Cautious Clicks:
Analyzing the Perceived Risks on the Web

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Abstract

In this report, we study the public perception of technology related risks (e.g., fear while expressing opinions on a controversial issue) and try to understand the factors that make people sensitive to certain kinds of *risks*. We analyse the Internet Supplement from CPS Survey and focus on questions on internet usage, concerns, and online behaviours which, to the best of our knowledge, is previously unexplored. Our contributions include identifying and categorizing features that are deemed important for the risk-perception. The results uncover the interesting insight that over time people are warming up to the convenience of using internet for automated tasks such as banking/shopping, but growing increasingly cautious of social interactions such as sharing opinions. The code and experiments can be found here.

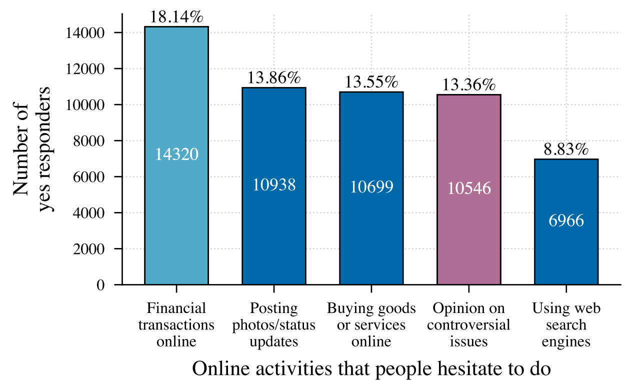

Figure 1. Various online activities and the number of people who expressed their hesitation (risk-perceptions) to do them. Most people (18.14%) have second thoughts while doing *financial transactions*, while $\sim 10k$ also expressed unwillingness to do other activities. But *who are these people*, i.e., is there a correlation between other attributes and the tendency to perceive such risks?

1. Introduction

The internet has emerged as a powerful tool for communication, information dissemination, and social interaction in this era. However, with the increasing reliance on the online landscape, concerns about privacy, security, and the potential risks associated with internet are also on the rise. This project report studies how the population perceive such technology-induced risks, using a recent (2021) dataset from the Current Population Survey (CPS) in the United States (US). The title, "Cautious Clicks" encapsulates the essence of our research: to unravel the factors influencing individuals' decisions on a spectrum of things (shown in Figure 1), on the internet. For the rest of this report, we will keep referring to the activities (that people are often hesitant to do) mentioned in Figure 1, as "risks" or "target variables" interchangeably, and it is for these set of activities that we will analyze the risk-perceptions, which we define as:

Definition 1.1. Given a particular online activity, we define the *risk-perception* associated with it to be the proportion of people who responded in affirmative when asked if they ever hesitated to carry out *that* online activity fearing any kind of privacy or security related concern or social repercussions.

Risk-perception (for an activity or risk) can also be thought of as the probability that a random person responds positively to such questions. Similarly, the *risk-perception for a group* (e.g., people with income $> 150k$, or with a higher degree) is defined as the same proportion but when the universe of the population is restricted to that group.

Outline As stated earlier, the aim of this report is to understand which factors shape the risk-perception of the population on digital spaces. We first look at the attribute present in the data: `HEPSCYBA`, which tells if the respondent has been affected by any kind of cyber crime in real life. We derive the (normalized) cyber crime rate per state using this

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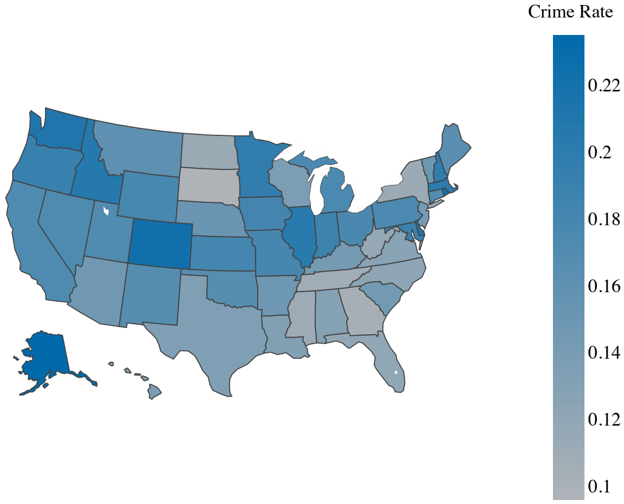

Figure 2. Fraction of people in each US state who were affected by online security or data breach, identity theft, or a similar crime on the web. We normalized the total count of affected people by the number of respondents (in each state) to obtain the fractions.

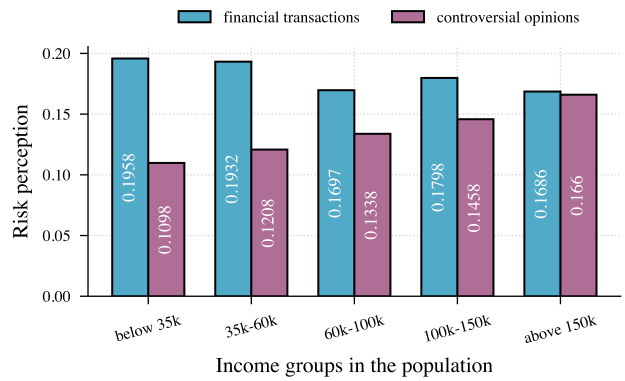

Figure 3. Here we take two such activities from Figure 1 and see if it correlates with different income groups in the population. We observe that wealthier people tend to become more conservative while expressing opinions on controversial topics online. Interestingly, their concerns on doing financial transactions also drops. More such plots also show similar trends and can be found here.

feature, and plot its geographic distribution over the US states (Fig. 2). Interestingly, we also find this distribution correlates with the internet access/usage rates over the country (Pearson coefficient: 0.46, p-value: 10^{-3}). To find other factors associated with specific risks, we group the population under different categories and perform hypothesis testing (Sec. 4.1). Sec. 4.2 scales finding correlated features over the large number of features using feature importance scores from an *XGBoost* model. The subsequent importance plots contain a high degree of presence of digital access and wealth related features, which perhaps supports our initial observation of the association between digital access and cyber crime rates over the country. We end this report by looking at how the risk-perceptions evolved (Sec. 4.3) over the last four versions of the CPS internet dataset since 2015.

2. Related Works

This work touches upon several active areas of research in modeling the perception of technology related risks, and understanding fears in digital spaces that we briefly summarize here. Knuutila et al. (2020a) used the *2019 World Risk Poll* dataset to identify three prominent publicly perceived risks on the internet: misinformation, fraud and harrassment. They observed misinformation, i.e., the fear of receiving false information was the most important risk perceived by respondents from over a 100 countries. In a follow-up work (Knuutila et al., 2020b), they delved deep into the perceived risk of misinformation and found that it varies greatly across geographies. They also identified that young, educated people worry the most, and degree of actual misinformation and press freedom have little to no correlation with its perceived risk. None of these works however have considered modeling risk perceptions for other concerns as the world risk poll data had limited information on them.

A recent study (Weeks et al., 2024) analyzed the fears of social judgement or rejection on expressing political opinion on social media. They tried to attribute the fear to the opinion diversity in the respondent's social network, the network's size and various other factors such as sharing or liking political posts, and their political affiliation; and they concluded being embedded in a network with diverse political ideologies actually threatens the individual and decreases the likelihood of expression online. Our work is complementary to this study as we try to identify several other socio-demographic factors correlated with this fear, and we also consider other kinds of seemingly innocuous expressions on social media such as posting photos or texts.

3. Data

We use the Computer and Internet Use Supplement dataset collected by the US Census Bureau, comprising data collected bi-annually through a combination of interviews and surveys. This dataset contains responses from over $90k$ individuals, and ~ 560 attributes that capture several aspects that are of importance to our analysis: job, income, insurance, location, demographics, family, and most importantly, privacy concerns, hesitations, and internet usage. Specifically, the dataset includes yes/no responses to safety-related questions such as *"Have you been affected by an online security breach, identity theft, or a similar crime?"*, and questions relevant to risk-perception such as: *"Have concerns regarding privacy or security stopped you from* *conducting financial transactions such as banking, investing, or paying bills online?"*. Some example of (coded) raw features in the dataset can be seen in Table 2.

4. Methods & Results

First, we focus on the latest release of the dataset (November 2021) to draw some preliminary conclusions, then we also explore data from the previous years (upto 2015) to analyze overall trends in the risk-perceptions in the digital space, and specifically show how the factors for one particular risk (expressing opinions) evolved during these years.

4.1. Hypothesis Testing

As stated earlier, we treat the online activity related features as response variables and try to find other variables correlated with them. Here we discuss one such example where we try to identify possible correlations between the two reponse variables: hesitates to do financial transactions (lightblue in Fig. 1), and hesitates to express opinions on controversial issues (violet in Fig. 1) independently with the annual family income of the respondent. The data has a categorical variable `HEFAMINC` with 16 levels, ranging from "less than $\$5k$" to "$\$150k$ or more". We stratify the population into 5 income groups (x-axis of Fig. 3) following US poverty guidelines for 2021 (Govt., 2024; Yahoo, 2024) and assuming average family size of 4 to 6. The response variable on expressing opinions, and the fraction of the people who responded "yes" to that question seems to show an increasing trend with income as seen in Figure 3.

Here, we want to test if there is some suggestion or evidence of an association between the two variables: the binary response variable, and the explanatory variable income level. Since both variables are categorical, we consider doing a *chi-square test* to test the null hypothesis that there is no overall difference between people from different income levels with respect to how safe they feel while expressing something controversial on the internet. To perform the test, we first construct the 5×2 contingency table (5 income groups, 2 response outcomes) for the two variables, and compute the expected counts under the null hypothesis, that is simply the (row total $\times$ column total) / total sample size for a (row, column) cell in the contingency table as also explained in the caption of Table 1.

With all the observed and expected counts for the 5×2 table, we compute the χ^2 statistic as: $\chi^2 = \sum_r \sum_c \frac{(O_{rc}-E_{rc})^2}{E_{rc}}$. Since this is two-dimensional table, the degree-of-freedom in our case is $= (R-1)(C-1) = (5-1)(2-1) = 4$. The statistic in our case comes out to be 246.37 with a p-value of the order of 10^{-51}, so we can comfortably reject the null hypothesis, and conclude that there is at least a suggestion of an association between the two variables.

Income levels	**Yes**	**No**	**Row totals**
below 35k	1830	14,844	16,674
35k-60k	1948	14,184	16,132
60k-100k	2636	17,064	19,700
100k-150k	1843	10,796	12,639
above 150k	2289	11,499	13,788
Column totals	10,546	68,387	78,933

Table 1. Contingency table with observed counts for the income level categorical variable and the binary response variable of hesitation for expressing opinions on controversial topics. Row totals show the sample size of each group. Under null hypothesis, the expected count, for example, for the *below 35k* and the *Yes* entry would be $(16,674 \times 10,546)/78,933 \approx 2227.76$.

Category	**Feature code**	**Description**
Digital access	`HEINTRAV`	uses internet while travelling?
Online activities	`HEMEDINF`	gets info. on health or medical topics?
Wealth related	`PXERN`	weekly overtime earnings

Table 2. Features are labelled into 5 categories for ease of interpretation. In this table, we show one example feature for 3 categories.

4.2. Feature importances using *XGBoost* modeling

After analysing the socio-demographic attributes that correlate with hesitations above, we next find other attributes that could affect risk-perceptions on the internet. Since the dataset contains a large number of features, (~ 560), we train an *XGBoost* classifier to discover factors relevant for predicting a person's response. Particularly, we use the *XGBoost* (Chen & Guestrin, 2016) model to classify whether an individual is likely to have a privacy related hesitation based on the remaining attributes. We optimize the hyperparameters of the algorithm using the bayesian optimization library (Nogueira, 2014). The model is able to fit to our dataset, with a 3-fold cross-validation error rate of $\sim$ 8-14$\%$ for each individual target variable.

Our data contains a large number of fine-grained variables (such as responses to *"Have access to the internet at **home**?"*, and *"Have access to the internet at **work**?"*), making it cumbersome to visualize the broad aspects that contribute to risk perception. Hence, we group the top 20 features into high-level categories as described in Table 2.

The importance plots[1] for several target variables are dominated by aspects that capture digital access and wealth. Figure 4 shows important factors for the target variable for

[1]Please refer to our Streamlit web application.

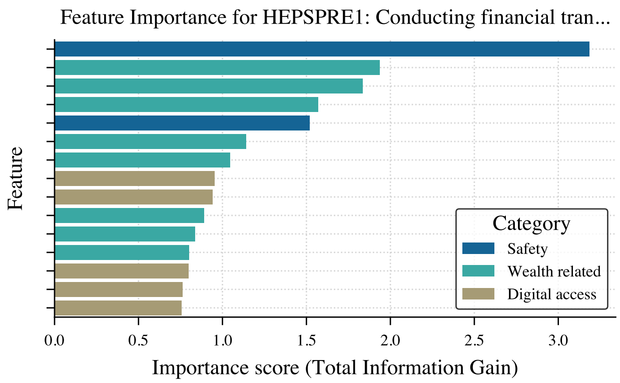

Figure 4. Top 15 factors by importance for determining the target variable "hesitates to conduct online financial transactions". We notice three main categories of features: safety, wealth-related, and features that describe modes of digital access, with the latter contributing the least information gain.

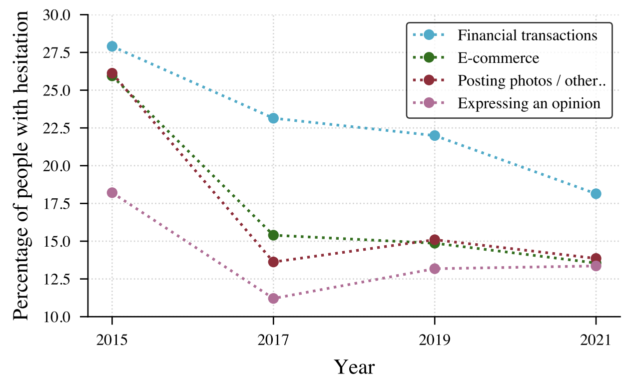

Figure 5. Overall trends in hesitation responses from 2015 to 2021. We observe that frac. of people fearing to do financial transactions is on a steady decline over the years, however other behavious show non-monotonic trends, e.g., the fear for expressing opinions on controversial topics is actually increasing slowly 2017 onwards.

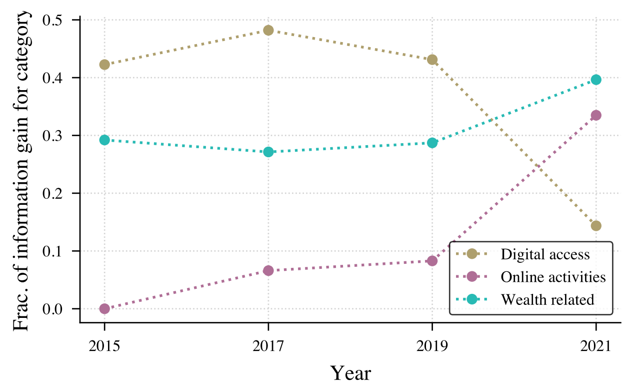

Figure 6. Fraction of information gain attributed to the 3 major categories for the target variable (or risk of) "expressing opinions online" over the years. The plot shows a steady increase in the fraction of features related to wealth and online behaviour, while the mode of digital access reduces in importance over time.

risk-perception of financial transactions online. We note that several of the most important features constitute the safety concerns and wealth status of an individual, while we see few attributes related to the mode of access of internet, and no contribution from features belonging to online activities.

4.3. Evolution of risk-perceptions and their factors

We now study the risk-perception of the online activities over the *years*. Figure 5 shows the trends in the risk perception over the last four surveys, starting from 2015. The risk-perception for automated financial activities, such as conducting bank and e-commerce transactions exhibits a steady decline, indicating that people are becoming increasingly comfortable to do them. Further, we notice a steady increase in the hesitation rate for social activities involving other humans, starting from 2017. This prompted us to explore the factors behind hesitation while using social media. We see from Figure 6 that online behaviour and wealth related features are rising in significance since 2015, while the means of digital access is losing pertinence.

5. Discussion & Limitations

We set out to explore factors that affect users' perception of risks while on the internet. To do so, we analysed the US Computer and Internet Use Supplement data. After finding strong correlations with several common socio-demographic variables such as age, education and income levels, we explored other features that are of relevance by ranking them using information gain in a classifier, and found modes of digital access, and wealth related attributes to be major factors. We then looked at trends in risk perception over the last four releases of the dataset, extending upto 2015, which indicated that users are growing increasingly comfortable with the use of technology for automated tasks like finance, while also becoming wary of social interactions such as posting opinions or photos online.

We acknowledge that the factors we identified from the data might not reflect the true causal relationships in play here, and formulating a qualitative social study trying to understand what caused an individual to have certain fears (e.g., news or personal tragedy) could be a future work.

Contribution Statement

Gaurav Niranjan found and preprocessed the datasets and built the webapp. Swagatam Haldar performed the analyses for hypothesis testing. Pradyumna YM led the *XGBoost* importance analysis. Farha Baig produced interactive visualizations on the app. All authors contributed in annotating the features, making figures and writing this manuscript.

References

Chen, T. and Guestrin, C. Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, KDD '16. ACM, August 2016. URL http://dx.doi.org/10.1145/2939672.2939785.

Govt., U. 2021 Poverty Guidelines. https://aspe.hhs.gov/2021-poverty-guidelines, 2024.

Knuutila, A., Neudert, L.-M., and Howard, P. N. Global fears of disinformation: Perceived internet and social media harms in 142 countries. *COMPROP Data Memo*, 2020a.

Knuutila, A., Neudert, L.-M., and Howard, P. N. Who is afraid of fake news? modeling risk perceptions of misinformation in 142 countries. *Harvard Kennedy School (HKS) Misinformation Review.*, 2020b. URL https://doi.org/10.37016/mr-2020-97.

Nogueira, F. Bayesian Optimization: Open source constrained global optimization tool for Python, 2014. URL https://github.com/fmfn/BayesianOptimization.

Weeks, B. E., Halversen, A., and Neubaum, G. Too scared to share? fear of social sanctions for political expression on social media. *Journal of Computer-Mediated Communication*, 2024.

Yahoo. Income for poverty level. https://finance.yahoo.com/news/income-considered-poverty-level-2023-130051437.html, 2024.