How Well Do Experts Understand End-Users' Perceptions of Manipulative Patterns?

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ABSTRACT

How well do experts understand end-users' perceptions of manipulative patterns? We conducted online surveys with end-users and with experts assessing perceptions of manipulative patterns. Participants saw images of interfaces and evaluated each through a series of semantic scales (e.g., deceitful to honest). After being shown a definition of manipulative patterns, they then decided whether each interface exemplified a manipulative pattern. End-users correctly identified images as manipulative approximately half of the time, and though experts were more often correct, the differences were not statistically significant. However, end-users' descriptions of the images were significantly more positive than experts assumed, resulting in experts over-estimating end-users' ability to recognize when they were being manipulated by an interface.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in interaction design**; • **Security and privacy** → *Usability in security and privacy*.

KEYWORDS

dark pattern, manipulative design, survey, end-users, experts

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1 INTRODUCTION

Manipulative design has increasingly become the target of scrutiny in HCI and legal circles in recent years. Most commonly known as "dark patterns" (a term that is undergoing transformation, see Background section), this form of design disadvantages users by coercing or tricking them into taking an action they might not otherwise take if facing more neutral design. Considered intentional, the choice to implement these manipulative designs is typically attributed to financial goals of platforms, benefiting the latter by swaying users to devote more time [28], spend more money [10], or provide more of their personal data [23].

To date, research have shown that manipulative design is both widespread – for example, on 95% of apps on the Google Play Store [7] – and effective in changing user behaviour [21]. Users are generally unaware of most manipulative patterns [7], typically noticing or pushing back against only those more "aggressive" [18]. When users do feel they are being manipulated by a platform, it has been shown to manifest as annoyance [26] or distrust [11]. However, even when users *do* recognize manipulative patterns, it does not predict their ability to resist them [1].

This has led to concerns over compromised autonomy for users, and has raised ethical concerns [9, 12]. Each year sees more high-profile cases of manipulative design online, including social media giants pushing tracking cookies onto users [25], credit-reporting agencies using deceptive marketing practices [13], and a US president tricking users into recurring donations [10]. Growing attention paid to unethical manipulative design has led to the creation of legislation against their use in certain contexts, such as through the EU's General Data Protection Regulation, which requires informed, freely given consent, and California's privacy law, which bans design which "subvert[s] or impair[s] a consumer's choice to opt-out" of the sale of their personal information [24].

The development and enforcement of legislation surrounding manipulative design requires subject matter experts who have a strong understanding of when end-users' consent is being impaired, in order to determine which patterns should be flagged, reported, and fought against.

To assess whether a given pattern is of legitimate concern, experts must be able to accurately predict how end-users or "laypersons" may perceive and interact with patterns when they see them. While some academic studies have focused on better understanding user behaviour and perceptions surrounding manipulative design, none to date have been conducted to test whether self-reported experts have an accurate understanding of those end-users' perceptions. To address this gap, we conducted online surveys with

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end-users and experts assessing perceptions of manipulative patterns and compared the two groups. Our two research questions are: *RQ1: How do end-users perceive manipulative patterns?* and *RQ2: How well do experts understand end-users' perceptions of manipulative patterns?*

Our main contributions of this paper are that as a first impression, end-users generally tended to describe interfaces using positive adjectives despite the presence of manipulative patterns. Even after being shown a definition of manipulative patterns, end-users identified only about half of images containing manipulative patterns. Experts correctly identified more images with manipulative patterns, but a comparison between the two user groups showed no statistically significant differences. Experts also significantly over-estimated end-users' use of negative adjectives to describe the images containing manipulative patterns. As a result, experts over-estimated end-users' ability to recognize when they were being manipulated by an interface, which can have important implications given that experts are often asked for their opinion on such matters.

2 BACKGROUND

2.1 Evolving terminology

Our study of manipulative design follows research of what is currently most well known as "dark patterns," a term coined by Harry Brignull to describe "tricks used in websites and apps that make you do things that you didn't mean to, like buying or signing up for something" [3]. Since its inception, the term has gained traction amongst HCI researchers to describe manipulative design more broadly. However, recent conversations in HCI circles have sparked debate over whether the somewhat ambiguous term has possible racial connotations [8]. Such conversations are part of larger efforts towards more inclusive language in computing spaces, resulting in the gradual replacement of terms including "whitelist/blacklist" and "white hat/black hat" with more descriptive and "neutral" language that avoids the "dark = bad /light = good" binary, such as "allowlist/denylist" and "ethical hacker/unethical hacker," respectively [5]. Brignull has recently opted to replace the term "dark patterns" with "deceptive design," "in an effort to be clearer and more inclusive" [3]. In this paper, we opt for the term "manipulative patterns," as we believe it is more descriptive than the term "dark patterns" while encompassing problematic designs beyond those which are strictly deceptive.

2.2 Legislating against manipulative design

Manipulative patterns have increasingly gained the attention of legislators for their widespread use on platforms where "user value is supplanted in favor of shareholder value" [12]; they may be seen as a form of "growth hacking" [11]. Most recently, the Consumer Financial Protection Bureau (CFPB) is suing the American credit-reporting agency TransUnion for deceptive marketing practices, "such as putting information in low-contrast fine print or including a disclosure in an image that took longer to load than the rest of the webpage" [13]. Efforts have been made to reduce the prevalence and impact of manipulative patterns, such as through the GDPR and California Data Privacy Laws. The California regulation, set to go into effect in 2023, applies only to designs which negatively impact that user's ability to opt out of the sale of their personal data – a relatively narrow scope – and includes a limited number of manipulative patterns, such as using confusing language (e.g., double negatives), forcing users to click through screens meant to dissuade them from opting out, and forcing an undue amount of scrolling in order to find an opt-out option or button [24]. While it is encouraging to see legislators becoming more aware of manipulative patterns, the limited nature of these laws and regulations may mean their impact is limited, may even *encourage* the use of manipulative patterns, or may lead to the adoption of even more insidious manipulations. Several academic and legal sources have suggested manipulative patterns have indeed been used to get around minimum GDPR requirements, particularly in relation to notorious cookie consent banners [15]. Two years after the adoption of the GDPR, only 12% of websites met its minimum requirements [21]. The GDPR has been criticized for its lack of clarity in regard to manipulative patterns [17].

2.3 End-Users' perceptions of manipulative design

Several recent studies have explored users' perceptions of manipulative patterns. Di Geronimo et al. [7] found that users are largely unaware of manipulative patterns in mobile applications, despite their presence on nearly 95% of apps on the Google Play Store. Luguri et al. [18] found that "aggressive" manipulative patterns are more likely to receive a strong negative reaction from users than those more "mild"; nevertheless, "aggressive" manipulative patterns were still found to be more effective in swaying user behaviour. They also found that "[l]ess educated subjects were significantly more susceptible to mild dark [sic] patterns than their well-educated counterparts." However, even education may not be sufficient. Bongard et al. [1] found that users' ability to recognize manipulative patterns did not predict their ability to resist such designs, suggesting awareness alone is insufficient to prevent user manipulation.

Other work has quantitatively explored users' emotional states in relation to manipulative patterns. A study by Voigt et al. [26] asked users to use one of two versions of a fictitious online shop and then indicate their levels of annoyance and brand trust with likert-scale questionnaires. They found users exhibited higher levels of annoyance and lower brand trust when exposed to the manipulative pattern-laden online shop compared to users in the neutral shop condition. In a mixed-methods study, Gray et al. [11] asked users to recall past instances where they had felt manipulated online, and then rank their agreement with a provided list of negative emotions on a likert-style scale. Amongst other findings, they found that "82.24% of users mistrusted smartphone applications and 89.3% of users mistrusted websites at least 'sometimes"' [11], suggesting most users have at least a general awareness of being manipulated online.

2.4 Categorization of manipulative designs

From an expert perspective, researchers have been defining and consolidating terminology relating to manipulative patterns [2, 20] and identifying them in the wild, such as in the offerings of app stores, social networks and e-commerce websites [6, 7, 19]. Researchers have also investigated the mechanics behind why manipulative patterns are so effective. Psychological and cognitive biases [27] are a common explanation. Manipulative patterns may prompt and take advantage of automatic or "System 1" thinking processes, encouraging users to make impulsive choices against their own best interests [2]. Manipulative patterns can also exploit basic human social needs, such as the "need to belong" [2]. Westin et al. [28] found that participants continued to stay on manipulative platforms even when voicing privacy concerns due to the Fear of Missing Out, itself a construct based on deficits in basic psychological needs [22].

Mathur et al. [20] conducted a literature review relating to manipulative patterns, categorizing existing patterns into two distinct types of choice architecture and six subcategories. Patterns that "modify the decision space" overload the user with or eliminate choices, treat users unequally, and hides influence mechanisms. Patterns that "manipulate the information flow" deceive by using misleading language, and obscure or delay the visibility of necessary information to the user. In this paper, we adopt Mathur et al.'s categorization to ensure that our images (included in Appendix A) cover a wide range of patterns.

2.5 Research Gap

Understanding of end-users' perceptions and the mechanisms behind manipulative patterns has been steadily growing with the help of academic studies. Nonetheless, to date, we have not found any studies which directly compare experts' expectations of user perceptions to the reality of those end-users' perceptions. It is important to study how well experts' expectations of users' perceptions align with reality, as the direction of further research, education, and legislation largely relies on the decisions of experts. By investigating this alignment, we can identify gaps in understanding. Are all manipulative patterns noticed or considered negatively by end-users to the same extent that experts expect? Accordingly, we can discuss whether current understanding by experts is satisfactory or whether mitigations are warranted to close gaps. Our paper addresses that gap, to help provide guidance going forward for areas of investigation and possible solutions.

3 METHODOLOGY

We designed our study to address two research questions: *RQ1: How do end-users perceive manipulative patterns?* and *RQ2: How well do experts understand end-users' perceptions of manipulative patterns?*

Our online survey study was reviewed and cleared by our institution's ethics review board. We showed sample user interfaces to both groups (end-users and experts), then asked participants to describe the interface and to determine whether each interface was an instance of a manipulative pattern.

3.1 Recruitment

End-users: We recruited end-users using the UK-based crowdsourcing technology company Prolific[1]. End-users had to be at least 18 years of age, currently live in Canada, and be capable of reading and completing a survey in English. Based on Prolific's suggested payment rates, we paid participants 2.25GBP upon completion of the survey.

Experts: The recruitment of experts was more direct since we required that they be researchers knowledgeable about manipulative patterns and/or be authors of publications on the topic. We directly emailed authors of previous work on manipulative patterns to participate in the survey and posted to online forums, LinkedIn, Slack, or Facebook groups relevant to manipulative patterns. We compensated the experts with an optional raffle for a $50 Amazon gift card. We did not place any restriction on where experts lived.

Data Collection. We collected data from both user groups during the summer of 2021. We received 138 end-user responses but discarded 23 responses because the participants did not answer any questions related to the interface images. This left us with 115 valid end-user responses. We collected 37 expert responses but discarded 10 responses where participants did not answer any questions or did not confirm their consent to participate at the end of the survey. We were left with 27 valid expert responses for our analysis.

3.2 Participants

End-users: End-users were between 18 and 60 years old, with a mean age of 30 years. 64 of the end-users were men, 62 were women, 3 were non-binary, and 1 preferred not to say. 50 participants had a formal education in some technical field such as computer science and 80 did not. 73% of our end-users had obtained some form of post-secondary certificate or degree. 27% had achieved at least a high school diploma or equivalent, and 1 participant had not completed high school.

Experts: Experts were between 21 and 50 years old with a mean age of 32 years. 16 experts were women, 12 were men and 1 preferred not to say. Experts responded to the question regarding education with "Doctorate or professional degree (e.g. MD, DDS, PhD)" (approximately 55%), "Master's degree (e.g. MA, MS, MEd)" (approximately 35%), or "Bachelor's degree (e.g. BA, BS) (3 or 4 year program)" (approximately 10%). 13 experts responded that they lived in North America, 13 were from 7 different countries in Europe and 1 was from India.

3.3 Survey Design

The survey was hosted on the online survey platform Qualtrics[2]. A copy of the survey is available in Appendix A. The survey contained four main sections:

(1) **Demographics:** We asked 7 questions relating the participants demographics.
(2) **Interface images:** We had 18 screenshots of interfaces which exhibited characteristics aligning to various degrees with manipulative patterns defined in the literature. Each participant saw a subset of 6 images from the larger pool along with a short description of the scenario in which they were to imagine encountering the pattern. For each image, participants answered ten 6-point semantic scale questions anchored by opposing adjectives which might describe the interface (e.g., honest – deceitful). There are no directly applicable scales in the literature. Therefore, we generated our own scales for describing manipulative patterns, loosely referring to more general usability semantic scales. We pilot

[1]https://www.prolific.co/

[2]https://www.qualtrics.com/

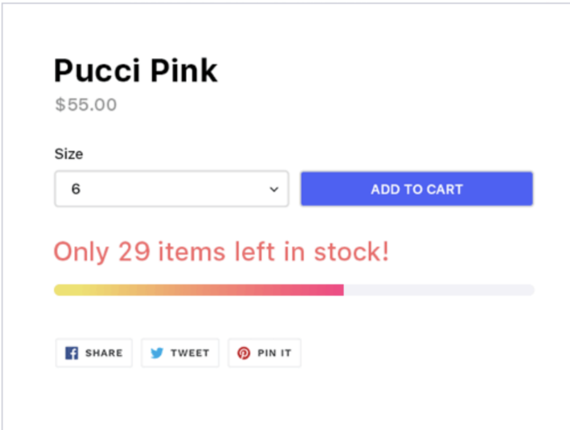


Figure 1: Example `Fake Scarcity` interface image (see full set in Appendix). End-users were prompted with *"Imagine you were online shopping and saw this image."* Experts were prompted with *"Imagine an end-user was online shopping and saw this image."*

tested our scales with several colleagues to refine wording. Each image was shown to roughly the same number of participants (see N in Table 2. End-users were asked for their reactions to the interface images directly. However, experts were asked to anticipate how end-users would react to the interface. Figure 1 demonstrates one interface image and includes the the wording difference in the caption. We also asked a few questions about their understanding of the interface and the available actions, though these are not included in our current analysis as they are tangential to our research questions.

(3) **Categorization:** We provided participants with the following definition of manipulative patterns: *Dark Patterns*[3] *are tricks used in websites and apps that make you do things that you didn't mean to, like buying or signing up for something. These patterns help companies earn money at the expense of users.* We then repeated the 6 images and asked participants: *Based on the above definition of "Dark Patterns" would you characterize this image as a Dark Pattern?*. For this particular question, experts were asked to answer from their own perspective and not from the end-users' because we explicitly wanted the experts' own assessment of the images.

(4) **General questions:** We asked a few general questions about dark patterns and solicited feedback about the survey.

The end-user survey had 114 questions (7 demographic questions, 17 questions per interface image, and 5 general questions). The expert survey had 112 questions (2 fewer general questions). end-users had a 15 minute median completion time and experts had a 22 minute median completion time.

[3]In the survey, we used the term "dark pattern" as it was the most common term at the time. We have since opted to use the more descriptive "manipulative patterns" in this paper.

3.4 Interface images

We selected 18 images of interfaces to include in the survey. Our intent was to gather a set of images that covered a wide range of manipulative patterns. We tried to cover varying degrees of explicitness, including some that we believed to be 'blatantly manipulative' and clear instances of identifiable manipulative patterns. Others were more subtle, 'mild', or may conceivably be classified as 'normal advertising'. We also needed interface examples that were self-explanatory in static format since participants would only be viewing a single screenshot for each. We have included the 18 chosen interfaces images in Appendix A. While we conferred and agreed on the classification of the images, we note that these are subjective assessments and there is no absolute 'correct' response.

Using Mathur et al. [20]'s collection of patterns, seven of our images are *Explicit* instances of manipulative patterns as defined in the existing literature. We classify four of our images as *Implicit* meaning that they contain some element or component of manipulative patterns from the literature and are not as obviously manipulative. We added a third category of *Not Established* to cover five of our images that display milder manipulations and that do not appear to match any of the manipulative patterns identified in Mathur et al.

During analysis, we decided that two of our images, representing `User Choice` and `Privacy Zuckering`, were not clear archetypes of their associated pattern. Therefore, we did not include them in our analysis. The remaining 16 images are described in Table 1.

4 RESULTS

To address our research questions, we report descriptive statistics about each user group separately, then offer comparisons between groups where appropriate.

4.1 Is This a Manipulative Pattern?

Using the three categories first described in Table 1, Figure 2 presents responses to the binary question, "Would you categorize this image as a dark [sic] (manipulative) pattern?". In this case, the question was posed to both experts and end-users with the same wording. After being shown a definition of manipulative patterns, both end-users and experts generally tended to categorize images in ways that aligned with the definitions from the literature; in other words, there are more 'yes' responses in the Explicit category, and fewer 'yes' responses in the Not Established category.

Explicit: Considering the images in the Explicit category, there are two notable exceptions for end-users. End-users mostly categorized `Fake Scarcity` and `Price Comparison Prevention` as "non-manipulative". Responses to the `Fake Scarcity` image suggest that many end-users fall for the manipulation and simply believe the interface when it says only a few items are left. For `Price Comparison Prevention`, participants may not have noticed the different units of measure on our screenshot, or they may fallen for the manipulation. Interestingly, more than half of experts also classified `Price Comparison Prevention` as "non-manipulative".

Implicit: Roughly half of end-users identified the images in the Implicit category as being "manipulative", suggesting that these implicit manipulations were not as easily recognized by end-users.

Category	Image ID	Description
Explicit	`Bait and Switch`	Users are met with this offer right after they purchase a set of tickets rather than seeing the expected confirmation screen.
	`Fake Scarcity`	A visually highlighted indicator suggests that there is a low quantity of a particular item, intended to pressure users to buy before it is sold out.
	`Price Comparison Prevention`	The units of measurement for two similar items are different, making it difficult to compare the price per unit.
	`Disguised Ad`	An ad includes an image of a download button to trick users on a page where users are already trying to download something else.
	`Forced Action`	Users are required to provide an email before they are able to read the article they clicked on.
	`Confirm-Shaming`	The language on the link to dismiss the pop-up shames the user for saying no.
	`Nagging`	A pop-up appears without the option to permanently prevent pop-ups.
Implicit	`Countdown`	A countdown for a deal pressures users to act before the offer expires.
	`Misleading`	The interface misleads users by not being transparent about how their donation will be used.
	`Preselection`	The interface defaults to a paid planned which users may not take the time to change.
	`Confusing Wording`	The interface is unclear whether clicking 'Continue' or 'Cancel' will cancel the membership.
Not Established	`Related Content`	The interface presents users with additional products that may be of interest.
	`Push Notification`	A pop-up notification appears unprompted by users.
	`Autoplay`	The next episode of a TV show will play automatically after a short countdown.
	`Goal Gradient`	A pleasant visual display indicates the user's progress in completing their profile to encourage further data entry.
	`Fancy Wording`	The language on the interface is designed to elicit a positive emotional response from users to encourage user action.

Table 1: Description and categorization of interface images used in the survey

On the other hand, most experts believed that these implicit images were "manipulative".

Not Established: For Not Established images, both end-users and experts commonly categorized them "non-manipulative", suggesting that these interface manipulations were seen as benign or as 'normal advertising'.

We ran two-tailed Fisher's Exact tests on the responses for every image and found only two instances where there was a statistically significant difference between the end-users' and experts' categorizations. `Fake Scarcity` ($p = 0.042; end - userN = 37, expertN = 7$) and `Confusing Wording` ($p = 0.0212; end - userN = 37, expertN = 9$). We note that since each participant only saw a subset of images, we have fewer participant responses per image. In particular, our N for experts is quite small (ranging from 7 to 9), which likely contributed to the lack of statistical significance even when a trend was observed in the descriptive statistics.

4.2 Semantic Scales Image Descriptions

For each image, we presented participants with ten 6-point semantic scales questions (as a reminder, this was done prior to participants seeing the definition of manipulative patterns). End-users were directly asked to describe the images using the semantic scales; and experts were asked to predict the responses of end-users. For analysis, we aligned positive and negative sides of all ten semantic scales questions. For each participant, we summed the responses (1 = positive and 6 = negative) for each image, giving a possible total per image ranging from 10 (most positive) to 60 (most negative). We refer to this sum as the *Semantic Score*. Each participant had one Semantic Score per image. We ran Mann-Whitney U tests to determine whether there were statistically significant differences between the sums of the end users' and experts' semantic scales responses. Table 2 summarizes the results of these statistical tests.

Based on the median Semantic Scores, experts rated the images more negatively than end-users for all but one image (`Fancy`

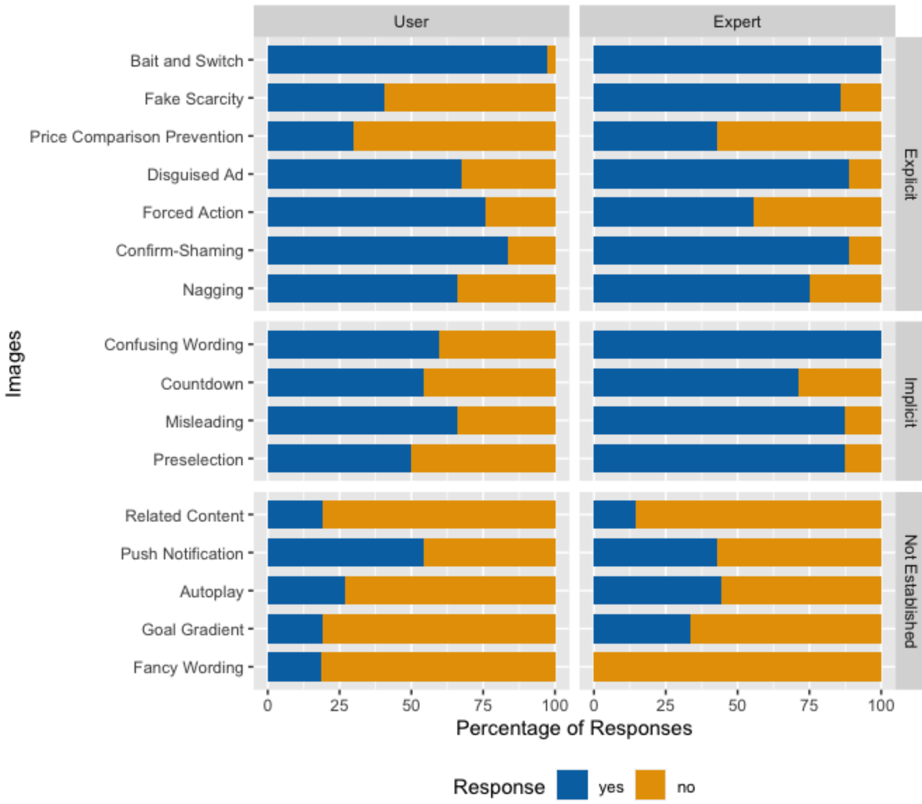


Figure 2: Percentage of end-user and expert responses to whether they personally consider each interface image to be a manipulative (dark) pattern)

Table 2: Median Semantic Scores per image and Mann-Whitney U tests comparing end-user and expert Semantic Scores per image. Images with statistically significant results are bolded and shaded. Higher Semantic Scores represent a more negative impression of the images.

Category	Image ID	Median Semantic Score (SD) End-user		Median Semantic Score (SD) Expert		N End-user	N Expert	U	p
Explicit	**Bait and Switch**	**26**	**(6.5716)**	**33**	**(5.9161)**	**38**	**7**	**56.0**	**0.0136**
	Fake Scarcity	23	(7.1150)	26	(4.8550)	38	7	97.5	0.2754
	Price Comparison Prevention	**21**	**(7.8595)**	**30**	**(7.1464)**	**38**	**8**	**61.5**	**0.0070**
	Disguised Ad	**29**	**(8.4930)**	**36**	**(3.3541)**	**39**	**9**	**71.0**	**0.0044**
	Forced Action	**25**	**(6.6798)**	**30**	**(4.9357)**	**37**	**9**	**81.0**	**0.0160**
	Confirm-Shaming	**17**	**(7.2507)**	**26**	**(5.1720)**	**39**	**9**	**51.5**	**0.0005**
	Nagging	**24**	**(6.8267)**	**28**	**(4.4641)**	**38**	**8**	**72.0**	**0.0185**
Implicit	Countdown	27	(7.1855)	30	(3.7417)	38	8	94.5	0.0967
	Misleading	**24**	**(6.2631)**	**31**	**(3.2318)**	**38**	**9**	**53.5**	**0.0008**
	Preselection	**20**	**(5.7935)**	**29**	**(4.4378)**	**38**	**9**	**44.5**	**0.0003**
	Confusing Wording	**16**	**(8.7118)**	**35**	**(4.6756)**	**39**	**9**	**26.0**	**9.29E-06**
Not Established	**Related Content**	**18**	**(5.0943)**	**21**	**(1.8127)**	**37**	**7**	**48.5**	**0.0070**
	Push Notification	22	(6.5684)	22	(6.0178)	37	8	156.0	0.8213
	Autoplay	**14**	**(5.3548)**	**24**	**(6.2849)**	**39**	**9**	**49.0**	**0.0004**
	Goal Gradient	17	(4.9142)	20	(3.2702)	39	9	109.5	0.0814
	Fancy Wording	22	(6.6664)	20	(2.9490)	38	8	152.0	1.0000

Wording). In fact, the median Semantic Score for end-users all tend towards the positive to neutral side of the scale. For most images in the Explicit and Implicit categories, these differences between end-users and experts were statistically significant (Table 2), suggesting that experts expected end-users to react much more negatively to manipulative patterns.

Only two out of five images in the Not Established category show statistically significant differences between the Semantic Scores. For all five images, both end-users and experts have Semantic Scores that fall on the positive end of the scale, suggesting that both groups are generally accepting of these interfaces.

Due to space constraints, Figure 3 includes details for three individual scales that most directly reflect the potential manipulation: *Honest – Deceitful*, *Ethical – Unethical*, *Respectful of Privacy – Intrusive*. However, Appendix A includes graphs visualizing participant responses for all ten scales.

4.2.1 Honest – Deceitful.

End-users: As seen in Figure 3a (leftmost), the end-user responses tended towards *honest*, though some Explicit and Implicit images were deemed at least somewhat *deceitful* by up to half of participants. End-users largely deemed the Not Established images as *honest*, though about a quarter of end-users thought `Push Notification` and `Fancy Wording` were *deceitful*.

Experts: In Figure 3a (rightmost), expert expectations about end-users tended towards *deceitful* for the Explicit and Implicit categories, with three images gathering entirely negative assessments (`Disguised Ad`, `Confusing Wording` and `Misleading`). Experts thought the images in the Not Established category were generally *honest*.

Overall, end-users perceived the Explicit and Implicit images to be considerably more *honest* than the experts assumed. This suggests that end-users may be less able to recognize when they are being manipulated by an interface than experts assume.

4.2.2 Ethical – Unethical.

End-users: End-users tended to generally describe images from all three categories as *ethical* (Figure 3b), though we note a trend that Explicit had more *unethical* ratings, followed by Implicit, and then Not Established. Considering individual images, `Bait and Switch`, `Disguised Ad`, and `Countdown`, had more than half of end-users assigning ratings of *unethical*.

Experts: Experts largely answered that end-users would feel that the Explicit and Implicit images were *unethical* (Figure 3b), with the exception of `Forced Action`, where about half of experts found it mildly *ethical*. Most experts rated the Not Established images to be mildly *ethical*. Of the Not Established images, `Autoplay` was rated most *unethical*.

We again note that end-users overall tended to assess interfaces as being *ethical*, while experts expected end-users to find the Explicit and Implicit images to be *unethical*. For example, one of the most noticeable differences is that the majority of end-users found `Confusing Wording` to be *ethical*, but all experts labeled it as *unethical*. This further suggests that end-users are unaware that they are being manipulated by interfaces, and that experts over-estimate end-users' ability to recognize these manipulations.

4.2.3 Respectful of Privacy – Intrusive.

End-users: Interestingly, end-user responses to the *Respectful of Privacy – Intrusive* scale were more mixed (Figure 3c). End-user responses for the Explicit images generally tended towards *intrusive*, with the exception of `Price Comparison Prevention`, which the majority of end-users found *respectful of privacy*. End-users thought that two Implicit images were *respectful of privacy* and two were *intrusive*. They generally thought that the Not Established images were *respectful of privacy*, with the exception of `Related Content` and `Push Notification`.

Experts: Experts generally expected end-users to described images from all three categories as *intrusive* (Figure 3c). The most significant exception is `Fancy Wording`, which all experts predicted as *respectful of privacy*.

Of our described scales, the *Respectful of Privacy – Intrusive* scale showed the most agreement between end-users and experts, largely because end-users recognized that many of these Explicit and Implicit images were *intrusive*.

5 DISCUSSION

In our study, we sought to learn more about end-users' perceptions of manipulative patterns (RQ1) and to determine whether experts have an accurate understanding of end-users' perceptions of manipulative patterns (RQ2). We showed participants images of interfaces where the manipulative pattern was *Explicit*, where the pattern was more *Implicit* or subtle, and where the manipulation was mild or *Not Established* as a common manipulative pattern in the literature.

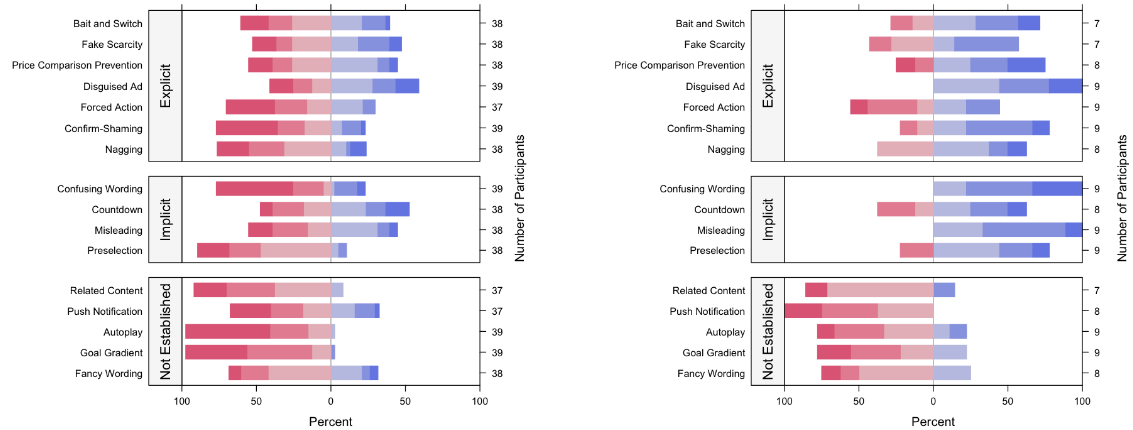
5.1 End-Users Struggle to Identify Manipulations

We found that while end-users identified more images from the Explicit and Implicit categories as displaying a manipulative (dark) pattern than those from the Not Established category, many end-users nonetheless did not recognize several images displaying manipulative patterns as manipulative, even after being shown a definition. Furthermore, end-users' first reactions to the images when considering the semantic scales adjectives were generally positive. Taken together, this suggests that **end-users often do not recognize when they are being manipulated by an interface and tend to 'take things at face value'.**

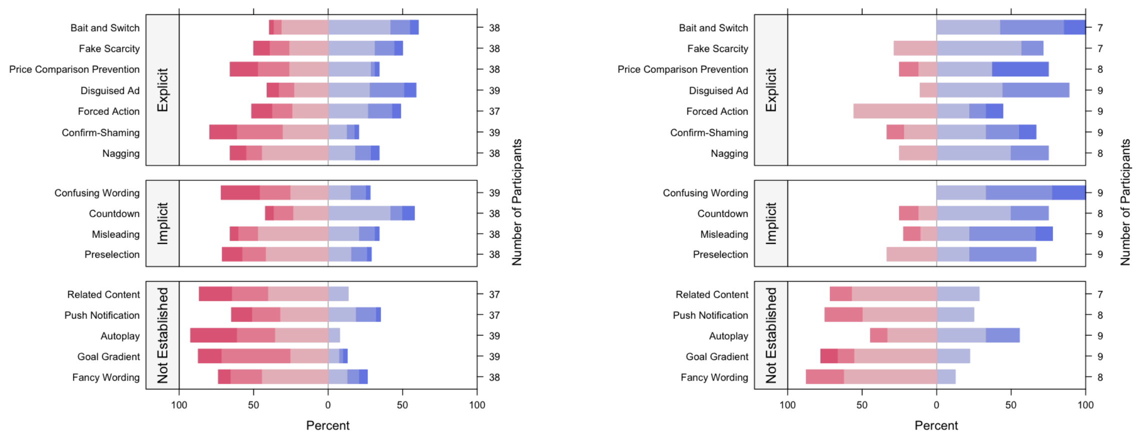
Additionally, end-users tended to be more positive about images in the Implicit category compared to those in the Explicit category, even though the interfaces from both were manipulative. Perhaps unsurprisingly, end-users appear even more susceptible to manipulation from interfaces which are more subtle or which include smaller manipulative components within the larger interface, even when these manipulations are common. This is in line with Luguri et al.'s [18] finding that aggressive manipulative patterns face a much stronger backlash than those more "mild." Similarly, Gray et al. [11] found that users were aware of certain explicit manipulation tactics (e.g., moving UI elements so that users are more likely to click them without thinking) which they looked for when identifying manipulative patterns. From our results, it is plausible that users do not have such heuristics for more subtle manipulations. It appears that end-users lack a comprehensive understanding of the fundamental mechanisms employed by manipulative patterns.

5.2 Experts Overestimate End-User Responses

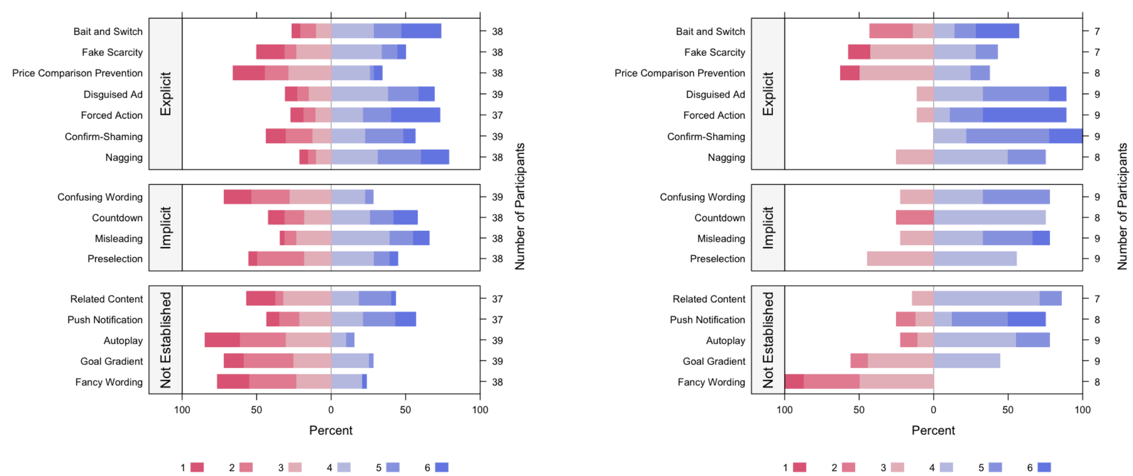
Addressing RQ2, we noted a trend where experts recognized more of the Explicit and Implicit images as displaying manipulative patterns than end-users, however, the results were not statistically significant for most images. We suspect that our small sample size



(a) Honest (1/red) to Deceitful (6/blue) scale.



(b) Ethical (1/red) to Unethical (6/blue) scale.



(c) Respectful of Privacy (1/red) to Intrusive (6/blue) scale

Figure 3: End-user (leftmost graphs) responses and expert (rightmost graphs) predictions of how end-users would respond to semantic scale questions per image where 1=positive adjective and 6=negative adjective.

for experts is the cause of this discrepancy, but further data would be necessary to confirm. Considering the semantic scales adjectives, our statistics show that experts over-estimated end-users' negative responses on nearly every image. This leads to a problematic situation: **experts are over-estimating end-users' ability to recognize when they are being manipulated.**

Research [4, 14] in other domains suggests that experts are poor estimators of novices' abilities, and similar effects appear at play in our study. Our experts may have been confident that end-users would recognize images from the Explicit and Implicit categories because these manipulations are thoroughly analysed and discussed in the literature. This may result in a knowledge bias on behalf of experts who are well-versed on the topic of manipulative patterns (and who may well have written some of the key literature in the area). The *curse of expertise* [14] combines several cognitive biases (availability heuristic, anchoring, and oversimplification) that together explain why experts have difficulty ignoring their own existing knowledge and skill, and why they tend to have difficulty estimating what it is like to perform a task as a novice.

5.3 Education

We see a need to educate both experts and end-users with respect to manipulative patterns. End-users need improved ability to recognize when they are being manipulated and experts need improved ability to estimate end-user perspectives.

Existing literature has recommended better education to the general public [1, 7]. This can include more targeted awareness campaigns to aid them in identifying manipulative patterns in their day-to-day lives. Educating users on what to look for in a manipulative interface (as users are educated in how to identify misinformation) can help them avoid manipulation online. For instance, a user who recognizes "fake scarcity" as a manipulative sales tactic may not feel as pressured to make impulsive shopping decisions. Additionally, educating users can help to raise awareness and aid in lobbying for better legislation or in putting public pressure on platforms to decrease their use of manipulative patterns. In an effort to increase awareness and provide a public resource, the *Dark Patterns Tip Line* website [16] was recently launched to collect instances of manipulative patterns reported by consumers. But user education should not be the only route to addressing the proliferation of manipulative design. Research [1] has already shown that even when users are aware of manipulation, it does not necessarily predict their ability to avoid it.

We further highlight the need for increased awareness among the expert community, particularly in relation to experts' ability to anticipate end-user reactions to manipulative interfaces. This has implications when experts are called upon to discuss the effects of certain manipulative designs (e.g., as expert witnesses), to act in advisory roles (e.g., in relation to regulation, or to consulting on implementations), or to provide education on the topic. Educational materials designed by experts with these misconceptions will be ineffective if they do not address the issues from the right perspectives.

5.4 Regulation

We also echo previous work [1, 17, 23] calling for better regulation of manipulative interfaces. We further recommend that regulators and/or legislators pay special attention to more subtle and less overt forms of user manipulation because these forms are more likely to be overlooked by users, thus making their manipulation go unseen. We also highlight that existing regulation which targets explicit manipulations has resulted in a proliferation of more subtle and insidious manipulations (e.g., as many platforms have resorted to manipulative design to get around GDPR requirements [15, 23]) that are equally if not more problematic and more difficult for users to recognize.

5.5 Limitations and Future Work

Approximately 38% of our end-user participants had some amount of formal education in technical fields such as computer science. This is a greater proportion that we might expect in a representative population. Moreover, this may have positively influenced experts' ability to predict the end-user group's answers due to shared background. However, only 15% of end-users indicated that they were familiar with manipulative (dark) patterns before this survey and only 16% responded that they had previously encountered manipulative (dark) patterns despite their technical backgrounds.

When designing our survey, we were unable to find a set of established semantic scales for describing manipulative patterns, so we iteratively created our own. While these led to interesting results, we would further refine our word choices to improve clarity and to ensure that all scales are targeting distinct attributes.

We opted for an online survey to address our research questions and consequently were limited in how we could present the interfaces to our participants. To complement our findings, future studies could observe participants interacting with "live" interfaces.

6 CONCLUSION

In this study we sought to understand how end-users describe manipulative patterns and whether experts in the field have an accurate understanding of end-users' perceptions. We conducted two surveys, one for end-users and one for experts. We found that end-users missed identifying many images displaying manipulative patterns. They also tended to describe the images using positive adjectives, suggesting that end-users often do not recognize when they are being manipulated by an interface. While experts recognized more of the manipulative patterns than end-users, the results were not statistically significant for most images. Furthermore, experts incorrectly assumed that end-users' would describe the images with negative responses on nearly every image. Our results show that experts over-estimated end-users' ability to recognize when they are being manipulated. We highlight the need for improved education for both end-users and experts, and the need for regulation against manipulative design that considers more subtle manipulations.

ACKNOWLEDGMENTS

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The authors also would like to thank the members of the CHORUS Lab for their help with reviewing the semantic scale wording.

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APPENDICES

A QUESTIONNAIRE

Disclaimer: When we conducted the survey, we used the term "dark pattern" as it was the most common term at the time. We have since opted to use the more descriptive "manipulative patterns" in this paper.

Questionnaire (for End User Group)

Demographic Questions:

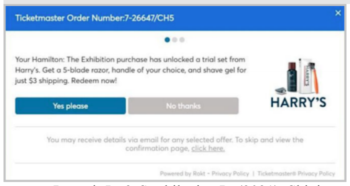
1. Select the option that best describes your current gender identity
    a. Man
    b. Woman
    c. Non-binary
    d. Prefer not to answer
    e. Prefer to self describe
2. What is your age? [text entry question]
3. What is the highest level of education you have completed?
    a. Less than secondary school (e.g., up to grade 8)
    b. Some of secondary school (e.g., between grade 8 and 12)
    c. Completed secondary school (e.g., completed grade 12)
    d. Trade/Technical/Polytechnic
    e. Some undergraduate (College/University)
    f. Completed undergraduate
    g. Some graduate or professional degree (e.g., Masters, PhD, medical)
    h. Completed graduate or professional degree (e.g, Masters, PhD, medical)
4. How many hours do you spend online on a typical day? [text entry question]
5. What is your area of expertise/study? [text entry question]
6. What is your level of online technical expertise?
    a. Excellent
    b. Good
    c. Average
    d. Poor
    e. Terrible
7. Do you have any formal education in Computer Science, Information Technology, or related technical field? [Yes/No]

Website Design Questions:

The End User group will be given a random sample of 6 images from the set of 18 (source below image):

Explicit Group

Bait and Switch

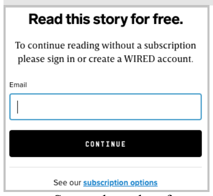


source: Luguri, J., & Strahilevitz, L. (2021). Shining a Light on Dark Patterns (SSRN Scholarly Paper No. 3431205). Social Science Research Network. https://papers.ssrn.com/abstract=3431205

Disguised Ad

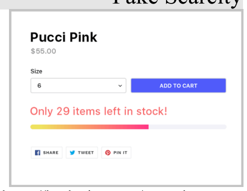
source: https://www.shopify.com/partners/blog/dark-patterns

Forced Action



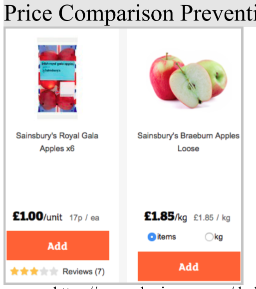
source: Screenshot taken from Wired.com, Google Chrome May 2021

Fake Scarcity



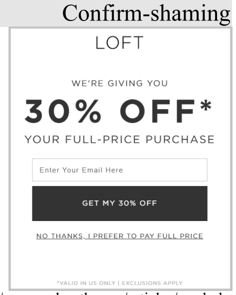
source: https://beeketing.com/countdown-cart

Price Comparison Prevention



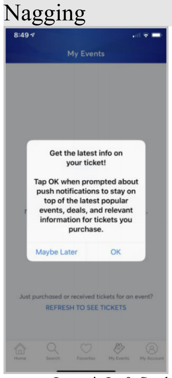
source: https://www.sharing.agency/dark-patterns/

Confirm-shaming



source: https://www.uxbooth.com/articles/ux-dark-patterns-manipulinks-and-confirmshaming/

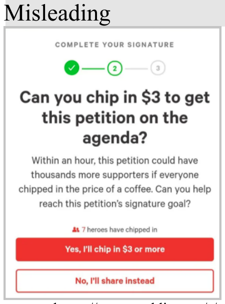
Nagging



source: Luguri, J., & Strahilevitz, L. (2021). Shining a Light on Dark Patterns (SSRN Scholarly Paper No. 3431205). Social Science Research Network. https://papers.ssrn.com/abstract=3431205

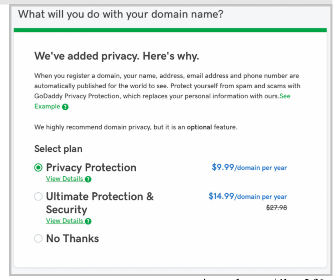
Implicit Group

Misleading



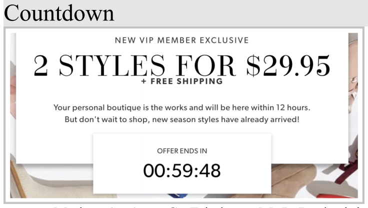
source: https://www.reddit.com/r/assholedesign/

Preselection



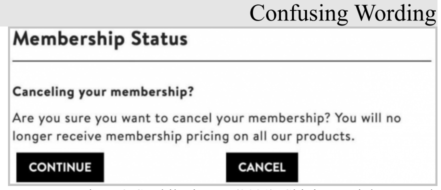
source: tinyurl.com/4btz3f6y

Countdown



source: Mathur, A., Acar, G., Friedman, M. J., Lucherini, E., Mayer, J., Chetty, M., & Narayanan, A. (2019). Dark Patterns at Scale: Findings from a Crawl of 11K Shopping Websites. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW), 1–32. https://doi.org/10.1145/3359183

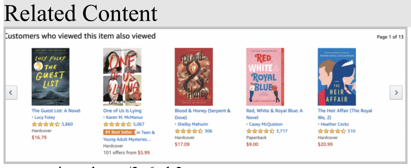
Confusing Wording



source: Luguri, J., & Strahilevitz, L. (2021). Shining a Light on Dark Patterns (SSRN Scholarly Paper No. 3431205). Social Science Research Network. https://papers.ssrn.com/abstract=3431205

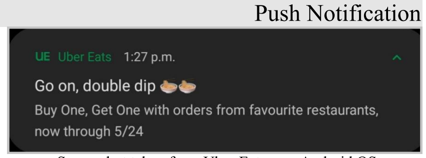
Not Established Group

Related Content



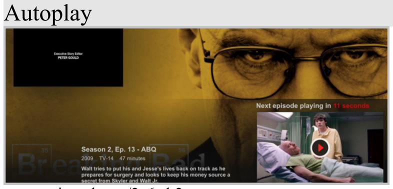
source: tinyurl.com/2y6cdr2p

Push Notification



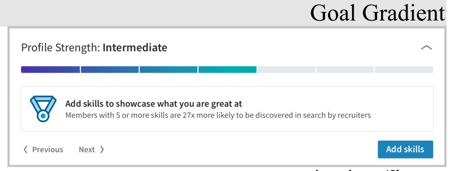
source: Screenshot taken from Uber Eats app, Android OS version May 2021

Autoplay



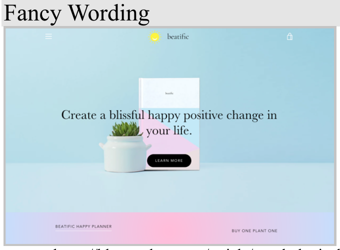
source: tinyurl.com/2y6cdr2p

Goal Gradient



source: tinyurl.com/5hpcctpv

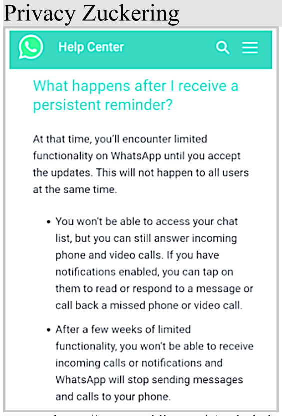
Fancy Wording



source: https://blog.crobox.com/article/psychological-marketing-examples

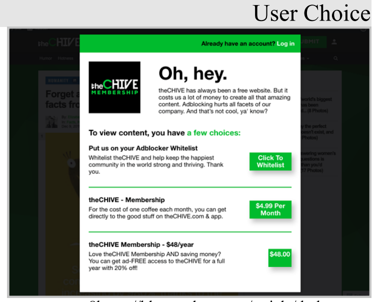
Not Analysed Group

Privacy Zuckering



source: https://www.reddit.com/r/assholedesign/

User Choice



source: 8https://blog.crobox.com/article/dark-patterns

They will be asked the following questions about each image displayed to them:

Imagine that you are visiting a website and see the interface pictured in this image. Take a minute to review it.

1. I am confident that I understand what is happening in this image. [6-point Likert (1=strongly disagree, 6 = strongly agree)]
2. I am confident that I understand all the actions I can take in the image at this point. [6-point Likert (1=strongly disagree, 6 = strongly agree)]
3. Rate the interface on the following categories. The words on either side of a row are opposites and the bubbles between them represent the degree to which you would describe the interface as being more aligned with either word.

Helpful	○	○	○	○	○	○	Useless
Easy to understand	○	○	○	○	○	○	Confusing
Honest	○	○	○	○	○	○	Deceitful
Annoying	○	○	○	○	○	○	Enjoyable
Common (I've seen it many times before)	○	○	○	○	○	○	Unusual
Stressful	○	○	○	○	○	○	Relaxing
Ethical	○	○	○	○	○	○	Unethical
Organized	○	○	○	○	○	○	Cluttered
Carefully crafted	○	○	○	○	○	○	Thoughtless
Intrusive	○	○	○	○	○	○	Respectful of privacy

4. Why did you choose these ratings for the image? (optional) [text entry question]
5. Are there any other words you would use to describe this image? (optional) [text entry question]
6. Which option (button, word, etc.) does the designer of the interface want you to select? Why do you think that? [text entry question]
7. As a user of the website in the above image, what would your next action be and why? [text entry question]

<u>Dark Pattern Questions:</u>

Participants will be shown the definition of dark patterns and asked to identify which of the images they viewed during the survey are dark patterns based on that definition.

Definition of "Dark Patterns": Dark Patterns are tricks used in websites and apps that make you do things that you didn't mean to, like buying or signing up for something. These patterns help companies earn money at the expense of users.

1. Is this the first time you hear about the term **dark patterns**? [Yes/No]
2. Based on the above definition of "Dark Patterns" would you characterize this image as a Dark Pattern? [will be asked for each of the 6 images they encountered in the survey] [Yes/No]
3. Have you encountered dark patterns before this survey? [Yes/No]

<u>End of Survey Questions:</u>

1. Did you answer the questions in this survey honestly? [Yes/No]
2. Is there anything else you would like to share about dark patterns? (optional) [text entry question]
3. Do you have any feedback for us about this survey? (optional) [text entry question]

Questionnaire (for Expert Group)

<u>Demographic Questions:</u>

1. Select the option that best describes your current gender identity
    a. Man
    b. Woman
    c. Non-binary
    d. Prefer not to answer
    e. Prefer to self describe
2. What is your age? [text entry question]
3. What country are you from? [text entry question]
4. What is the highest level of education you have completed? [text entry question]
5. What is your area of expertise/study? [text entry question]
6. How many years have you been in your field? [text entry question]
7. Briefly, how does your expertise relate to dark patterns?

<u>Website Design Questions:</u>

The Expert group will be given a random sample of 6 images from the same set of 18 images given to the End User group.

You should answer the following questions from the perspective of how you think end users would react. Imagine that an end user is visiting a website and sees the interface pictured in this image. Take a minute to review it.

They will be asked the following questions about each image displayed to them:

Imagine that and end user is visiting a website and see the interface pictured in this image. Take a minute to review it.

1. I am confident that end users will understand what is happening in this image. [6-point Likert (1=strongly disagree, 6 = strongly agree)]
2. I am confident that end users understand all the actions that they can take in the image at this point. [6-point Likert (1=strongly disagree, 6 = strongly agree)]
3. Rate the interface on the following categories based on what you think end users will perceive. The words on either side of a row are opposites and the bubbles between them represent the degree to which a user would describe the interface as being more aligned with either word.

Helpful	○ ○ ○ ○ ○ ○	Useless
Easy to understand	○ ○ ○ ○ ○ ○	Confusing
Honest	○ ○ ○ ○ ○ ○	Deceitful
Annoying	○ ○ ○ ○ ○ ○	Enjoyable
Common (I've seen it many times before)	○ ○ ○ ○ ○ ○	Unusual
Stressful	○ ○ ○ ○ ○ ○	Relaxing
Ethical	○ ○ ○ ○ ○ ○	Unethical
Organized	○ ○ ○ ○ ○ ○	Cluttered
Carefully crafted	○ ○ ○ ○ ○ ○	Thoughtless
Intrusive	○ ○ ○ ○ ○ ○	Respectful of privacy

4. Why did you choose these ratings for the image? (optional) [text entry question]
5. Are there any other words you think end users would use to describe this image? (optional) [text entry question]
6. Which option (button, word, etc.) does the designer of the interface want the end user to select? Why do you think that? [text entry question]
7. What would the next action be for a user of the above website and why? [text entry question]

<u>Dark Pattern Questions:</u>

Participants will be shown the definition of dark patterns and asked to identify which of the images they viewed during the survey are dark patterns based on that definition.

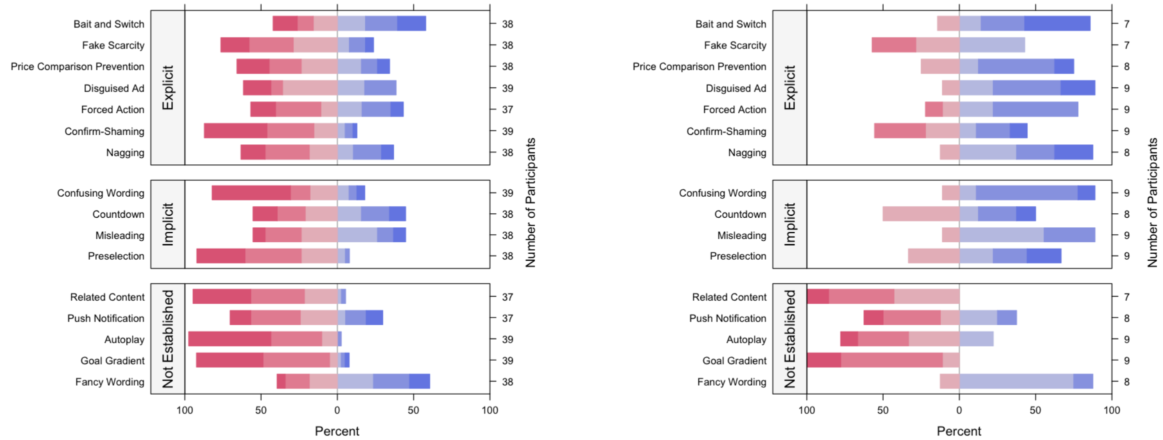
Definition of "Dark Patterns": Dark Patterns are tricks used in websites and apps that make you do things that you didn't mean to, like buying or signing up for something. These patterns help companies earn money at the expense of users.

1. Based on the above definition of "Dark Patterns" would you characterize this image as a Dark Pattern? [will be asked for each of the 6 images they encountered in the survey] [Yes/No]

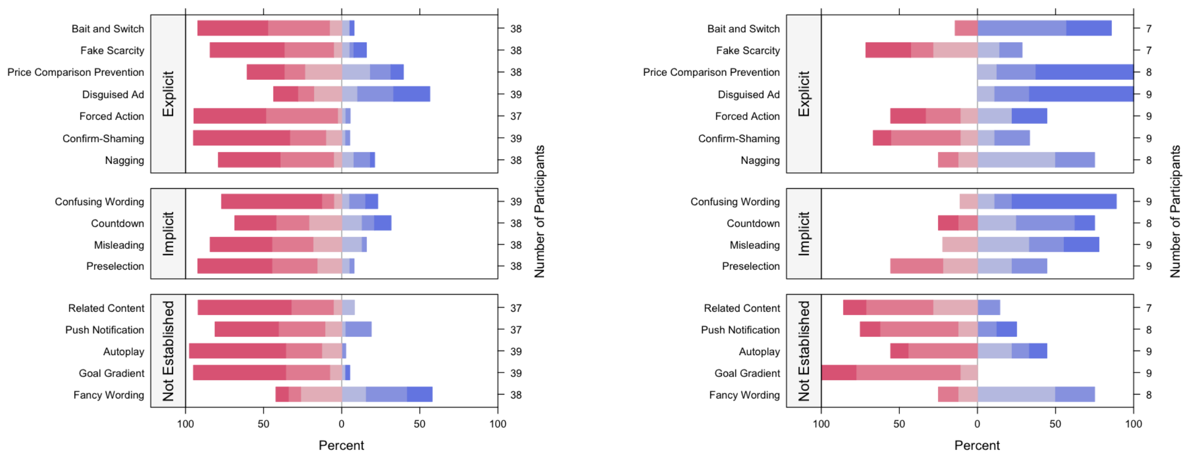
<u>End of Survey Questions:</u>

1. Did you answer the questions in this survey honestly? [Yes/No]
2. Is there anything else you would like to share about dark patterns? (optional) [text entry question]
3. Do you have any feedback for us about this survey? (optional) [text entry question]
4. Do you want to be entered in the raffle to win a $50 Amazon gift card? [Yes/No]

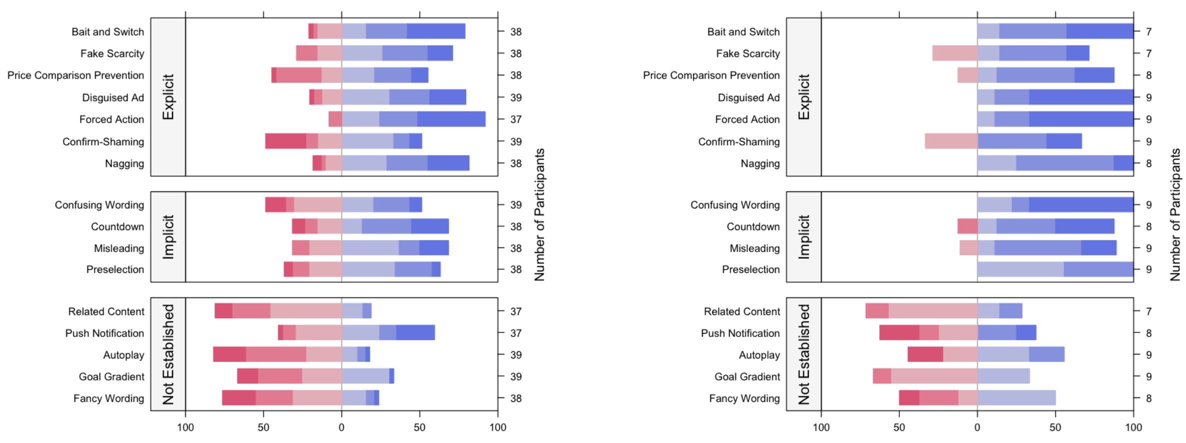
B FIGURES



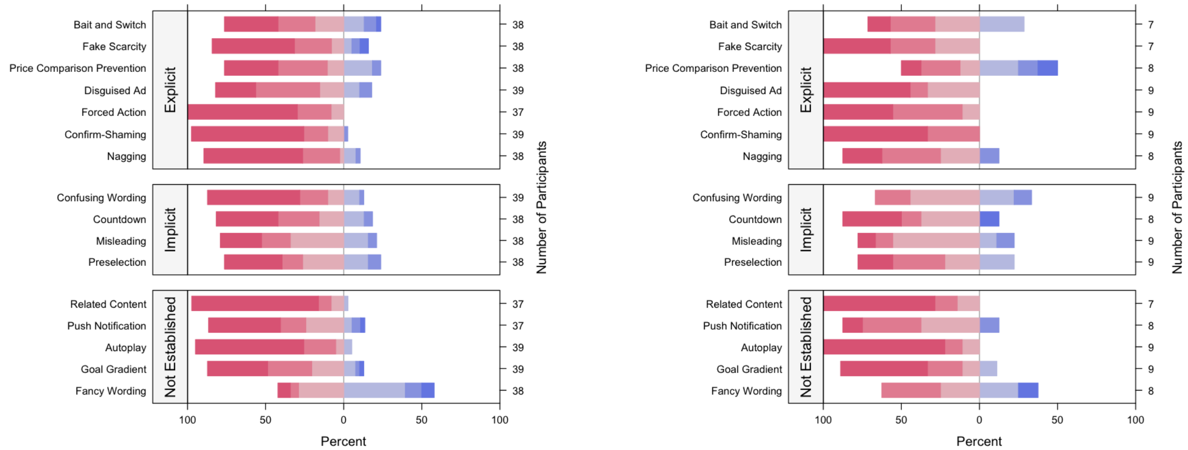
(a) Helpful (1/red) to Useless (6/blue) scale



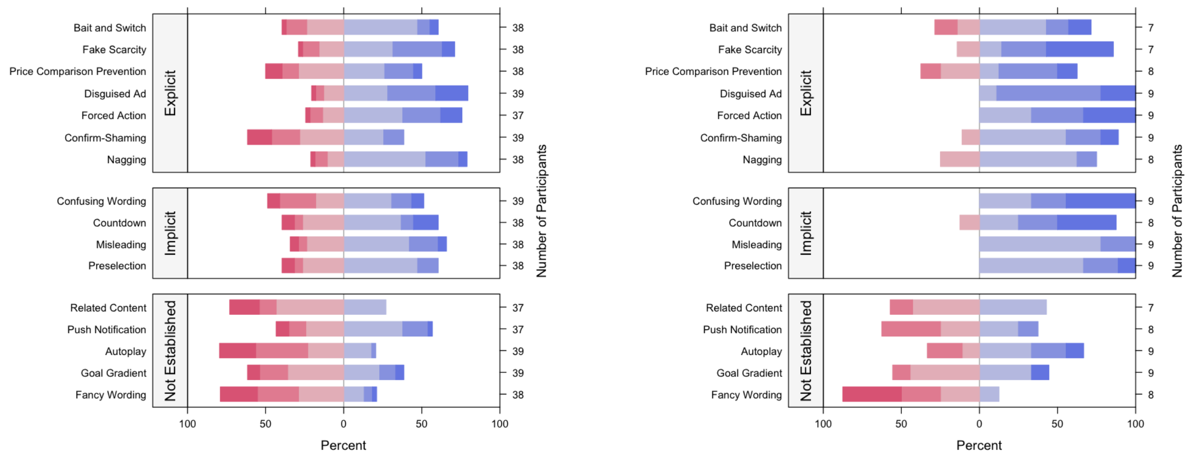
(b) Easy to Understand (1/red) to Confusing (6/blue) scale



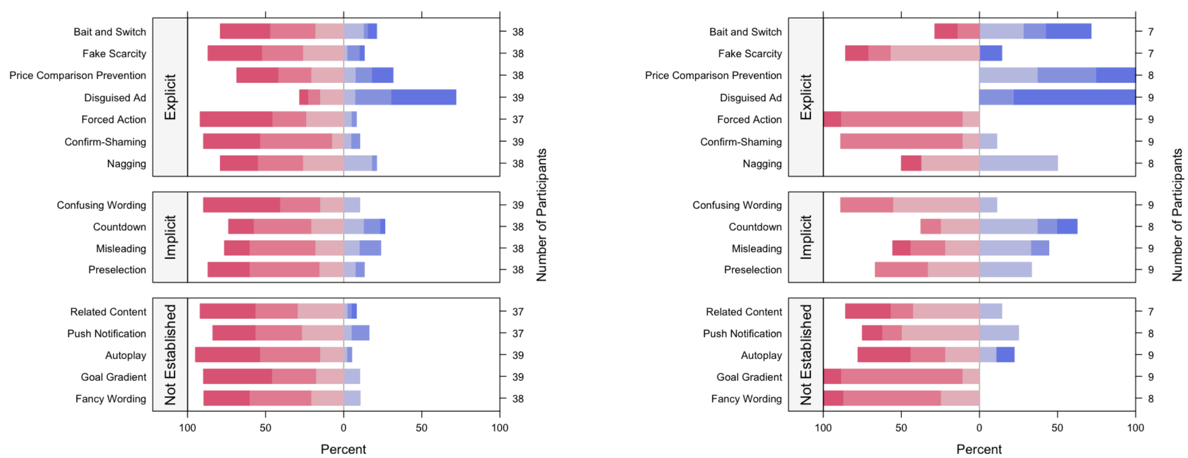
(c) Enjoyable (1/red) to Annoying (6/blue) scale



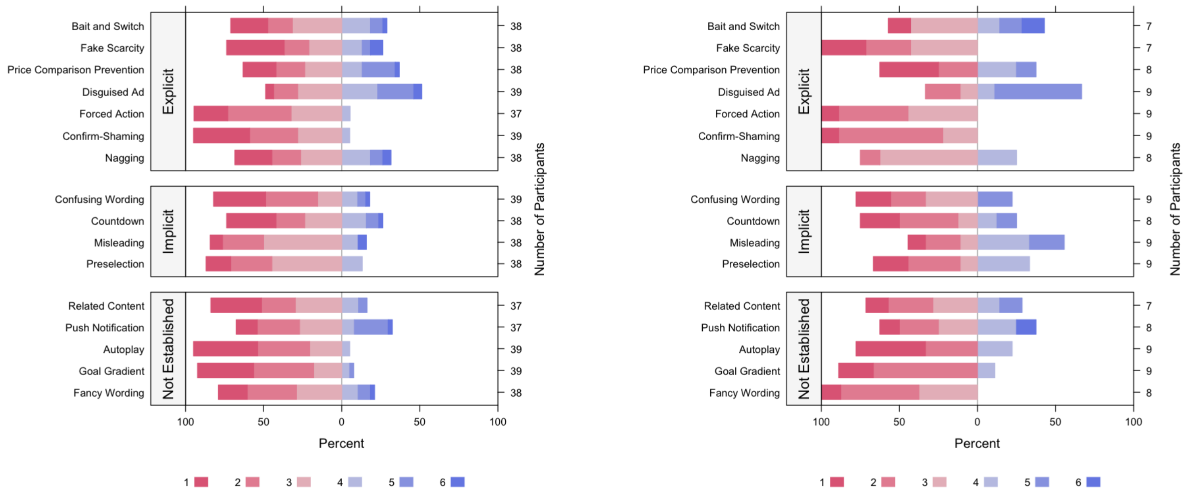
(d) Common (1/red) to Unusual (6/blue) scale



(e) Relaxing (1/red) to Stressful (6/blue) scale



(f) Organized (1/red) to Cluttered (6/blue) scale



(g) Carefully Crafted (1/red) to Thoughtless (6/blue) scale

Figure 4: End-user (leftmost graphs) and expert (rightmost graphs) responses to semantic scale questions per image where 1=positive adjective and 6=negative adjective.