2.0971	0.0360	1.2498	1.0147	1.5393
Discriminated...	sensitive_high	1	0	0.2061	0.1429	1.2188	0.2229	1.1536	0.9168	1.4516
Discriminated...	legal_high	1	0	0.7227	0.5009	4.0389	0.0001	1.6502	1.2941	2.1043
Discriminated...	relationship_high	1	0	0.7934	0.5499	5.2852	0.0000	1.7331	1.4134	2.1252

Table 13: Model 2: contextual risk factors + demographics x digital-safety attacks. Part 2 of 5 tables includes dependent variables: Been stalked and Been discriminated or harassed based on your identity

Dependent Variable	Independent Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Had an account hacked	gender	Male	Female	-0.1268	-0.0879	-1.3094	0.1904	0.9159	0.8030	1.0446
Had an account hacked	gender	Non-binary	Female	-0.4607	-0.3194	-0.6105	0.5416	0.7266	0.2606	2.0258
Had an account hacked	race	American Indian...	White	0.0936	0.0648	0.2000	0.8414	1.0670	0.5653	2.0141
Had an account hacked	race	Asian	White	-0.7355	-0.5098	-2.6881	0.0072	0.6006	0.4141	0.8710
Had an account hacked	race	Black or African American	White	-0.0621	-0.0430	-0.4536	0.6501	0.9579	0.7954	1.1536
Had an account hacked	race	Hispanic, Latino, or Spanish	White	-0.5000	-0.3466	-2.8489	0.0044	0.7071	0.5571	0.8975
Had an account hacked	race	Middle Eastern...	White	0.3412	0.2365	0.3655	0.7148	1.2668	0.3563	4.5042
Had an account hacked	race	Native Hawaiian...	White	-0.5860	-0.4062	-0.4388	0.6608	0.6662	0.1086	4.0877
Had an account hacked	sexuality	LGBT	non-LGBT	0.6405	0.4440	3.6371	0.0003	1.5589	1.2272	1.9802
Had an account hacked	disability	Disability	non-Disability	0.4095	0.2839	3.4332	0.0006	1.3283	1.1295	1.5620
Had an account hacked	political_party	Independent	Democrat	0.4321	0.2995	3.6725	0.0002	1.3492	1.1499	1.5830
Had an account hacked	political_party	Republican	Democrat	0.2691	0.1865	2.3263	0.0200	1.2051	1.0298	1.4101
Had an account hacked	urbanicity	Rural	Suburban	0.2283	0.1582	1.9168	0.0553	1.1714	0.9964	1.3771
Had an account hacked	urbanicity	Urban	Suburban	0.1695	0.1175	1.5296	0.1261	1.1247	0.9675	1.3075
Had an account hacked	age	18-24	65	0.6314	0.4376	2.6108	0.0090	1.5491	1.1153	2.1515
Had an account hacked	age	25-34	65	0.6989	0.4844	3.4853	0.0005	1.6232	1.2362	2.1315
Had an account hacked	age	35-44	65	0.5510	0.3820	2.7965	0.0052	1.4651	1.1210	1.9149
Had an account hacked	age	45-54	65	0.5075	0.3518	2.7593	0.0058	1.4216	1.1073	1.8252
Had an account hacked	age	55-64	65	0.1898	0.1316	1.1760	0.2396	1.1406	0.9160	1.4203
Had an account hacked	parentage	Has kids	Does not have kids	0.3703	0.2567	3.7293	0.0002	1.2926	1.1295	1.4793
Had an account hacked	work_status	Part-time	Full-time	0.0194	0.0134	0.1215	0.9033	1.0135	0.8159	1.2590
Had an account hacked	work_status	Retired	Full-time	0.0250	0.0173	0.1502	0.8806	1.0175	0.8114	1.2759
Had an account hacked	work_status	Stay-at-home parent	Full-time	-0.1312	-0.0910	-0.5080	0.6114	0.9130	0.6428	1.2969
Had an account hacked	work_status	Student	Full-time	-0.2330	-0.1615	-0.7391	0.4598	0.8509	0.5545	1.3057
Had an account hacked	work_status	Unemployed / Not working	Full-time	0.0286	0.0198	0.1787	0.8581	1.0200	0.8209	1.2674
Had an account hacked	education	College degree	High school	0.1818	0.1260	1.2686	0.2046	1.1343	0.9336	1.3782
Had an account hacked	education	Professional schooling or degree	High school	0.3595	0.2492	2.2220	0.0263	1.2830	1.0298	1.5984
Had an account hacked	education	Some college...	High school	0.3529	0.2446	2.8228	0.0048	1.2771	1.0776	1.5135
Had an account hacked	education	Some or no high school	High school	0.2834	0.1965	1.1066	0.2685	1.2171	0.8594	1.7236
Had an account hacked	resource_high	1	0	0.1701	0.1179	1.6974	0.0896	1.1251	0.9819	1.2892
Had an account hacked	access_high	1	0	0.1872	0.1298	1.6328	0.1025	1.1386	0.9743	1.3304
Had an account hacked	underserved_high	1	0	0.0690	0.0478	0.5614	0.5745	1.0490	0.8876	1.2397
Had an account hacked	prominence_high	1	0	-0.0713	-0.0494	-0.5683	0.5698	0.9518	0.8027	1.1286
Had an account hacked	marginalization_high	1	0	0.0466	0.0323	0.3371	0.7361	1.0328	0.8561	1.2460
Had an account hacked	reliance_high	1	0	0.0439	0.0304	0.4129	0.6797	1.0309	0.8922	1.1912
Had an account hacked	social_high	1	0	-0.1132	-0.0785	-1.0007	0.3169	0.9245	0.7928	1.0781
Had an account hacked	sensitive_high	1	0	0.0296	0.0205	0.2199	0.8259	1.0207	0.8500	1.2257
Had an account hacked	legal_high	1	0	0.1364	0.0945	0.9219	0.3566	1.0991	0.8990	1.3438
Had an account hacked	relationship_high	1	0	0.6537	0.4531	5.3943	0.0000	1.5732	1.3344	1.8548
Had money stolen	gender	Male	Female	-0.1686	-0.1169	-1.5533	0.1204	0.8897	0.7677	1.0311
Had money stolen	gender	Non-binary	Female	-0.2684	-0.1861	-0.3218	0.7476	0.8302	0.2673	2.5783
Had money stolen	race	American Indian...	White	-0.0569	-0.0394	-0.1100	0.9124	0.9614	0.4765	1.9397
Had money stolen	race	Asian	White	0.0207	0.0143	0.0688	0.9452	1.0144	0.6742	1.5263
Had money stolen	race	Black or African American	White	0.4927	0.3415	3.3669	0.0008	1.4071	1.1534	1.7166
Had money stolen	race	Hispanic, Latino, or Spanish	White	-0.0999	-0.0693	-0.5245	0.6000	0.9331	0.7203	1.2088
Had money stolen	race	Middle Eastern...	White	-1.6912	-1.1723	-1.0940	0.2740	0.3097	0.0379	2.5292
Had money stolen	race	Native Hawaiian...	White	0.3519	0.2439	0.2601	0.7948	1.2762	0.2032	8.0159
Had money stolen	sexuality	LGBT	non-LGBT	0.5030	0.3486	2.7450	0.0061	1.4171	1.1048	1.8177
Had money stolen	disability	Disability	non-Disability	0.5630	0.3902	4.3048	0.0000	1.4773	1.2368	1.7645
Had money stolen	political_party	Independent	Democrat	0.1455	0.1008	1.1075	0.2681	1.1061	0.9253	1.3222
Had money stolen	political_party	Republican	Democrat	0.2143	0.1485	1.6517	0.0986	1.1601	0.9727	1.3837
Had money stolen	urbanicity	Rural	Suburban	0.2358	0.1634	1.7767	0.0756	1.1775	0.9833	1.4102
Had money stolen	urbanicity	Urban	Suburban	0.0775	0.0537	0.6281	0.5300	1.0552	0.8923	1.2478
Had money stolen	age	18-24	65	0.5017	0.3477	1.8618	0.0626	1.4159	0.9818	2.0418
Had money stolen	age	25-34	65	0.7109	0.4927	3.1304	0.0017	1.6368	1.2023	2.2283
Had money stolen	age	35-44	65	0.6993	0.4847	3.1481	0.0016	1.6237	1.2007	2.1956
Had money stolen	age	45-54	65	0.6177	0.4281	2.9389	0.0033	1.5344	1.1533	2.0415
Had money stolen	age	55-64	65	0.0873	0.0605	0.4545	0.6495	1.0624	0.8183	1.3793
Had money stolen	parentage	Has kids	Does not have kids	0.0394	0.0273	0.3579	0.7204	1.0277	0.8849	1.1935
Had money stolen	work_status	Part-time	Full-time	-0.0371	-0.0257	-0.2140	0.8305	0.9746	0.7702	1.2333
Had money stolen	work_status	Retired	Full-time	-0.5046	-0.3497	-2.6044	0.0092	0.7049	0.5418	0.9171
Had money stolen	work_status	Stay-at-home parent	Full-time	-0.6796	-0.4711	-2.2745	0.0229	0.6243	0.4160	0.9369
Had money stolen	work_status	Student	Full-time	-0.1181	-0.0819	-0.3500	0.7263	0.9214	0.5825	1.4574
Had money stolen	work_status	Unemployed / Not working	Full-time	-0.5326	-0.3692	-3.0347	0.0024	0.6913	0.5447	0.8774
Had money stolen	education	College degree	High school	-0.2749	-0.1906	-1.6947	0.0901	0.8265	0.6630	1.0303
Had money stolen	education	Professional schooling or degree	High school	-0.1310	-0.0908	-0.7178	0.4729	0.9132	0.7128	1.1701
Had money stolen	education	Some college...	High school	0.2459	0.1705	1.8026	0.0714	1.1859	0.9852	1.4273
Had money stolen	education	Some or no high school	High school	-0.3076	-0.2132	-1.0724	0.2836	0.8080	0.5472	1.1930
Had money stolen	resource_high	1	0	0.2294	0.1590	2.0517	0.0402	1.1723	1.0071	1.3646
Had money stolen	access_high	1	0	0.2182	0.1512	1.7488	0.0803	1.1633	0.9819	1.3782
Had money stolen	underserved_high	1	0	0.0929	0.0644	0.6892	0.4907	1.0665	0.8881	1.2807
Had money stolen	prominence_high	1	0	-0.0127	-0.0088	-0.0931	0.9258	0.9912	0.8231	1.1936
Had money stolen	marginalization_high	1	0	0.1429	0.0991	0.9660	0.3340	1.1042	0.9031	1.3500
Had money stolen	reliance_high	1	0	0.1074	0.0745	0.9143	0.3605	1.0773	0.9184	1.2638
Had money stolen	social_high	1	0	0.1234	0.0855	0.9974	0.3186	1.0893	0.9208	1.2887
Had money stolen	sensitive_high	1	0	0.0858	0.0594	0.5937	0.5527	1.0613	0.8721	1.2914
Had money stolen	legal_high	1	0	0.1239	0.0859	0.7908	0.4291	1.0896	0.8808	1.3480
Had money stolen	relationship_high	1	0	0.6876	0.4766	5.4231	0.0000	1.6106	1.3557	1.9133

Table 14: Model 2: contextual risk factors + demographics x digital-safety attacks. Part 3 of 5 tables includes dependent variables: Had an account hacked and Had money stolen

Dependent Variable	Independent Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Virus or malware...	gender	Male	Female	0.5940	0.4117	5.8111	0.0000	1.5094	1.3137	1.7343
Virus or malware...	gender	Non-binary	Female	0.7859	0.5447	0.9666	0.3337	1.7241	0.5713	5.2029
Virus or malware...	race	American Indian...	White	0.2215	0.1536	0.4417	0.6587	1.1660	0.5899	2.3045
Virus or malware...	race	Asian	White	-0.3872	-0.2684	-1.3647	0.1723	0.7646	0.5200	1.1242
Virus or malware...	race	Black or African American	White	0.0244	0.0169	0.1677	0.8668	1.0171	0.8346	1.2394
Virus or malware...	race	Hispanic, Latino, or Spanish	White	-0.1814	-0.1258	-0.9652	0.3345	0.8818	0.6831	1.1384
Virus or malware...	race	Middle Eastern...	White	0.8404	0.5825	0.8506	0.3950	1.7905	0.4678	6.8534
Virus or malware...	race	Native Hawaiian...	White	0.3163	0.2193	0.2355	0.8138	1.2452	0.2009	7.7191
Virus or malware...	sexuality	LGBT	non-LGBT	0.2539	0.1760	1.3852	0.1660	1.1924	0.9296	1.5296
Virus or malware...	disability	Disability	non-Disability	0.5396	0.3740	4.3053	0.0000	1.4536	1.2260	1.7234
Virus or malware...	political_party	Independent	Democrat	0.3385	0.2346	2.7161	0.0066	1.2644	1.0675	1.4977
Virus or malware...	political_party	Republican	Democrat	0.1680	0.1164	1.3665	0.1718	1.1235	0.9507	1.3277
Virus or malware...	urbanicity	Rural	Suburban	0.0286	0.0198	0.2251	0.8219	1.0200	0.8583	1.2123
Virus or malware...	urbanicity	Urban	Suburban	0.0242	0.0168	0.2065	0.8364	1.0169	0.8670	1.1928
Virus or malware...	age	18-24	65	-0.7598	-0.5266	-2.8602	0.0042	0.5906	0.4117	0.8473
Virus or malware...	age	25-34	65	-0.5636	-0.3907	-2.6373	0.0084	0.6766	0.5061	0.9045
Virus or malware...	age	35-44	65	-0.1651	-0.1144	-0.8034	0.4217	0.8919	0.6746	1.1791
Virus or malware...	age	45-54	65	-0.3466	-0.2402	-1.7893	0.0736	0.7864	0.6045	1.0232
Virus or malware...	age	55-64	65	-0.0430	-0.0298	-0.2562	0.7978	0.9706	0.7727	1.2193
Virus or malware...	parentage	Has kids	Does not have kids	0.1600	0.1109	1.5290	0.1263	1.1173	0.9692	1.2880
Virus or malware...	work_status	Part-time	Full-time	0.0451	0.0312	0.2648	0.7912	1.0317	0.8188	1.3001
Virus or malware...	work_status	Retired	Full-time	-0.1170	-0.0811	-0.6736	0.5006	0.9221	0.7283	1.1675
Virus or malware...	work_status	Stay-at-home parent	Full-time	-0.6984	-0.4841	-2.2392	0.0251	0.6163	0.4034	0.9414
Virus or malware...	work_status	Student	Full-time	0.1398	0.0969	0.3952	0.6927	1.1018	0.6813	1.7819
Virus or malware...	work_status	Unemployed / Not working	Full-time	-0.1897	-0.1315	-1.0992	0.2717	0.8768	0.6936	1.1084
Virus or malware...	education	College degree	High school	0.6044	0.4189	3.9703	0.0001	1.5203	1.2363	1.8696
Virus or malware...	education	Professional schooling or degree	High school	0.7385	0.5119	4.3154	0.0000	1.6685	1.3223	2.1052
Virus or malware...	education	Some college...	High school	0.5058	0.3506	3.7530	0.0002	1.4199	1.1823	1.7052
Virus or malware...	education	Some or no high school	High school	-0.0935	-0.0648	-0.3184	0.7502	0.9372	0.6288	1.3969
Virus or malware...	resource_high	1	0	0.2164	0.1500	2.0281	0.0426	1.1618	1.0051	1.3430
Virus or malware...	access_high	1	0	0.2061	0.1429	1.6999	0.0892	1.1536	0.9784	1.3601
Virus or malware...	underserved_high	1	0	-0.0544	-0.0377	-0.4135	0.6792	0.9630	0.8052	1.1516
Virus or malware...	prominence_high	1	0	-0.0399	-0.0277	-0.3007	0.7636	0.9727	0.8122	1.1649
Virus or malware...	marginalization_high	1	0	0.2208	0.1531	1.5246	0.1274	1.1654	0.9572	1.4189
Virus or malware...	reliance_high	1	0	-0.0119	-0.0082	-0.1048	0.9165	0.9918	0.8503	1.1569
Virus or malware...	social_high	1	0	-0.0492	-0.0341	-0.4067	0.6842	0.9665	0.8200	1.1391
Virus or malware...	sensitive_high	1	0	0.2816	0.1952	2.0250	0.0429	1.2155	1.0063	1.4683
Virus or malware...	legal_high	1	0	0.1507	0.1045	0.9711	0.3315	1.1101	0.8991	1.3706
Virus or malware...	relationship_high	1	0	0.5426	0.3761	4.2742	0.0000	1.4566	1.2259	1.7308
Scam, phishing, trick...	gender	Male	Female	0.4019	0.2786	4.1686	0.0000	1.3212	1.1590	1.5061
Scam, phishing, trick...	gender	Non-binary	Female	1.0706	0.7421	1.2302	0.2186	2.1003	0.6439	6.8506
Scam, phishing, trick...	race	American Indian...	White	-0.0091	-0.0063	-0.0195	0.9845	0.9937	0.5264	1.8758
Scam, phishing, trick...	race	Asian	White	-0.5533	-0.3835	-2.1146	0.0345	0.6815	0.4776	0.9723
Scam, phishing, trick...	race	Black or African American	White	0.0341	0.0236	0.2485	0.8038	1.0239	0.8499	1.2335
Scam, phishing, trick...	race	Hispanic, Latino, or Spanish	White	-0.0718	-0.0498	-0.4170	0.6767	0.9515	0.7531	1.2021
Scam, phishing, trick...	race	Middle Eastern...	White	-0.1094	-0.0758	-0.1173	0.9067	0.9270	0.2609	3.2932
Scam, phishing, trick...	race	Native Hawaiian...	White	0.2593	0.1797	0.1944	0.8459	1.1969	0.1955	7.3288
Scam, phishing, trick...	sexuality	LGBT	non-LGBT	0.4342	0.3010	2.4335	0.0150	1.3512	1.0603	1.7218
Scam, phishing, trick...	disability	Disability	non-Disability	0.4719	0.3271	3.9180	0.0001	1.3870	1.1776	1.6335
Scam, phishing, trick...	political_party	Independent	Democrat	0.4307	0.2985	3.6781	0.0002	1.3479	1.1496	1.5802
Scam, phishing, trick...	political_party	Republican	Democrat	0.2657	0.1842	2.3115	0.0208	1.2022	1.0284	1.4054
Scam, phishing, trick...	urbanicity	Rural	Suburban	0.2348	0.1627	1.9758	0.0482	1.1767	1.0013	1.3829
Scam, phishing, trick...	urbanicity	Urban	Suburban	0.0272	0.0189	0.2463	0.8054	1.0190	0.8770	1.1841
Scam, phishing, trick...	age	18-24	65	-0.1801	-0.1248	-0.7461	0.4556	0.8827	0.6359	1.2252
Scam, phishing, trick...	age	25-34	65	-0.5661	-0.3924	-2.8321	0.0046	0.6754	0.5148	0.8862
Scam, phishing, trick...	age	35-44	65	-0.4689	-0.3250	-2.3849	0.0171	0.7225	0.5532	0.9437
Scam, phishing, trick...	age	45-54	65	-0.3393	-0.2352	-1.8444	0.0651	0.7904	0.6156	1.0148
Scam, phishing, trick...	age	55-64	65	-0.2652	-0.1838	-1.6538	0.0982	0.8321	0.6692	1.0346
Scam, phishing, trick...	parentage	Has kids	Does not have kids	0.1554	0.1077	1.5803	0.1140	1.1138	0.9744	1.2730
Scam, phishing, trick...	work_status	Part-time	Full-time	0.0278	0.0193	0.1754	0.8608	1.0195	0.8217	1.2649
Scam, phishing, trick...	work_status	Retired	Full-time	0.0562	0.0389	0.3393	0.7344	1.0397	0.8303	1.3019
Scam, phishing, trick...	work_status	Stay-at-home parent	Full-time	-0.1748	-0.1212	-0.6740	0.5003	0.8859	0.6228	1.2601
Scam, phishing, trick...	work_status	Student	Full-time	-0.0404	-0.0280	-0.1273	0.8987	0.9724	0.6318	1.4967
Scam, phishing, trick...	work_status	Unemployed / Not working	Full-time	0.1814	0.1257	1.1346	0.2565	1.1340	0.9126	1.4090
Scam, phishing, trick...	education	College degree	High school	0.7562	0.5241	5.3067	0.0000	1.6890	1.3917	2.0498
Scam, phishing, trick...	education	Professional schooling or degree	High school	0.9499	0.6584	5.8735	0.0000	1.9318	1.5507	2.4065
Scam, phishing, trick...	education	Some college...	High school	0.5636	0.3906	4.5365	0.0000	1.4779	1.2484	1.7496
Scam, phishing, trick...	education	Some or no high school	High school	0.0979	0.0679	0.3804	0.7037	1.0702	0.7544	1.5184
Scam, phishing, trick...	resource_high	1	0	0.5033	0.3489	5.0253	0.0000	1.4175	1.2371	1.6241
Scam, phishing, trick...	access_high	1	0	0.2388	0.1655	2.0800	0.0375	1.1800	1.0096	1.3791
Scam, phishing, trick...	underserved_high	1	0	-0.1670	-0.1158	-1.3561	0.1751	0.8907	0.7534	1.0529
Scam, phishing, trick...	prominence_high	1	0	-0.1372	-0.0951	-1.0956	0.2732	0.9093	0.7671	1.0779
Scam, phishing, trick...	marginalization_high	1	0	-0.0472	-0.0327	-0.3394	0.7343	0.9678	0.8011	1.1692
Scam, phishing, trick...	reliance_high	1	0	-0.1175	-0.0814	-1.1086	0.2676	0.9218	0.7982	1.0645
Scam, phishing, trick...	social_high	1	0	-0.1450	-0.1005	-1.2824	0.1997	0.9044	0.7755	1.0546
Scam, phishing, trick...	sensitive_high	1	0	0.0517	0.0358	0.3834	0.7014	1.0365	0.8631	1.2447
Scam, phishing, trick...	legal_high	1	0	0.1859	0.1289	1.2416	0.2144	1.1375	0.9282	1.3941
Scam, phishing, trick...	relationship_high	1	0	0.7640	0.5295	6.1877	0.0000	1.6981	1.4359	2.0082

Table 15: Model 2: contextual risk factors + demographics x digital-safety attacks. Part 4 of 5 tables includes dependent variables: Been the target of a virus or malware attack and Been the target of a scam or phishing attack

Dependent Variable	Independent Variable	Treatment	Baseline	β (log2)	Log Odds (β)	t statistic	P r (> t)	Odds Ratio	CI (lower)	CI (upper)
Insulted, treated badly...	gender	Male	Female	0.0431	0.0299	0.3865	0.6991	1.0303	0.8855	1.1989
Insulted, treated badly...	gender	Non-binary	Female	1.4684	1.0178	1.5698	0.1165	2.7672	0.7765	9.8615
Insulted, treated badly...	race	American Indian...	White	0.8413	0.5832	1.7339	0.0829	1.7917	0.9268	3.4638
Insulted, treated badly...	race	Asian	White	-1.0027	-0.6950	-3.0977	0.0020	0.4991	0.3215	0.7747
Insulted, treated badly...	race	Black or African American	White	-0.7302	-0.5062	-4.6695	0.0000	0.6028	0.4874	0.7455
Insulted, treated badly...	race	Hispanic, Latino, or Spanish	White	-0.1126	-0.0780	-0.6024	0.5469	0.9249	0.7175	1.1923
Insulted, treated badly...	race	Middle Eastern...	White	0.0794	0.0550	0.0763	0.9392	1.0565	0.2571	4.3427
Insulted, treated badly...	race	Native Hawaiian...	White	-0.9334	-0.6470	-0.6386	0.5231	0.5236	0.0719	3.8148
Insulted, treated badly...	sexuality	LGBT	non-LGBT	0.6851	0.4749	3.6929	0.0002	1.6079	1.2496	2.0688
Insulted, treated badly...	disability	Disability	non-Disability	0.8445	0.5853	6.3162	0.0000	1.7956	1.4974	2.1532
Insulted, treated badly...	political_party	Independent	Democrat	0.2134	0.1479	1.6029	0.1089	1.1595	0.9676	1.3894
Insulted, treated badly...	political_party	Republican	Democrat	-0.0685	-0.0475	-0.5126	0.6082	0.9536	0.7952	1.1436
Insulted, treated badly...	urbanicity	Rural	Suburban	0.2271	0.1574	1.6613	0.0967	1.1705	0.9721	1.4094
Insulted, treated badly...	urbanicity	Urban	Suburban	0.1175	0.0814	0.9305	0.3521	1.0848	0.9139	1.2878
Insulted, treated badly...	age	18-24	65	2.6932	1.8668	9.7654	0.0000	6.4676	4.4466	9.4073
Insulted, treated badly...	age	25-34	65	2.1964	1.5224	9.2716	0.0000	4.5833	3.3221	6.3233
Insulted, treated badly...	age	35-44	65	1.5605	1.0817	6.6589	0.0000	2.9496	2.1453	4.0554
Insulted, treated badly...	age	45-54	65	0.8746	0.6062	3.8759	0.0001	1.8335	1.3494	2.4913
Insulted, treated badly...	age	55-64	65	0.8924	0.6186	4.4688	0.0000	1.8563	1.4152	2.4348
Insulted, treated badly...	parentage	Has kids	Does not have kids	0.0514	0.0357	0.4529	0.6506	1.0363	0.8881	1.2092
Insulted, treated badly...	work_status	Part-time	Full-time	0.2412	0.1672	1.3632	0.1728	1.1820	0.9294	1.5031
Insulted, treated badly...	work_status	Retired	Full-time	-0.0819	-0.0567	-0.4078	0.6834	0.9448	0.7193	1.2410
Insulted, treated badly...	work_status	Stay-at-home parent	Full-time	-0.1014	-0.0703	-0.3478	0.7280	0.9322	0.6274	1.3849
Insulted, treated badly...	work_status	Student	Full-time	-0.0359	-0.0249	-0.1101	0.9123	0.9754	0.6265	1.5187
Insulted, treated badly...	work_status	Unemployed / Not working	Full-time	0.1621	0.1123	0.9272	0.3538	1.1189	0.8824	1.4188
Insulted, treated badly...	education	College degree	High school	0.1965	0.1362	1.1795	0.2382	1.1459	0.9138	1.4370
Insulted, treated badly...	education	Professional schooling or degree	High school	0.3820	0.2648	2.0400	0.0413	1.3032	1.0104	1.6807
Insulted, treated badly...	education	Some college...	High school	0.4040	0.2800	2.8117	0.0049	1.3231	1.0885	1.6083
Insulted, treated badly...	education	Some or no high school	High school	-0.2476	-0.1716	-0.8627	0.3883	0.8423	0.5703	1.2439
Insulted, treated badly...	resource_high	1	0	0.1449	0.1005	1.2640	0.2062	1.1057	0.9462	1.2920
Insulted, treated badly...	access_high	1	0	0.2054	0.1423	1.6093	0.1075	1.1530	0.9695	1.3712
Insulted, treated badly...	underserved_high	1	0	-0.1875	-0.1300	-1.3175	0.1877	0.8781	0.7237	1.0654
Insulted, treated badly...	prominence_high	1	0	-0.0860	-0.0596	-0.6111	0.5411	0.9421	0.7782	1.1406
Insulted, treated badly...	marginalization_high	1	0	0.6413	0.4445	4.2868	0.0000	1.5598	1.2729	1.9113
Insulted, treated badly...	reliance_high	1	0	-0.2875	-0.1993	-2.3391	0.0193	0.8193	0.6933	0.9682
Insulted, treated badly...	social_high	1	0	0.0821	0.0569	0.6367	0.5243	1.0585	0.8885	1.2612
Insulted, treated badly...	sensitive_high	1	0	0.0905	0.0628	0.6107	0.5414	1.0648	0.8705	1.3023
Insulted, treated badly...	legal_high	1	0	0.0624	0.0433	0.3842	0.7008	1.0442	0.8374	1.3021
Insulted, treated badly...	relationship_high	1	0	1.2001	0.8318	9.4107	0.0000	2.2976	1.9321	2.7322
Unwanted explicit content...	gender	Male	Female	-0.0524	-0.0364	-0.5107	0.6096	0.9643	0.8387	1.1087
Unwanted explicit content...	gender	Non-binary	Female	1.1362	0.7875	1.4504	0.1470	2.1980	0.7583	6.3709
Unwanted explicit content...	race	American Indian...	White	-0.0232	-0.0161	-0.0464	0.9630	0.9840	0.4986	1.9421
Unwanted explicit content...	race	Asian	White	-0.6898	-0.4782	-2.2827	0.0224	0.6199	0.4112	0.9346
Unwanted explicit content...	race	Black or African American	White	0.0097	0.0068	0.0678	0.9459	1.0068	0.8282	1.2238
Unwanted explicit content...	race	Hispanic, Latino, or Spanish	White	0.0409	0.0284	0.2291	0.8188	1.0288	0.8071	1.3112
Unwanted explicit content...	race	Middle Eastern...	White	1.9885	1.3783	1.9266	0.0540	3.9683	0.9764	16.1282
Unwanted explicit content...	race	Native Hawaiian...	White	0.9468	0.6563	0.6891	0.4907	1.9276	0.2981	12.4637
Unwanted explicit content...	sexuality	LGBT	non-LGBT	0.3798	0.2632	2.1182	0.0342	1.3011	1.0199	1.6600
Unwanted explicit content...	disability	Disability	non-Disability	0.6088	0.4220	4.8735	0.0000	1.5250	1.2869	1.8070
Unwanted explicit content...	political_party	Independent	Democrat	0.2009	0.1393	1.6152	0.1063	1.1494	0.9707	1.3611
Unwanted explicit content...	political_party	Republican	Democrat	0.1756	0.1217	1.4278	0.1534	1.1294	0.9556	1.3349
Unwanted explicit content...	urbanicity	Rural	Suburban	0.2214	0.1535	1.7632	0.0779	1.1659	0.9830	1.3828
Unwanted explicit content...	urbanicity	Urban	Suburban	-0.1058	-0.0733	-0.8960	0.3703	0.9293	0.7916	1.0909
Unwanted explicit content...	age	18-24	65	1.5233	1.0559	5.9941	0.0000	2.8745	2.0353	4.0599
Unwanted explicit content...	age	25-34	65	1.0391	0.7203	4.8392	0.0000	2.0550	1.5350	2.7510
Unwanted explicit content...	age	35-44	65	0.9292	0.6440	4.4163	0.0000	1.9042	1.4308	2.5342
Unwanted explicit content...	age	45-54	65	0.5621	0.3897	2.8296	0.0047	1.4765	1.1272	1.9339
Unwanted explicit content...	age	55-64	65	0.3789	0.2626	2.1550	0.0312	1.3003	1.0241	1.6511
Unwanted explicit content...	parentage	Has kids	Does not have kids	0.3045	0.2111	2.8894	0.0039	1.2350	1.0703	1.4251
Unwanted explicit content...	work_status	Part-time	Full-time	0.2033	0.1409	1.2233	0.2212	1.1514	0.9186	1.4430
Unwanted explicit content...	work_status	Retired	Full-time	-0.0320	-0.0222	-0.1776	0.8591	0.9781	0.7659	1.2491
Unwanted explicit content...	work_status	Stay-at-home parent	Full-time	-0.3010	-0.2086	-1.0840	0.2784	0.8117	0.5566	1.1836
Unwanted explicit content...	work_status	Student	Full-time	0.3556	0.2465	1.1162	0.2643	1.2795	0.8300	1.9723
Unwanted explicit content...	work_status	Unemployed / Not working	Full-time	0.0267	0.0185	0.1597	0.8731	1.0187	0.8119	1.2781
Unwanted explicit content...	education	College degree	High school	0.4618	0.3201	2.9938	0.0028	1.3773	1.1169	1.6983
Unwanted explicit content...	education	Professional schooling or degree	High school	0.5436	0.3768	3.1207	0.0018	1.4576	1.1505	1.8468
Unwanted explicit content...	education	Some college...	High school	0.6980	0.4838	5.2006	0.0000	1.6223	1.3519	1.9468
Unwanted explicit content...	education	Some or no high school	High school	0.0519	0.0360	0.1909	0.8486	1.0367	0.7163	1.5003
Unwanted explicit content...	resource_high	1	0	0.3623	0.2511	3.4274	0.0006	1.2854	1.1135	1.4839
Unwanted explicit content...	access_high	1	0	0.1957	0.1357	1.6310	0.1029	1.1453	0.9730	1.3481
Unwanted explicit content...	underserved_high	1	0	-0.2183	-0.1513	-1.6643	0.0961	0.8596	0.7193	1.0272
Unwanted explicit content...	prominence_high	1	0	0.0523	0.0362	0.3985	0.6903	1.0369	0.8677	1.2391
Unwanted explicit content...	marginalization_high	1	0	0.1979	0.1372	1.3851	0.1660	1.1470	0.9447	1.3927
Unwanted explicit content...	reliance_high	1	0	-0.1595	-0.1106	-1.4101	0.1585	0.8953	0.7677	1.0441
Unwanted explicit content...	social_high	1	0	-0.1073	-0.0744	-0.8875	0.3748	0.9283	0.7876	1.0941
Unwanted explicit content...	sensitive_high	1	0	-0.0434	-0.0301	-0.3086	0.7576	0.9704	0.8017	1.1746
Unwanted explicit content...	legal_high	1	0	0.1872	0.1297	1.2250	0.2206	1.1385	0.9251	1.4012
Unwanted explicit content...	relationship_high	1	0	0.9149	0.6341	7.4412	0.0000	1.8854	1.5954	2.2282

Table 16: Model 2: contextual risk factors + demographics x digital-safety attacks. Part 5 of 5 tables includes dependent variables: Been insulted or treated badly online and Been exposed to unwanted explicit content