# Analysing Technical Background as a Predictor for Success in Dark Pattern Identification

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## Abstract

Dark patterns are various practices adopted in software design in to trick users into making decisions they might not otherwise want to make. The use of these practices has become quite prevalent and public backlash against them even more so. Class-action lawsuits have been filed against companies like Intuit in the past for charging customers eligible for free services by using these techniques. With this study we intended to take a data driven approach to identify if there exists any correlation between technical knowledge and the ability to avoid these dark patterns. We conducted a survey with 54 participants, recording their technical backgrounds and posing multiple questions that required them to identify and avoid dark patterns commonly found across the web. Although our study was not able to establish any correlation between technical knowledge and the ability to identify the use of dark patterns, we were still alarmed to see that great proportion of respondents who fall for such practices.

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## 1 Problem Definition

Is a business beholden to its shareholders or its customers? How a business chooses to answer this question, in large part also determines the values and ethics it chooses to abide by. Whether maximising shareholder profits is considered paramount or customer interests reign supreme, the choice gives birth to a clear ethical dilemma. The impact of these values can be seen in the product offered. Within the domain of software engineering, Harry Brignull coined the term "Dark Patterns", which is now used as an umbrella term to describe various practices adopted while designing a product in order to trick users into making decisions they might not otherwise want to or mean to [2]. These are practices where user value is intentionally supplanted over shareholder value [6]. Some examples are [2]:

- **Trick Questions**: Questions in a form are deliberately framed in a manner that tricks users into giving an answer they didn't intend.
- **Sneak into Basket**: The user attempts to purchase something, but during the purchasing journey another item is automatically added to the users cart.
- **Disguised Ads**: Advertisements are disguised as other kinds of content or navigation, in order to get users to click on them.
- **Misdirection**: The design purposefully focuses user attention on one thing in order to distract them attention from another.

At the surface level the practice of using these dark patterns seems to bear certain similarities with Nudge theory, an idea that has its roots in behavioral economics. Thaler and Sunstein are two behavioral economists who conceptualised the term "nudge" as any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives [11]. Huitink et al. [7] designed an experiment to test nudge theory and showed how incorporating a designated inlay for vegetables in shopping carts led to customers buying more vegetables. The key phrase here though is "without forbidding any options or significantly changing their economic incentives". Implementations of dark patterns are intentionally designed so as to limit the options available to


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users and to change their economic incentives which is precisely what makes them unethical. Gray et al. [5] conducted a survey to determine end user perceptions of manipulation when faced with such dark patterns. Through their survey they found that users frequently experienced strong negative emotions on interacting with manipulative products. They were also very likely to blame the designers of the product for this manipulation.

There is no dearth of cases where the use of such practices has led to wide spread public criticism. Intuit faced a class action law suit against their product called TurboTax that claimed to offer free tax filing services for eligible users, but always redirected them to the paid version stating that the user was ineligible for one of many reasons [8]. Businesses prey on user ignorance, unawareness and lack of technical literacy when they indulge in these practices. We posit that the ability to identify and avoid dark patterns when they are encountered can have some correlation with technical know-how. Understanding whether such a correlation exists or not can give us valuable insights on educating users. Given the widespread use of these practices in the industry, the massive costs to customers and its obvious ethical ramifications we felt that this was a good problem to explore as part of our final project.

## 2 Hypothesis

Students of computer science are in general fairly well versed with technology and the thought that goes behind its development. They spend most of their waking hours using computers and the internet. Our hypothesis was that students in technical majors would be more adept at identifying and catching dark patterns and would fall prey to them far less often as compared to people in non-technical majors or those who spend much less time dealing with or thinking about these things.

In order to test our hypothesis, we designed a survey that presented various examples of dark patterns that can be found on the internet and asked users to identify them. The survey also recorded if respondents belonged to a technical or non-technical major and their self-reported "tech-savyness" on a scale of 1 to 5, 1 indicating not savvy at all and 5 indicating very tech savvy. Our expectation was to see some differences in the way different people answered these questions based on their technical backgrounds. The details of our experimental setup, the results, their interpretation and conclusions can be found in the following sections.

## 3 Literature Survey

In order to learn more about the subject matter that we are conducting research on and have a better sense of the overall perception of dark patterns among other researchers, it is important that we look at some sources. These sources are from all different kinds of mediums. Some are peer reviewed papers and other are online forums for communities to discuss issues that users are faced with on the internet. The remainder of this section is to explain the kind of insight that we got from a select few sources and what we took away from them. In this Literature Survey, we would like to focus mainly on the dark patterns themselves and how they can be identified by users because this is where our research is diving in deeper.

Geronimo et al. [4] conducted a large scale study on 240 different apps on the google store that conclude that close to 95% of the apps tested had implemented dark patterns and that most users are unable to detect them. We needed to find out how other studies were being conducted. While our research is different from this, we liked being able to learn about how most dark patterns are implemented. Ravenscraft [10] wrote an online article about how to be able to detect dark patterns and be able to avoid them when using services on the internet. This is important for when it came for us to design our own dark patterns to see if we could trick people in similar ways. Mathur et al. [9] conducted a web crawl of 11,000 shopping websites to identify and categorize different types of dark patterns. We need to be able to find categories for different dark patterns so we can find out which types are more effective and make it easier to report. Bhoot et al. [1] present a study of five elements that play an important role in the identification of dark patterns by users, even if they are not aware of the unethical intentions behind the design. Another article to learn about what people should be thinking about in the identification of such dark patterns. Gray et al. [6] present a more ethics based approach to dark patterns and Human Computer Interaction(HCI). This work specifies that when it comes to HCI, design is of the utmost importance in assessing ethical implications. The author also give a detailed list of common dark patterns to which they did testing and then concluded that there were 5 primary dark pattern categories. Friedman et al. [3] is a much older but very highly cited study from the University of Washington Computer Science Department. The focus on age in this article makes it more relevant due to its ability to predict the path of design of technology to be used by consumers. It also hits on the fact that human values and ethics should be the central design criteria for user technology.

All of these sources were great to gain knowledge for ourselves and how we can carry out our research. A lot of the mentioned aspects of identifying, categorizing, and figuring out how to reduce ones susceptibility to dark patterns are essential in creating meaningful tests to see who is more likely to fall victim to these such dark patterns.

## 4 Methodology

Until now, we have only discussed the general perception of dark patterns on the internet and how we can begin to deal with them as users. Recall that we hypothesise that there is a difference in how susceptible people are given their "tech-savyness". We believe that people within technical backgrounds are less likely to fall for such things than people with non technical backgrounds due to their particular expertise. We also would like to see if there is a difference in the amount of time spent on the internet between the two groups of people and if that is a factor that plays a role in their ability to identify dark patterns. If there is no difference in the time spent online, but the non technical people show to be more likely to fall for dark patterns, then that just makes less informed consumers more of a target.

In order to conduct this research, we needed to collect data. Data like this is not too widely available on the internet for us to use so we went with the strategy of collecting our own. We did this in the form of a survey[1] given to people of both technical and non technical backgrounds. This survey tackles things like asking for simple pieces of information as well as testing out some common dark patterns that one may come across when shopping or reading things on the internet. The following sections describe the survey design, the questions asked and what they were used for.

### 4.1 General Screening

This section consists of three questions. The first question asks whether the subject is working or schooling in a technical related field. The second question asks the subject how many hours they spend on the internet per day. These are the general questions that were intended to partition the results with. We wanted to explore the difference between people within CS and not, along with the relationship between the hours spent on the internet and whether the subject falls for certain dark patterns. We asked subjects to not spend too much time on questions and to answer swiftly so we could get honest answers and so that the answers would reflect how most people generally conduct themselves on the internet. The final part of this section is for the participants to rate themselves on a scale of 1-5, how "tech savy" they think they are. This is another piece of anecdotal data that could help in finding meaningful relationships.

### 4.2 Dark Pattern Tests

The next portion of the survey consists of four questions. All of these questions present the subject with a web page that has a dark pattern implemented and then asks what their action on the web page would be. An example would be showing a web page from which you would like to download a file from that has 3 different download buttons and asking what download button you would choose. Figure 5 shows the question as it was presented in the survey.

[1]https://docs.google.com/forms/d/e/1FAIpQLSd4Vgw_PplI7D7Ij5MolFWUBegAhAX3dkUsCDZKpj-KFeTwRg/viewform?usp=sf_link

It is reasonable to see that one may get confused and hit a download button that may not actually give them the file especially when acting quickly, which is what the participant were asked to do. Figure 1 is an example of how confusing language can be use for misdirection of users:

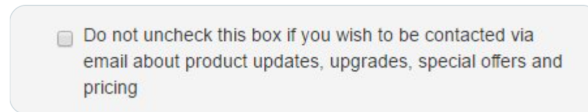


**Figure 1.** Check box prompt with use of confusing double negatives

Participants are then asked to quickly answer whether they would check the box or not. Both of these examples show different types of dark patterns. One that relies heavily on misleading visuals, and one that relies heavily on using confusing wording to mislead people. Figures 3, 4, 5 and 6 show the questions

### 4.3 Debriefing

This third and final section of the survey asks a couple of simple questions for the participants to possibly reflect on what they have experienced in the earlier parts of the survey. This is again a three question section. The first question asks if the participant has ever heard of the term "dark pattern". Even if people are not great at picking up tricks that are being played on them, we would like to see if even hearing the term vaguely before is helpful to make people less susceptible. The next question simply asks if you have taken any measure in the past to learn general guidelines of internet safety. The third question states "If Yes to the previous question please explain which measures below, otherwise type "no" in the box". This is our last ditch effort to put a small dark pattern in a place where people might not be expecting it. Our thought is that the survey takers may look at that question and decide to stop reading it after the first part. One may have answered no to the second question of this section and then not bothered to answer after seeing that the first part of the next question says "If yes to the previous question". This can be referred to as the human version of Boolean short circuiting. We are interested to see if people tend to not follow the instruction as this is a common practice in getting users to do things they do not want to on the internet.

We take the responses from this survey and perform statistical analysis which is discussed in section 5. We felt that at least 50 responses was a sufficient amount to get an accurate representation of a population of internet users. As always, the size of the sample is not the most important thing so long as the sample is representative.

## 5 Survey Result and Discussion

In order to test our hypothesis, we ran many statistical tests on the data we've collected. We summarize the methods and the purpose of the methods as we introduce them in this section. It is important to note that our survey collected 54 responses with approximately *one-third* of the responses coming from non-technical backgrounds and the balance being from technical.

### 5.1 Difference in respondents

The first order of business is addressing the difference between the students coming from a non-technical background vs a technical background. Figure 2 shows the difference in average time spent on the internet per day based on background.

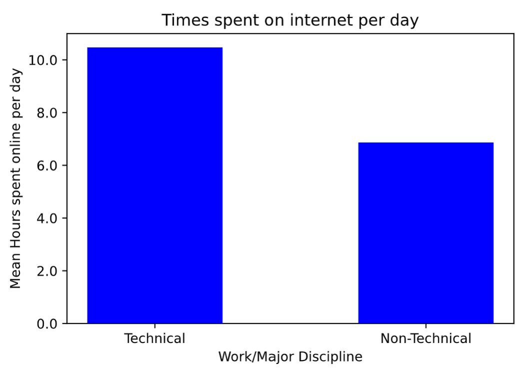


**Figure 2.** Distribution of average time spent on the internet depending on background

It can be seen from Figure 2 that respondents with a technical background seem to spend more time on the internet than non-technical respondents. We see an average for the technical category of about 10.5 hours and a non-technical average of approximately 6.8 hours spent online every day. In order to see if this is a significant difference, we've employed a very elementary statistical test for significance of the difference of means. Every statistical test was performed using a significance level of $\alpha = 0.05$ as it seems to be standard practice. We used a two-sample T-test to test the difference of the means here. In order to find out whether we should use the T-test or Welch's test, we conducted Levene's test for equal variances. Levene's test yields us a p-value of 0.63 which tells us that there is no evidence of the variances between the two groups being different and we are good to go ahead with the regular one-tailed two-sample T-test. The T-test statistic is calculated as:

$$t = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{s^2(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where $\bar{x}_1, \bar{x}_2$ are the sample means, $n_1, n_2$ are the sample sizes, $t$ is a student t distribution quantile with $n_1 + n_2 - 2$ degrees of freedom and $s^2$ is the pooled sample variance which can be calculated using:

$$s^2 = \frac{\sum_{i=1}^{n_1} (x_i - \bar{x}_1)^2 + \sum_{j=1}^{n_2} (x_i - \bar{x}_2)^2}{n_1 + n_2 - 2}$$

When using these formulas, we draw a T-test statistic of 1.25, which for a one sided test, yields a p-value of approximately 0.11. This does not give us evidence that people of non technical backgrounds are spending less time on the internet per day. Since right now we can only assume that the two groups are spending similar amounts of time on the internet, we can speculate that non technical users are more susceptible based on the result of how they were able to identify the dark patterns.

We continue to run tests like this for the questions regarding spotting dark patterns. The first thing we would like to observe is if there is a difference between the demographics in whether to check the box with confusing use of double negatives. This question is further outlined in Case-1 of the description of the questions. We find that 4 of the 15 (26.6%) non-technical respondents elected to click the button and that 11 of the 37 (29.7%) technical respondents elected to click the button given that the goal is to not receive promotion offers. These proportions are nearly identical and we can confirm the significance or lack thereof with a 2-proportion z-test, who's test statistic can be calculated using:

$$Z = \frac{(\hat{p}_1 - \hat{p}_2)}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where $\hat{p_1}, \hat{p}_2$ are the individual sample proportions, $\hat{p}$ is the pooled sample proportion, and $n_1, n_2$ are the sample sizes. This yields us a p-value of 0.825 which does not give evidence that the users with technical and non-technical backgrounds had different behavior in falling for this particular dark pattern. We perform computations like this for the rest of the questions, presenting results in a tabular form.

We will briefly readdress the previous question and results in Case 1 of our case breakdown. These cases all represent different questions that ask users to respond to a certain web page with a dark pattern being used. Each case addresses a different category of dark pattern. We found inspiration for these particular categories from some of the sources in the literature survey.

**Table 1.** Table highlighting the correct choice corresponding to the case and the proportion of respondents who made that choice

| | Case-1 | Case-2 | Case-3 | Case-4 |
|---|---|---|---|---|
| **Technical Major** | 71% | **71%** | **50%** | 24% |
| **Non-Technical Major** | **75%** | 69% | 31% | **50%** |
| **Chosen Option** | Uncheck Box | Without Donation | Download Button 2 | Chose number of options = 4 |

**Table 2.** Table expressing the one-sided p-values for each of the four cases

| | Case-1 | Case-2 | Case-3 | Case-4 |
|---|---|---|---|---|
| p-Value | .4125 | .166 | .0502 | .007 |
| Significance | No | No | No | Yes |

We refer to Table 1 to discuss the remainder of the results from each case defined below. It summarizes the responses indicating the percentage of people from technical and non-technical backgrounds who made the desired choices for the four case scenarios specified below: -

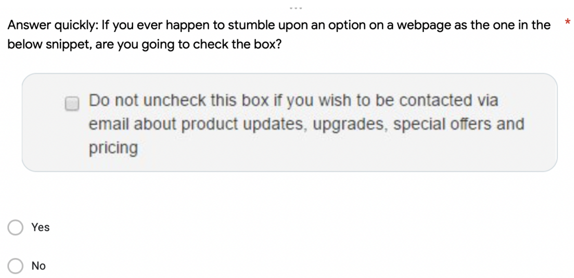


**Figure 3.** Survey question 4

**Case-1:** Case-1 is an example of a *Trick Question* dark pattern. The question as it was posed in the survey can be found in Figure 3. Oftentimes, websites use options with double-negative terms like the one shown in the proposed question to trick users into accepting their terms and conditions. So, we set out to analyze the responses to such options from people coming from technical and non-technical backgrounds. We wanted to see if technical majors are less prone to falling prey to such tricks than non-technical majors. But from Table 1 we can see that 71% of the people from technical background and 75% of the people from non-technical background chose to not check the box. This basically means that the majority of people who answered this question were able to recognise the usage of double-negatives and thus chose to uncheck the box so that they don't receive email updates. There is also no significant difference in the way that people with a technical and a non-technical background answered this question. However it should also be noted that close to 30% of the respondents did choose to check the box, indicating that they fell for the use of confusing language. Given the large number of people who use the internet, 30% would still result in a large number of people who end up falling for this tactic. The distribution of responses to this question can be found in Figure 11.

**Case-2:** Case-2 is an example of a *Sneak into Basket* type of dark pattern. The question as it was posed in the survey can be found in Figure 4. Some websites trick users into making

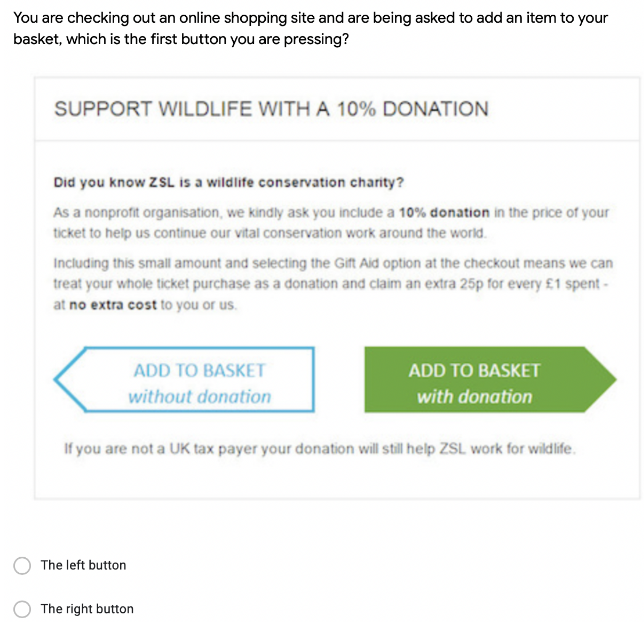


**Figure 4.** Survey question 5

unwanted payments disguised as charity or donations. Note here that the button with the donation is marked as green and the button without the donation is colorless making it pop and also making it seem like the "right" choice. Furthermore, the button with donation points towards right, which usually is a direction that indicates movement towards the next step on web UI's and the other button points towards the left, which usually means navigating backwards. These are subtle design choices that give the user an illusion that the button to click in order to move forward is the button with the donation.

From Table 1 we can see that, 71% of the people from technical background and 69% of the people from non-technical background chose to add an item to the basket without donation. This is not statistically significant using the two proportion z-test, yielding a p-value of 0.166. There is a very small difference in the responses but it may be so small that we can calculate these almost identical percentages. The narrow margin in the difference between the percentages might be because the users thought they were supporting a good cause. It is still however quite alarming to see that close to 30% of the respondents chose to go with second option of the right button. Given a larger sample size, 30% is a huge proportion of users who could potentially be tricked. The distribution of responses to this question can be found in Figure 12.

**Case-3:** Case-3 is an example of *Disguised Ad* type of dark pattern. The question as it was posed in the survey can be found in Figure 5. There are times when clicking on what

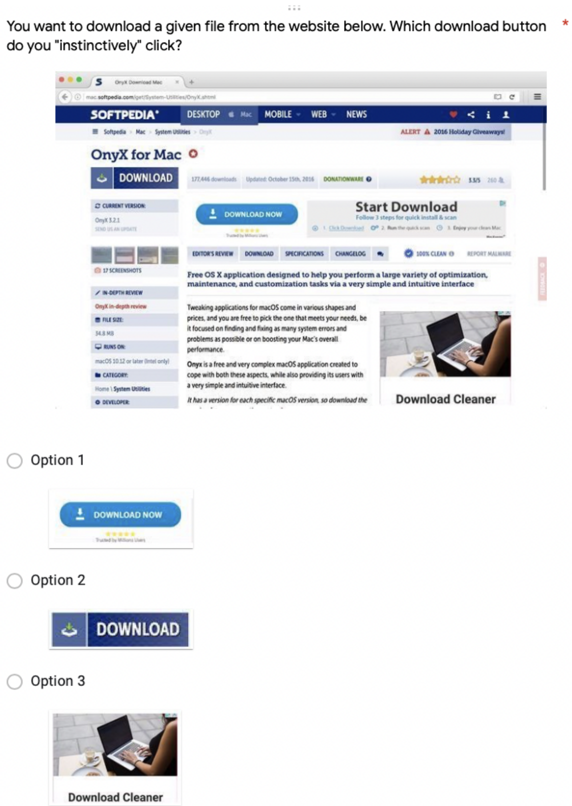


**Figure 5.** Survey question 6

seems to be a normal button on a website, leads to unsafe websites or a pop-up of an advertisement that the user does not want to see. This is the general pattern followed by malicious websites that link spam advertisements with buttons. The webpage presented in Figure 5 contains 3 download buttons. Only one of them (option 2) actually leads the user to download the file, the other two buttons redirect to unwanted ads. While framing the question too, we deliberately placed the most prominently visible button(the button in the center of the webpage) as the first option in the answers, so that the users attention falls on that button first. Table 1 shows that 50% of the people from technical background and 31% of the people from non-technical background decided to click on the download button located on the top-left part of the webpage, which is the correct option to choose in order to download the linked file. The p-value given by the test is 0.0502. This is very close to being statistically significant but we are unable to claim significance with our threshold of 0.05. This is a scenario where more exploration can be done if we had access to more data. This will be discussed in the future work section. Although there is no evidence to conclude that the non technical majors fell for this case more often, we have justification for looking further. Although we do not have sufficient evidence to claim statistical significance with respect to our hypothesis, a look at Figure 13 shows that more than half, close to 56% respondents chose the incorrect option 1 as the answer which is still a cause for concern.

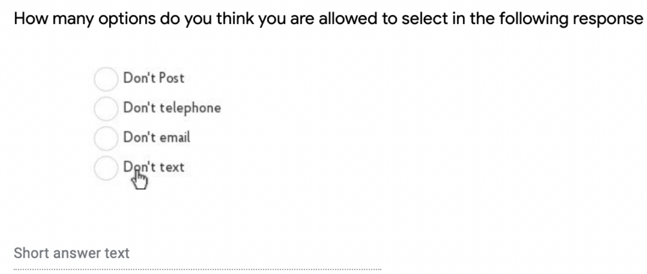


**Figure 6.** Survey question 7

**Case-4:** This case represents a *Misdirection* kind of a dark pattern. This is a very common dark pattern used on websites. The question posed in the survey can be found in Figure 6. The question takes advantage of the users preconceived notion of what checkboxes ought to be like. Generally users see empty circular buttons called radio buttons when there is only one option that is allowed to be picked and square checkboxes for a "check all that apply" scenario. This case presents the participant with options that have a radio button like (circular) style to them. It then asks the user how many options they believe they are allowed to choose for the question. The correct answer is that the user can select all 4 options. This will be able to show us evidence, if it exists, that the style of the check boxes have an effect on the users behavior.

From Table 1 we can see that 24% of the people from technical background and 50% of the people from non-technical background thought that they could pick all four options. Additionally, Figure 7 shows that majority of the people taking the survey thought that they had a choice to pick only one option out of the four available options. In this case we actually have a significant p value of 0.007. This however is to support that non-technical majors who were able to correctly pick out the dark pattern more than the technical ones. This is a very interesting result and it is completely opposite our hypothesis. The huge difference in percentages might be because the technical majors assumed that they could pick only one of the four options as they were presented as radio buttons (unlike the conventional check-boxes).

For Case-1, we have already shown that we do not see a difference between technical and non-technical backgrounds. Using the same statistical tests, Case-2 also does not seem to be significant. So we cannot conclude that the rates of failure to recognize the dark pattern are different there.

Apart from collecting responses to the above case scenarios from the people taking the survey, we also asked them

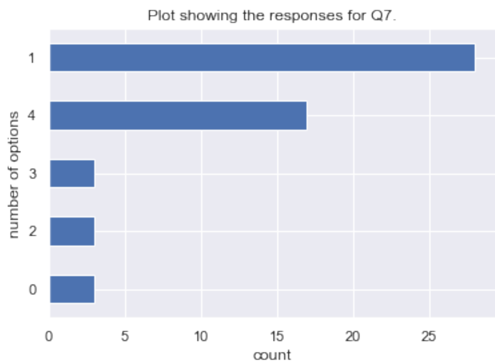


**Figure 7.** Distribution of the responses to survey question 7

**Table 3.** Table showing the percentage of people who claim to have knowledge of Dark Patterns and General Guidelines

| Technical Major | Know dark patterns | Know general guidelines |
|---|---|---|
| Yes | **24%** | **26%** |
| No | 6% | 12% |

about their knowledge of dark patterns and general guidelines of internet safety. The intent of this question in the survey is to test the extent of awareness in the people about the dark patterns. As per our observation indicated in Figure 15, majority (81.5%) of the people are not aware of the term dark pattern. It even includes technical and non-technical people. Only 18.5% of the population are aware of dark patterns. In case of internet safety, as per Figure 16, we have observed that 77.8% of people are not aware or not interested in learning about the internet safety.

These results are showcased in Table 3 from which we can clearly see that for both the cases, technical majors were more familiar with the terms and thus better prepared. When we asked them to briefly elaborate on how they learned about internet safety and the measures they have taken about the internet safety we have received a variety of responses which include to avoid suspicious sites, phishing malware or spam and some indicated that they enrolled in CS5024 etc.

## 6 Future Work

While we believe that our sample was representative of the populations that we were trying to test, adding more data will never hurt. The next thing we could do is to diversify the populations in question a little more. This could include testing different age groups or even separating the groups into more specific areas than just technical and non technical. Maybe business students have different types of insights than communications students. Those two demographics would be classified under the same category in our study but in reality could be behaving in a completely different way. There could also be the same trend in the technical portion. Maybe a developer who is responsible for design might have more insight than a Big Data Engineer who may not be designing user interfaces as much and would not be thinking about these patterns all of the time. This work is designed to help people become aware of how they can be more safe on the internet and avoid common dark patterns so the more areas of people that we can reach, the more successful this research will prove to be in its mission.

## 7 Conclusions

In this section we talk about the implications of our results and move on to a more ethical discussion. We have observed that there are indeed areas of dark patterns that are more distinguishable for people of a technical background. This brings up huge ethical issues that maybe these dark patterns are designed to target the less informed consumers. Targeting any particular group at all is always going to be considered unethical. However we could also claim that maybe the dark pattern is targeting everybody equally but people with a technical background were able to avoid them. In which case we could say yes, it does pay to be an informed consumer. But we should not have any more right to call these patterns ethical just because informed consumers are able to avoid them. Not everybody is going to be heavily trained in every field so there could be similar way of taking advantage of people no matter the industry. The consumers are then left unprotected in every sense if this were to be the trend.

We have also seen that there are different types of dark patterns where there is no difference in the success rate between our two demographics. While there is no difference, the dark patterns still seemed to "fool" a reasonable amount of people. Even if only 10% of all users fall for the pattern, that is a number that is still much too large. Our survey shows that depending on the type of dark pattern implemented, 30%-50% of participants fall for the trick in one way or the other. This means that even for informed consumers, it is still easy to get fooled due to simple human nature. Ethics must always come at the forefront for the criteria of design. If this is not the case, we will continue to see large companies use technology against their customers whether for reasons to get more money, or to get more information. Dark patterns as a whole are unethical. But we understand that some come about unintentionally. We believe after seeing our results in this study, that standard practice for designing user interfaces should happen similarly to how we have conducted this research. Surveys should be conducted for every user experience that is going to be put on a specific website so these patterns can be tracked down easily even if they were unintentionally put in. This would make the creation of websites and services an ethical practice again and restore the internet as an extremely useful tool for all of its users and not just an obstacle that one needs to get through.

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## A Survey Results

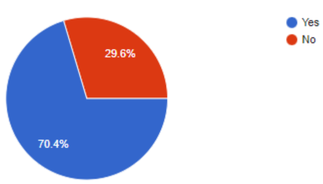


**Figure 8.** The proportion of respondents belonging to technical and non-technical backgrounds. Red indicates non-technical background and blue indicates technical background.

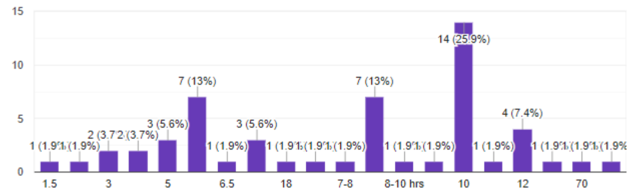


**Figure 9.** A distribution of the number of hours spent on the internet by respondents.

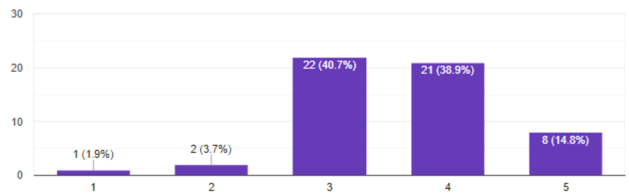


**Figure 10.** Respondents' self reported "tech-savvyness" on a scale of 1-5.

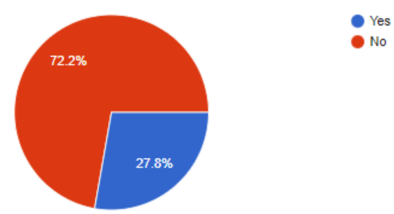


**Figure 11.** Responses to survey question 4. Red indicates people who refused to click the check box, blue indicates people who chose to click the check box.

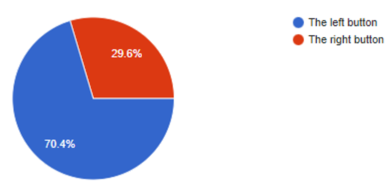


**Figure 12.** Responses to survey question 5. Red indicates people who chose the option with the donation, blue indicates people who chose the option without the donation.

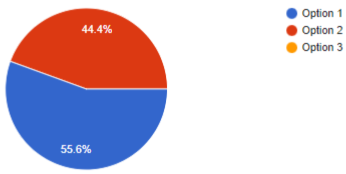


**Figure 13.** Responses to survey question 6. Blue indicates people who chose Option-1, red indicates people who chose Option-2 (safe), and yellow indicates people who chose Option-3.

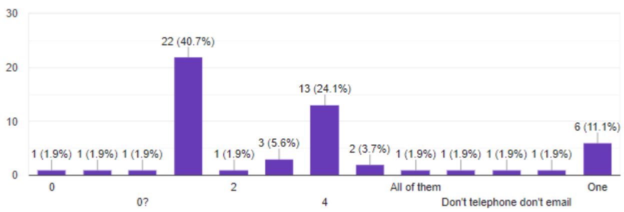


**Figure 14.** Responses to survey question 7.

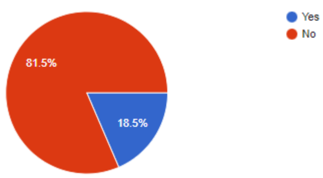


**Figure 15.** Pie-chart indicating the responses to the question about awareness of Dark patterns.

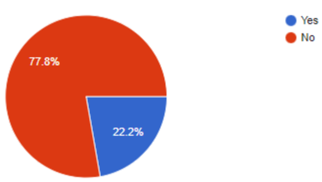


**Figure 16.** Pie-chart indicating the responses to the question about internet safety.

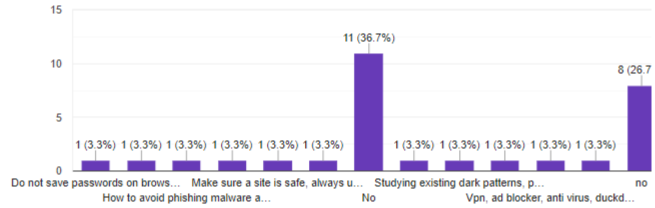


**Figure 17.** Bar-chart indicating the responses to the question about measures taken for internet safety.