The Time is Ticking: The Effect of Deceptive Countdown Timers on Consumers' Buying Behavior and Experience

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Abstract

People who shop online deal with dark patterns regularly, among which are also deceptive countdown timers. Deceptive countdown timers indicate a limited-time offer or deal that is not truly limited-time, as the deal does not expire when the timer reaches zero. Previous research has studied the taxonomies and prevalence of such dark patterns, but only a handful of studies have investigated the effects of dark patterns. This study investigates the effects of deceptive countdown timers on consumers' buying behavior and experience. We compared the reaction of participants that encountered no special offers, only a discount, and a discount accompanied by a deceptive countdown timer in an online experiment (N = 245). Our results show that deceptive countdown timers, like discounts, can affect product choice, but also induce a variety of responses ranging from participants mentioning they do not mind countdown timers to participants that deem them manipulative, deceptive, and feel negatively impacted by them. Furthermore, our results also suggest that the deceptive countdown timer can diminish the incentive of consumers to choose a product with a discount making the consumer skeptical and averse to offers with (deceptive) countdown timers. Future research should investigate the effects of other dark patterns, as our experimental setup is suitable for re-use. Also, future work could focus on the diminishing effects dark patterns have and explore different ways to protect consumers from dark patterns. Given the observed negative impact, we call for a ban on deceptive countdown timers and ask policymakers to consider studies such as this one when creating new policies.

Content

1 Introduction

Imagine a person who doubts whether they should buy a product online. Suddenly, that same person notices a countdown timer indicating only one hour is left to buy the product at a 20% discount. As a result, the imaginary person decides to purchase the product. However, the person was unaware that the countdown timer simply resets if the web page is refreshed. Such a 'deceptive' countdown timer is an example of a 'dark pattern'. Dark patterns can be described as user interface (UI) elements designed to trick users into doing things they might not want to do but benefit the business in question (Brignull, n.d.; Gray et al., 2018). The previous example illustrates a typical dark pattern found on online shopping websites. Still, dark patterns are not limited to online shopping only. Dark patterns exist in many domains, such as gaming, social media, privacy, cookie consents, advertisements, and subscriptions (Gray, Chen, et al., 2021; Mathur et al., 2019).

When looking at the history of dark patterns, especially those found in online shopping and social media, they go hand in hand with 'growth hacking', a trend focused on massive scaling and organization growth (Ellis, 2010). After some time, most organizations run into limits on growth, and growth hackers start adapting their techniques to maximize revenues (Narayanan et al., 2020). One technique used to maximize revenues is the implementation of online controlled experiments, A/B testing in particular. A/B tests are used to quickly evaluate ideas, such as new UI designs, using two or more variants (Kohavi & Longbotham, 2017). Hence, organizations found that some designs worked better than others, and the most effective design would be implemented to maximize revenue, despite it being a dark pattern (Narayanan et al., 2020).

This thesis presents an in-depth analysis of (deceptive) Countdown Timers and their effects on customers' online shopping experience and behavior. The rest of this paper is structured as follows. First, relevant literature regarding dark patterns and related concepts is covered. Next, research questions and hypotheses are stated, followed by a detailed description of the methodology used. Then, results followed from the online experiment and questionnaire are presented. Finally, results and limitations are discussed, and future research opportunities are provided.

2 Preliminaries

Throughout this thesis, we focus on dark patterns. However, one must also understand its related concepts to understand dark patterns. This chapter will discuss two of those concepts: Nudging and A/B testing.

2.1 Nudging

The idea of 'nudging' is that small details can have major impact on people's behavior (Wilkinson, 2013) in a positive way. For instance, placing stickers on the floor every two meters during COVID-19 times nudged people to keep a safe distance from each other. Another famous example by Johnson & Goldstein (2003) is organ donation consent rates. Countries that demand explicit consent have lower consent rates than countries that presume consent because people do not tend to change the default option. Hence, nudges are not mandates and should offer a choice. Putting fruit at eye level counts as a nudge, banning junk food does not (R. H. Thaler & Sunstein, 2009). As these examples show, policy makers adopt nudging to steer people's behavior in a paternalistic way by offering choices instead of implementing prohibitions.

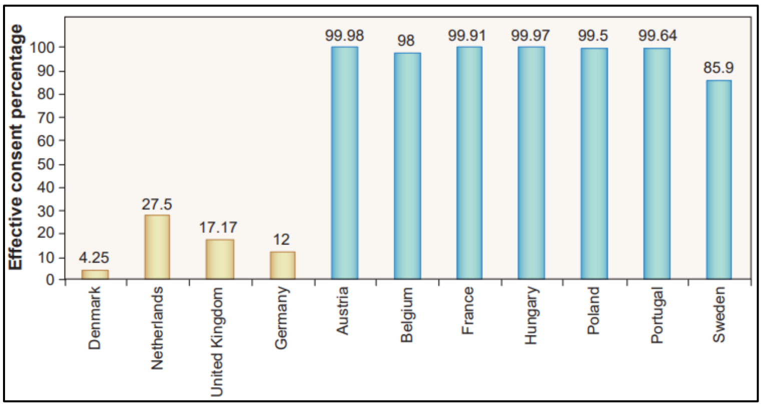

Figure 1 - Effective consent rates by country. Explicit consent (opt-in, gold) and presumed consent (opt-out, blue) (Johnson & Goldstein, 2003).

Implementing nudges is not limited to policy makers— businesses also implement nudges. However, businesses use nudges in a more adversarial rather than paternalistic way (Narayanan et al., 2020). For instance, grocery stores place children's items on lower shelves, so the products are within their line of sight. In addition, nudging is extended to the digital environment, called 'digital nudging' (i.e., the use of UI elements to guide people's behavior in digital environments) (Özdemir, 2020). The difference between digital nudging and traditional nudging is twofold. First, digital nudges can be implemented more frequently and faster. Second, the scale on which digital nudges make an impact is much more significant (e.g., if Amazon implements a change, the impact is much greater than if a physical store makes a change). Although this sounds beneficial, there is also a dark side to the story: dark patterns, to be precise. Although both (digital) nudges and dark patterns aim to lead users into certain actions, there is a clear property separating the two: nudges are generally designed to make people better off, while dark patterns trick users into actions they might not wish to carry out (Luguri & Strahilevitz, 2021; Özdemir, 2020).

2.2 A/B Testing

In order to keep users involved, (big) tech companies come up with new ideas and UI designs daily. In the past, the effectiveness of new UI designs would be tested using historical data. However, such traditional experiments often did not lead to breakthroughs. The example of Amazon Kindle Sales (Kohavi & Francisco, 2017) illustrates this nicely. On October the 26th, 2008, Amazon sold approximately 5 million kindles. The day after, Amazon decided to change the website and achieved a similar result. However, on October the 27th, kindle sales surged to over 25 million. What Amazon did not consider was that Oprah Winfrey, on that same day, called Amazon Kindle 'her new favorite thing'. This example of Amazon showcases why big tech companies had to develop new ways of testing their innovations using data. Consequently, this is what we now know as the concept called A/B testing (Kohavi & Longbotham, 2017).

The concept of A/B testing is trivial (Kohavi & Francisco, 2017; Kohavi & Longbotham, 2017): persistently, users are randomly split between variants (e.g., system A and system B). Next, their interactions with the website are documented, and key metrics are computed. Finally, the key metrics are evaluated using the Overall Evaluation Criteria (OEC), for example, the number of clicks on an advertisement. As a result, the experimenting company can quickly evaluate the most effective design choice (Kohavi & Longbotham, 2017).

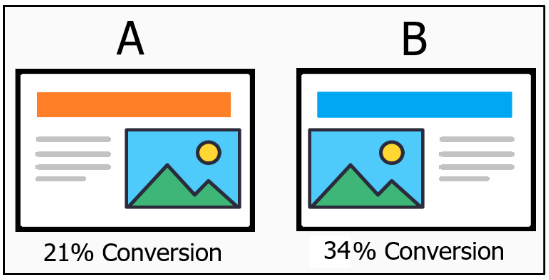

Figure 2 - A/B testing illustration. In this case, design B has a better conversion rate.

Nowadays, A/B testing is recognized as a critical tool to determine whether a design change should be made (Kohavi & Longbotham, 2017). In addition, the ability to set up experiments on already existing online platforms makes testing scalable and efficient.

As far as dark patterns are concerned, A/B tests prove to be a reliable way to measure their effectiveness (Narayanan et al., 2020), allowing designers to find the most effective (and sometimes dark) design choices with only a few lines of code.

2.3 Consumer Choice

Imagine a webshop visitor selecting a new webcam for his/her computer. The visitor is considering a full-HD webcam, selling for $40, and a 4K resolution webcam, selling for $80. The visitor knows the 4K resolution provides better image quality over the full-HD webcam, but it costs twice as much. After consideration, the 4K webcam seems worth the extra cost, and the visitor decides to purchase that one. A couple of weeks later, he/she revisits the webshop to purchase a webcam for the home office. This time the webshop offers a $20 discount on all products. Now, the full-HD webcam costs $20, and the 4K webcam sells for $60. The 4K image quality is still better, yet it is three times as expensive this time. After some thought, the visitor decides the full-HD webcam might work just as well and purchases that one. This example illustrates what happens to many people when they intend to buy a product: thinking in context and figuring out the best choice regarding the options presented (Bordalo et al., 2013). In literature, this concept is called 'consumer choice' (Bettman et al., 1998; R. Thaler, 1980).

One of the essential areas regarding consumer choice is understanding why a consumer chooses a specific option (Birdwell, 1968). Retailers are also aware of the importance of understanding why a consumer chooses a specific product and often try to influence the choices made. For example, retailers display sold-out items (Ge et al., 2009), implement image congruence influencing (Birdwell, 1968), or put the consumer under time pressure (Reutskaja et al., 2011). Those examples relate closely to another way consumers are influenced: dark patterns.

2.3.1 Urgency to Buy

As mentioned in the previous section, retailers tend to put customers under time pressure to steer their choices, usually in favor of the retailer. In other words, the retailer attempts to increase the customer's 'urgency to buy' a specific good or product, cultivating greater profits (Childs & Jin, 2020). Urgency to buy can be defined as *"an urge or a desire of the consumer to buy the product right away, thus limiting consumers' freedom to delay buying decisions."* (Gupta, 2013). Urgency to buy exploits a psychological concept called the 'scarcity bias', in which the value of a good increases due to its scarcity (Mittone & Savadori, 2009). However, it is still unknown how effective fake time pressuring tactics (i.e., deceptive countdown timers) used by retailers influence consumer choices, something we attempt to answer in this thesis.

2.3.2 Intention to Buy

Another relevant concept concerning consumer choice is ‘intention to buy’. Intention to buy, also known as ‘purchase intention,’ can generally be described as a situation where a consumer tends to buy a specific product in a certain condition (Morinez et al., 2007, as cited in Mirabi et al., 2015). Many definitions exist for intention to buy (Rezvani et al., 2012), one of which includes ‘online purchase intention’. Online purchase intention (i.e., online intention to buy) is defined as a customer’s willingness to purchase products via the Internet (Meskaran et al., 2013).

Previous research indicates that time pressure is associated with increased brand attitude (i.e., brand affinity) and increased intention to buy compared to the group without applied time pressure (H. Kim et al., 2020). When time pressure was applied using a countdown timer, the intention to buy increased again compared to the group that saw no countdown timer (H. Kim et al., 2020).

Although intention to buy is interesting, countdown timers are mainly linked to urgency (see previous section), and we expect them to affect consumers’ urgency to buy a product (i.e., accelerating the purchase made). Hence, in this thesis, we mainly study the urgency to buy and briefly touch upon intention to buy. However, we consider the effect of countdown timers on consumers’ purchase decisions, which likely results from the underlying intention to buy.

2.4 Dark Patterns and Law

Although one could argue that dark patterns are ‘unethical’, it is difficult to determine if they violate any laws (Luguri & Strahilevitz, 2021). Except for some cases issued by the Federal Trade Commission, little case law discusses unfairness in dark patterns (Luguri & Strahilevitz, 2021). In addition, taking into account the widespread implementation of dark patterns (Mathur et al., 2019; Nouwens et al., 2020), it is unlikely there are direct legal consequences bound to dark pattern implementation by organizations, although that is likely to change in the future.

2.4.1 European Union Law

Businesses within the European Union (EU) are bound to many EU laws and regulations, protecting EU residents and worldwide individuals being delivered online services from within the EU. One of the more known regulations is the General Data Protection Regulation (GDPR), which focuses on the European Union's data and privacy protection (Europian Union, 2016). While the GDPR does not explicitly ban dark patterns, they do breach the spirit of the GDPR (Graßl et al., 2021). For instance, the GDPR defines consent provided by internet users to be ‘freely given’ and ‘informed’ and requires it to be a separate action from the activity the user is carrying out. Hence, so-called ‘opt-out’ consent (i.e., if the user does not undertake any action, the user will continue without active notice) will not establish a valid legal basis to lay cookies or process data based on consent (Article 29 Working Party, 2017; Information Comissioners Office, 2012).

When focusing on online shopping, EU businesses are bound to multiple consent requirements in the Consumer Rights Directive (European Parliament and the Council, 2011). For example, websites that use Sneaking dark patterns (e.g., Sneak into Basket or Hidden Subscription; These dark patterns will be covered in chapter 3) are likely violating the directive (Mathur et al., 2019). Fortunately, recent activities show that legal institutions have started regulating the use of dark patterns (and their misguiding behavior). For example, in late 2021, the European Parliament passed the Digital Services Act (2021), prohibiting deceiving or nudging techniques to influence user behavior through dark patterns. Also, more recently, the European Data Protection Board (EDPB) established new guidelines for designers and users about recognizing and avoiding dark patterns on social media platforms (EDPB, 2022).

Furthermore, the European Commission conducted a behavioral study on dark patterns and manipulative personalization practices in the digital environment (European Commission et al., 2022). In this behavioral study, the European Commission et al. state that 97% of the most popular websites and apps used by EU consumers deploy at least one dark pattern, among which countdown timers prevalence in online shopping is also mentioned. The study concludes that despite the presence of a robust EU legal framework (e.g., GDPR, UCPD, and upcoming acts such as the Digital Services Act, Digital Markets Act, AI Act, and Data Act), some legislative adjustments may be needed to better respond to dark patterns and manipulative personalization.

3 Dark Patterns

Dark patterns come in many different shapes and sizes. The dark pattern domains mentioned earlier include gaming (Zagal et al., 2013), robotics (Lacey & Caudwell, 2019), proxemic interactions (Greenberg et al., 2014), social media (Mildner & Savino, 2021; Özdemir, 2020; Trice & Potts, 2018; Wagner et al., 2020), mobile apps (Bösch et al., 2016; Di Geronimo et al., 2020; Lewis, 2014), privacy and identity (Forbrukerrådet, 2018; Fritsch, 2017), cookies and consents (Graßl et al., 2021; Gray, Santos, et al., 2021; Nouwens et al., 2020; Soe et al., 2020), and E-commerce (Gray et al., 2018; Luguri & Strahilevitz, 2021; Mathur et al., 2019). However, dark patterns share certain characteristics despite the domains in which they are implemented. Put more simply, a dark pattern implemented in gaming could potentially also be implemented in the online shopping domain.

Prior work (Bösch et al., 2016; Brignull, n.d.; Conti & Sobiesk, 2010; Gray et al., 2018) has provided taxonomies to describe existing dark patterns and their characteristics, and the domains they are found in (Gray, Chen, et al., 2021; Mathur et al., 2019). The following step in research was establishing the prevalence of dark patterns, as multiple studies (Kampanos & Shahandashti, 2021; Mathur et al., 2019; Nouwens et al., 2020) used automated web scraping to investigate the prevalence of dark patterns. As stated and done by Luguri & Strahilevitz (2021), research should investigate the effects of dark patterns next. Some studies have already investigated the effect dark patterns have on users (Bongard-Blanchy et al., 2021; Conti & Sobiesk, 2010; Di Geronimo et al., 2020; Graßl et al., 2021), but still many other dark patterns' effects have not yet been researched.

3.1 The Goal of Dark Patterns

Although all dark patterns essentially aim to increase profit, they do this in different ways. Three different approaches can be recognized amongst dark patterns: dark patterns that demand people's *attention*, dark patterns that nudge people to give up *data,* and dark patterns that nudge people to spend *money* directly. Down below, each approach is described in more detail.

3.1.1 Attention

'Attention' dark patterns are often seen in social media, non-selling websites, or other similar platforms. Their goal is to keep the user involved as long as possible and to increase indirect profits such as income from advertisements or referrals (Mildner & Savino, 2021; Trice & Potts, 2018). For example, the longer a user spends time on a social media platform, the more advertisements that the user will see, the higher the advertisement income is for the social media platform.

3.1.2 Data

'Data' dark patterns are implemented to gather valuable data to make a profit by selling this to a third party or use this data for profiling. Profiling is used to serve more accurate advertisements or suggest customer-specific products, leading to higher profits for the selling organization. At the moment, such data dark patterns are most commonly seen in the privacy- and consent domains (Fritsch, 2017; Graßl et al., 2021; Gray, Santos, et al., 2021; Nouwens et al., 2020), asking for consent of the user. For example, a cookie banner on HuffPost, provides a positive option to consent to tracking and data collection while the negative option is hidden behind multiple 'Manage options' screens (Mathur et al., 2021). As seen in this example, HuffPost will use data to provide users with personalized ads on partner products, increasing profit for HuffPost and partners.

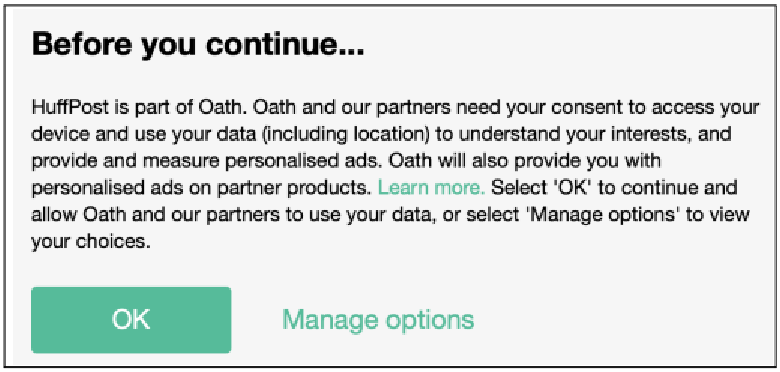

Figure 3 - Dark pattern in the cookie consent banner notice on HuffPost (Mathur et al., 2021).

3.1.3 Money

'Money' dark patterns strive for 'direct profit'. Such dark patterns are characterized by nudging users to spend or spend additional money, resulting in direct profit for the organization. Most dark patterns in E-commerce fall in this category, such as Low Stock Messages, Countdown Timers, and Price Comparison Prevention (these dark patterns are discussed in section 3.2). In other words, their ultimate goal is to capitalize on the customer's intention to buy a product (Hajli, 2015), and convert this to an actual decision to purchase that the customer could also have made on another shopping site. For instance, a deceptive Low Stock Message could nudge a customer to buy a certain product, resulting in direct profit for the organization.

In the next section, we will zoom in on money dark patterns in the online shopping domain, analyzing their characteristics and the underlying cognitive bias they exploit.

3.2 Dark Patterns in Online Shopping

As mentioned in the previous section, one of the dark pattern domains is E-commerce, which is the high-level focus of this thesis. The Organisation for Economic Co-operation and Development (OECD) issued a definition for E-commerce: "An E-commerce transaction is the sale or purchase of goods or services, conducted over computer networks by methods specifically designed for the purpose of receiving or placing of orders. The goods or services are ordered by those methods, but the payment and the ultimate delivery of the goods or services do not have to be conducted online. An E-commerce transaction can be between enterprises, households, individuals, governments, and other public or private organisations." (OECD, 2011, p. 72).

Regarding the definition of E-commerce by the OECD, one could argue that it is pretty broad and diverse. This thesis focuses on online shopping websites (i.e., webshops) and the dark patterns used within this subdomain of E-commerce.

In the following sections, we first categorize dark patterns in online shopping in a taxonomy table. Afterward, each dark pattern is further analyzed per category and the underlying psychological effect they exploit.

3.2.1 Taxonomy table

As seen in other studies (Gray et al., 2018; Luguri & Strahilevitz, 2021; Mathur et al., 2019, 2021), dark pattern taxonomy tables provide an overview of the different types of dark patterns. We present a table with the dark patterns seen in online shopping, using the taxonomies defined by Luguri and Strahilevitz (2021) as a basis since it is the most updated and complete. Next, these taxonomies are extended by categorizing each dark pattern along with their description (based on Luguri and Strahilevitz), cognitive bias they exploit as identified by Mathur et al. (2019), and relevant studies regarding that specific dark pattern. The three approaches (*attention, data, money*) are not included in the table since all dark patterns in the table use the *money* approach.

Table 1 - Summary of existing dark pattern taxonomies.

Category	Type	Description	Cognitive Bias	Study
Urgency	Countdown Timers	Indicates a deadline for a deal or discount, counting down until that deadline is reached.	Scarcity bias	Mathur et al. (2019)
	Limited-time Messages	Indicates there is limited time left for a deal or discount, without specifying the deadline.	Scarcity bias	Mathur et al. (2019)
Sneaking	Sneak into Basket	Adding additional items to the online shopping cart without consent.	Default effect	Brignull n.d.; Gray et al. (2018)
	Hidden costs	Introducing additional costs, often later in the checkout process.	Sunk fallacy cognitive bias	Brignull n.d.; Gray et al. (2018); Mathur et al. (2019)
	Hidden subscription/ Forced Continuity	A follow-up on a free trial, charging credit cards without any warnings to the users.	Default effect	Brignull n.d.; Gray et al. (2018); Mathur et al. (2019)
	Bait and Switch	The user set out to do one thing, but another (often undesirable) thing happens instead.	Muscle memory	Brignull, n.d.; Gray (2018)
Scarcity	Low-stock Messages	Signals to the user about limited product quantities.	Scarcity bias	Mathur et al. (2019)
	High-demand Messages	Signals to the user that a product is in high demand, implying the likelihood of selling out.	Scarcity bias	Mathur et al. (2019)
Social Proof	Activity Messages	Attention-grabbing messages that appears on product pages indicating other user-activities	Bandwagon effect	Mathur et al. (2019)
	Testimonials	Displaying customer testimonials from which the source is unknown	Bandwagon effect	Mathur et al. (2019)
Obstruction	Price Comparison Prevention	Making it difficult for the user to compare prices of different products.	Anchoring and Decoy effect	Brignull, n.d.; Nodder (2013)
Interface Interference	False Hierarchy	Providing users with one or more options that are visually more appealing over others.	Anchoring, Default effect, and Scarcity bias	Mathur et al. (2019)
	Pressured Selling	High-pressure tactics that steer users into purchasing a more expensive variant of a product.	Anchoring, Default effect, and Scarcity bias	Mathur et al. (2019)
	Toying with Emotion	Any language, style, color, or other elements to evoke emotion, in order to persuade the user into a particular action.	Emotion bias	Gray et al. (2018)

3.2.2 Urgency

Dark patterns in the 'Urgency' category impose a deadline on a sale or deal, accelerating user decision-making and purchasing (Aggarwal & Vaidyanathan, 2015; Cialdini, 2009; Inman & McAlister, 1994; Nodder, 2013). Urgency dark patterns exploit the scarcity bias (Mathur et al., 2019), in which the value of a good increases due to its scarcity (Mittone & Savadori, 2009). Put more simply, if there is limited time left for a sale or deal (i.e., the time left is scarce), the sale or deal becomes more desirable than it would otherwise be.

Furthermore, Urgency dark patterns create a potent 'fear of missing out', as Mathur et al. (2019) described. In addition, when combined with dark patterns categorized into 'Social Proof' and 'Scarcity', these dark patterns realize the effect of FOMO even more. In the study of Mathur et al. (2019), two types of Urgency dark patterns were observed: Countdown Timers and Limited-time messages.

Countdown Timers

The 'Countdown Timer' is a dark pattern that indicates a deadline for a special offer, counting down until that deadline is reached, and then the special offer expires. The figure below shows a Countdown Timer on *aliexpress.com* (AliExpress, n.d.).

Figure 4 - Countdown timer on *aliexpress.com* (AliExpress, n.d.), suggesting 'SuperDeals' that expire after the timer expires.

Countdown Timers come in two forms: the 'regular' Countdown Timer, as displayed above, and the 'deceptive' Countdown Timer (Mathur et al., 2019). Compared to the former, the deceptive Countdown Timer is a timer that indicates a deadline for a special offer, however, the special offer does not expire. For example, a timer can simply reset if it hits zero or if the page is opened with fresh cookies. Figure 4 showcases such a timer on *nordvpn.com* (NordVPN, n.d.). In the rest of our study, we will focus on deceptive countdown timers, as we consider deceptive countdown timers to be a dark pattern, whereas a regular countdown timer could be of use for a potential consumer with regards to product choice.

Figure 5 – Deceptive Countdown Timer on *nordvpn.com* (NordVPN, n.d.). The timer resets if the site is refreshed (including cookies)

Limited-time Messages

Contrary to (deceptive) Countdown Timers, 'Limited-time Messages' are Urgency dark patterns lacking a deadline. Hence, Limited-time Messages are static. Figure 4 shows a limited-time offer by *samsung.com* (Samsung, n.d.), but Samsung does not state when this offer ends. In addition, Mathur et al. (2019) indicate that Limited-time Messages often relate to Interface interference, a dark pattern most known for toying with emotion and hiding information (Luguri & Strahilevitz, 2021).

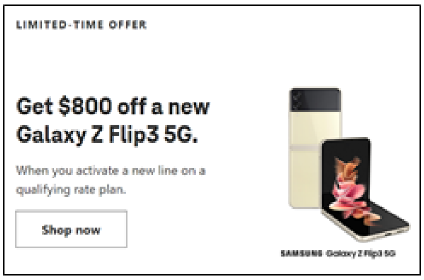

Figure 6 - Limited time offer on *samsung.com* (Samsung, n.d.). Samsung does not indicate when this offer ends.

3.2.3 Sneaking

The dark patterns categorized as 'Sneaking' refer to misdirecting- and hiding information to- the user (Gray et al., 2018; Mathur et al., 2019). Mathur et al. (2019) observed three different dark patterns: Sneak into Basket (Brignull, n.d.; Gray et al., 2018), Hidden Costs (Brignull, n.d.; Gray et al., 2018), and Hidden Subscriptions (Brignull, n.d.; Gray et al., 2018). Luguri and Strahilevitz (2021) added a fourth dark pattern to this category: Bait and Switch (Gray et al., 2018).

Sneak into Basket

The 'Sneak into Basket' dark pattern adds additional items not selected by the user to their online shopping cart, often suggesting based on the original item the user was trying to purchase (Brignull, n.d.; Gray et al., 2018). Sneak into Basket exploits the 'default effect' cognitive bias (or status quo bias): the tendency for the user to do nothing or maintain its current decision (Samuelson & Zeckhauser, 1988). Regarding Sneak into Basket, the selling party hopes the user leaves the additional item in the online basket, purchasing the item. Furthermore, some online shopping websites try to add items to the basket through 'Social Proof' (see 3.2.5), including elements such as 'often combined with products like these' or 'recommended items for this product'.

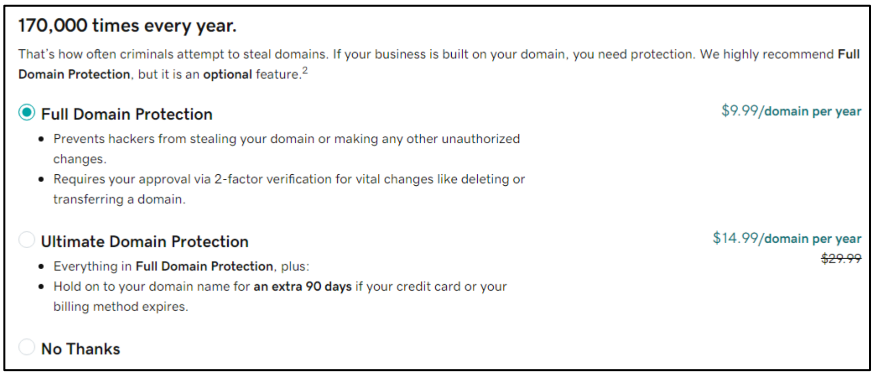

Figure 7 - Sneak into Basket on *godaddy.com* (GoDaddy, n.d.). Despite not opting for it, GoDaddy automatically adds 'full domain protection' to the cart.

Hidden Costs

The 'Hidden Costs' dark pattern exposes new, unexpected, and often unusually high costs while nearing the end of the checkout process (Brignull, n.d.; Gray et al., 2018; Mathur et al., 2019). Typical examples of Hidden Costs are 'service costs', delivery fees, and tax. This dark pattern exploits the sunk fallacy cognitive bias: "the sunk-cost fallacy (bias) is the irrational behavior of "throwing good money after bad," i.e., once found on a course of action to which they committed an investment (e.g., time, money, effort), people continue to stay on that course of action and invest even more resources despite it being unprofitable" (Haita-Falah, 2017). For instance, Airbnb (n.d.) is known for showing low prices until checkout, when hidden costs such as service fees, cleaning fees, and taxes are added to the final price.

Hidden Subscription/ forced continuity

'Hidden Subscription/ Forced Continuity' is a dark pattern that is often a follow-up on a free trial, charging credit cards without any warnings to the users (Brignull, n.d.; Gray et al., 2018; Mathur et al., 2019). In addition, most hidden subscriptions are hard to cancel, and signing up is significantly easier than cancellations (Brignull, n.d.; Mathur et al., 2019). Mathur et al. (2019) point out that Hidden Subscription/ Forced Continuity also exploit the default effect (Samuelson & Zeckhauser, 1988), profiting the selling party from users that do not cancel their subscription. The figure below showcases such hidden subscriptions on the jewelry website *ross-simons.com* (Ross-Simons, n.d.). The

'VIP membership' deal does not reveal the recurring subscription of $95 unless the 'Terms and Conditions' link is clicked.

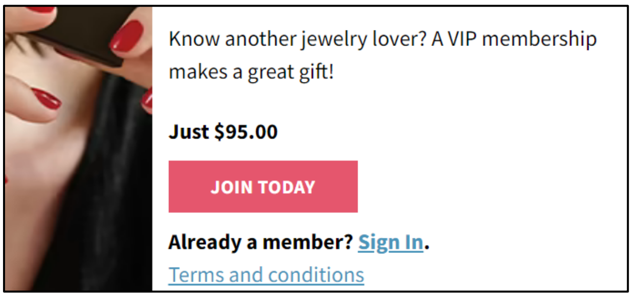

Figure 8 - Hidden subscription on *ross-simons.com* (Ross-Simons, n.d.). The recurring subscription is hidden under 'Terms and Conditions'.

Bait and Switch

The 'Bait and Switch' pattern makes the user set out to do one thing, but another (often undesirable) thing happens instead (Brignull, n.d.; Gray et al., 2018). Gray et al. (2018) provide the example of having a red 'X' button perform another operation other than closing a popup window. An example that illustrates this behavior nicely was Microsoft's Windows 10 upgrade. If users clicked the 'X' on the top right, the computer would still upgrade to Windows 10.

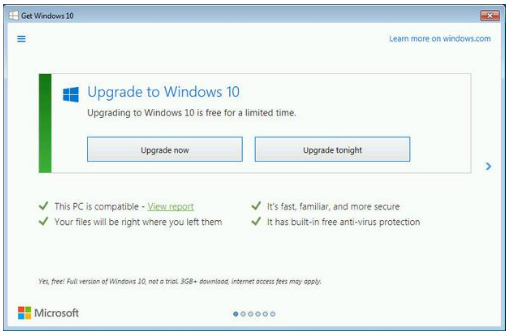

Figure 9 - Switch and Bait by Microsoft. Clicking 'X' to dismiss the upgrade does not stop the installation.

Bait and Switch often exploit 'muscle memory' (repetition of a specific task into memory), as Gray et al. (2018) point out. A mobile game called 'Royal Match' (Dream Games Ltd., 2022) illustrates this. The 'Start' button is the same size and color as the in-app purchase button. As a result, regular users accustomed to clicking the same button are likely to fall for the in-app purchase Bait and Switch trick.

Figure 10 - In the mobile game 'Royal Match' (Dream Games Ltd., 2022), the 'Start' button is almost identical to the purchase button.

Regulation and Protection

From a legal standpoint, some 'Sneaking' dark patterns (Sneak into Basket and Hidden Costs) stand out from other dark patterns, as they are deemed unlawful by a directive of the European Union (European Parliament and the Council, 2011). Furthermore, similar laws apply in the United States under section five of the FTC Act (Federal Trade Commission, 1914). Because of these legislations mentioned earlier, E-commerce websites figured out new ways to trick users and maximize profits. According to *deceptive.design* (formerly *darkpatterns.org),* a web page created by Brignull (n.d.), sneaking items into the basket is nowadays often done through an 'opt-out' radio button or checkbox on the page before checkout, often referred to as 'preselection' (Bösch et al., 2016; Gray et al., 2018).

3.2.4 Scarcity

Dark patterns categorized in 'Scarcity' are dark patterns that also thrive upon the scarcity bias (Mittone & Savadori, 2009), focused on the limited availability of a certain product and therefore increasing its perceived value and desirability (Cialdini, 2009; Nodder, 2013). Mathur et al. (2019) found two dark patterns related to Scarcity: Low-stock Messages and High-demand Messages.

Low-stock Messages

'Low-stock Messages' is a dark pattern that signals to the user about limited product quantities (Mathur et al., 2019). Like Countdown Timers, Mathur et al. (2019) found two types of Low-stock Messages: 'regular' Low-stock Messages and 'deceptive'. Regular Low-stock Messages are accurate messages that display the (limited) stock left. Legitimate Low-stock Messages could help users decide whether to choose a product or not; therefore, we do not consider a legitimate Low-stock Message a dark pattern by definition.

Figure 11 - Low-stock Message on *retrocitysunglasses.com* (Retrocitysunglasses, n.d.)

In contrast, deceptive Low-stock Messages are randomized or permanent Low-stock Messages, a practice we consider a dark pattern. In their study, Mathur et al. (2019) found that several online shopping websites used popular third-party JavaScript libraries to generate the stock values.

Figure 12 - Deceptive Low-stock Message on *revelationhealth.com* (Revelationhealth, n.d.). The website does not state the exact quantity that is left.

High-demand Messages

'High-demand Messages' are a dark pattern that signals to the user that a product is in high demand, implying the likelihood of selling out (Mathur et al., 2019). When implementing this dark pattern, selling parties hope to accelerate purchases of users still in doubt. Again, High-demand Messages could either be legitimate or deceptive, whereas deceptive High-demand Messages could show the indication of high demand permanently, regardless of the product displayed on the website (Mathur et al., 2019).

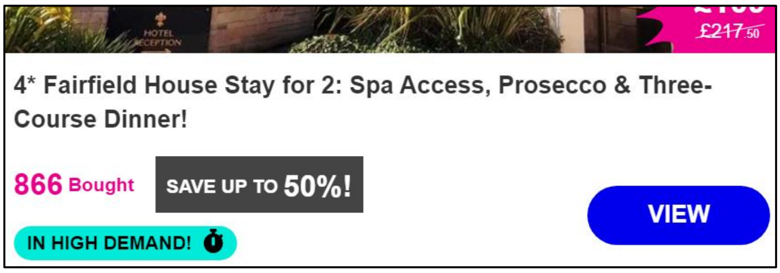

Figure 13 - High-demand Message and other dark patterns on *wowcher.co.uk* (Wowcher Ltd., n.d.).

3.2.5 Social Proof

Dark patterns categorized as 'Social Proof' are dark patterns where users evaluate their behavior by examining the action of others (Mathur et al., 2019), also called the 'bandwagon effect' (Cialdini, 2009; Nodder, 2013). Other studies (Borges et al., 2010; Luo, 2005) have shown that the presence of others influences purchasing behavior of individuals. Online shopping sites are aware of this, and Mathur et al. (2019) observed two dark patterns that use social proofing: Activity Notifications and Testimonials. However, since we adopt the taxonomy of Luguri and Strahilevitz (2021), 'Activity Notifications' is renamed 'Activity Messages'.

Activity Messages

According to Mathur et al. (2019), the Activity Messages dark pattern is a transient, often recurring, and attention-grabbing message that appears on product pages indicating other users' activities. Mathur et al. (2019) make the distinction between different messages: dynamic messages about products (e.g., 'John from Denver saved $28 on a new radio'), static messages about shopping carts (e.g., '23 people added this item to their basket), and messages about product views (e.g., '78 people viewed this product in the last 24 hours').

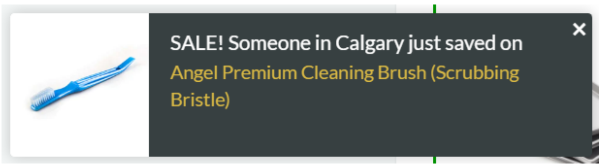

Figure 14 - Dynamic Activity Message at juicerville.ca

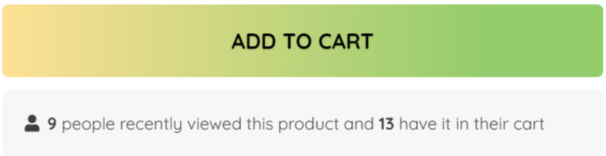

Figure 15 - Both static Activity Messages about product views and shopping carts are present on *dreamerdesigns.com* (Dreamer Networks Inc, n.d.)

In addition, both variants of Activity Messages could be deceptive or truthful. Hence, truthful Activity Messages could be of use to a potential customer. However, deceptive Activity Messages are randomized or permanently showing the message, which we consider a dark pattern.

Testimonials

'Testimonials' of uncertain origin is a dark pattern that includes customer testimonials from which the source is unknown (Mathur et al., 2019). Truthful testimonials could be very useful for customers who are looking for feedback on a certain product, for example, by examining product testimonials. Mathur et al. (2019) attempted to verify testimonials by scanning for submission possibilities and issuing the testimonial as a search query in a search engine. As a result, they found twelve websites that used testimonials from unknown sources. It is important to note that Mathur et al. (2019) could only filter out duplicates and testimonials of unknown origin and not uniquely made-up testimonials. For instance, any testimonial submitted under a fake identity would very likely not come forward in the results of Mathur et al. (2019). Hence, we estimate that the actual number of deceptive testimonials is much higher, which will remain a problem threatening the integrity of social proof (Hunt, 2014).

3.2.6 Obstruction

Dark patterns categorized as 'Obstruction' are characterized by making an action significantly harder than it should be (Gray et al., 2018). Different common dark patterns such as the 'roach motel' (Brignull, n.d.) are categorized as Obstruction. Within this study, we focus on online shopping and the dark patterns go hand in hand with that. Hence, we will only cover the dark pattern of 'price comparison prevention' (Brignull, n.d.; Gray et al., 2018; Mathur et al., 2019).

Price Comparison Prevention

'Price Comparison Prevention' is a dark pattern that makes it difficult for the user to compare the prices of different products (Brignull, n.d.; Nodder, 2013). As described by Mathur et al. (2019), Price Comparison Prevention dark patterns exploit a cognitive bias known as the anchor effect (Furnham & Boo, 2011; Nodder, 2013). In simple terms, the anchor effect influences the users' point of reference by providing one, 'the anchor'. In online shopping, this makes it hard for the user to make an informed decision about the sale or deal. For example, in one experiment (Ariely, 2008), researchers asked participants to write down two random numbers, after which they would be asked if they would pay that for a bottle of wine. Finally, they asked the participants to write down the maximum amount they would pay for that same bottle of wine. They found that the willingness to pay varied threefold based on the arbitrary number due to lacking knowledge of the market value of the bottle of wine.

Figure 16 - Example of the 'decoy effect' found on Shopify blog (Mullin, 2017). In this case, the 'iPhone 7 Plus (32GB)' is used as a decoy to stimulate the 'iPhone 7 (128GB)'

Another marketing concept similar to Price Comparison Prevention is the decoy effect (or asymmetric dominance effect) (Huber et al., 1982). The decoy effect is a concept often used in marketing, whereby users have to choose between two options when also presented with a third option. This third option, the 'decoy', should increase the likelihood of users purchasing one of the two original products (see figure 16).

3.2.7 Interface Interference

'Interface Interference' is a dark patterns category defined by Gray et al. (2018), which manipulates the users' interface and privileges specific actions over others, confusing the user in the process. Within this category, we will analyze two dark patterns: False Hierarchy/Pressured Selling (Mathur et al., 2019) and Toying with Emotion (Gray et al., 2018).

False Hierarchy

The 'False Hierarchy' dark pattern, also known as 'visual interference' (Mathur et al., 2019), provides users with one or more options that are visually more appealing than others, where items should be in parallel rather than in hierarchical order in particular (Gray et al., 2018). Therefore, the user is convinced to make a selection that they feel is the only- or best option. A simple example of this technique is a cookie consent in which the 'agree' button is often bright and large while the 'more options' (i.e. to reject cookies) is greyed out and small text (Graßl et al., 2021). Turning to online shopping, the figure below showcases the appliance of False Hierarchy by Adobe Acrobat individual pricing plans on *adobe.com* (Adobe Inc., n.d.).

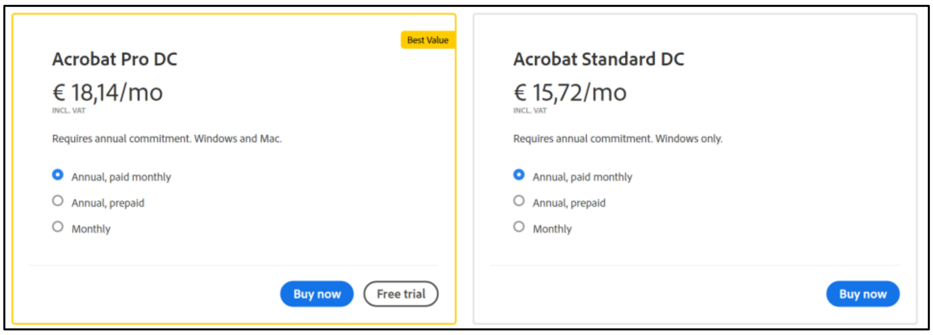

Figure 17 - Individual pricing plans for Adobe Acrobat (Adobe Inc., n.d.). The Acrobat Pro DC plan is visually more appealing (yellow box) than the standard plan.

Pressured Selling

'Pressured Selling' refers to defaults or often high-pressure tactics that steer users into purchasing a more expensive variant of a product (upselling) (Mathur et al., 2019). Similar to the previous example of Adobe Acrobat, Pressured Selling is often done using additional visual representations. Both False Hierarchy as Pressured Selling exploit different cognitive biases (default effect, anchoring effect, scarcity bias), and often attempt to upsell products to customers (Mathur et al., 2019).

Toying with Emotion

'Toying with Emotion' is a dark pattern that includes any language, style, color, or other elements to evoke an emotion to persuade the user into a particular action (Gray et al., 2018). Hence, Toying with Emotion exploits the emotion bias (see Guo et al. (2020)). An example of Toying with Emotion is the (deceptive) Countdown Timer mentioned earlier. The timer ticking away evokes the emotion that the user should hurry up.

3.3 Relevance

As previously mentioned, research should investigate the effects of dark patterns next (Luguri & Strahilevitz, 2021), as only a few studies (e.g., Di Geronimo et al., 2020; Graßl et al., 2021; Luguri & Strahilevitz, 2021; Nouwens et al., 2020) have done so. This thesis contributes to filling that gap by researching the effects of countdown timers. Investigation of different dark patterns and their effects should be repeated until a consensus is met amongst researchers. In other words, the effects of a dark pattern should be sufficiently studied before proceeding to the next step: effectively 'combatting' dark patterns. Combatting dark patterns is also where the societal relevance of dark pattern research is more significant for the public, as it aims to protect users from being manipulated by dark patterns on the internet. However, before any alternatives or combatting strategies should be developed, the effects of dark patterns need to be researched.

4 Countdown Timers

This study focuses on countdown timers, one of many dark patterns yet to be examined in depth. Countdown Timers are present in the online shopping domain (Mathur et al., 2019) and are relatively easy to recognize. Hence, Countdown Timers offer a good starting point for researching dark patterns' effects in online shopping.

To better understand how (deceptive) Countdown Timers appear ‘in the wild’, a corpus is constructed. The corpus analysis will help to understand which characteristics Countdown Timers have in common, and in what characteristics they may vary. Furthermore, we want to identify the ‘design space’ of Countdown Timers, to be able to design a representative experiment using realistic Countdown Timers as ‘seen in the wild’.

4.1 Constructing the Corpus

In total, we collected 60 instances of Countdown Timers from online shopping websites. Our corpus did not account for countdown timers in checkout pages and online shopping carts (Mathur et al., 2019), as this study focuses on deceptive countdown timers on the shopping pages. The constructed corpus consists of the following information:

- An URL to the web page where the countdown timer was found;
- If the countdown timer was deceptive;
- If the countdown timer referred to a discount;
- If the countdown timer included a Low Stock Message;
- Additional comments and things worth noting;
- Location of the timer (e.g., front page, product page, banner);
- Date of accessing;
- If the countdown timer displayed ‘Days’ and/or ‘Hours’;
- The duration of the countdown timer;
- Screenshot of the countdown timer.

In order to construct the corpus, different strategies were used. First, multiple search queries such as ‘countdown timer’, ‘countdown-wrapper’, ‘days hours minutes seconds’, and similar queries were issued manually in a source code search engine on *publicwww.com* (PublicWWW, n.d.). Each result was examined on two points: if the webpage sold items online (online shopping domain) and if a countdown timer was present. If so, the result would be added to the corpus. In total, 43 occurrences were added to the corpus using this method.

The second method combines *publicwww.com* (PublicWWW, n.d.) and Shopify (Shopify, n.d.-b). As described on Shopify their blog: “Shopify is a subscription-based software that allows anyone to set up an online store and sell their products”

(Voidonicolas & Odjick, n.d.). Shopify makes it easy for users to implement UI elements in their store, including countdown timers, using the 'Shopify App store' (Shopify, n.d.-a). First, the Shopify App store's most popular countdown timer plugins were scanned for any website demonstrating the countdown timer. If a demo website was present, the source code (the code that 'implements' the countdown timer on the Shopify store) was analyzed to find unique lines of code that indicate the presence of a countdown timer. For instance, this javascript: *https://cdn.hextom.com/js/eventpromotionbar.js*, is injected into each Shopify store that uses the popular 'Countdown Timer Bar' made by Hextom (Hextom, n.d.). Next, the source code characteristic (e.g., the javascript injection) was entered in the source code search engine on *publicwww.org* (PublicWWW, n.d.). All results were then downloaded to a CSV (comma-separated values) file. It was expected that all results would actively use the concerned add-on, but this was not the case. Hence, the final step was to examine the websites in the CSV file to see if they were actively using the Shopify add-on. Examining was done using a Python Selenium (Muthukadan, 2018) script, which scans each website from the CSV file on a specific '*classname*' that is identical for all websites that actively use the add-on. Finally, 10 websites that were actively using add-ons were added to the corpus.

The third and final method combined two CSV files of almost 2 million shopping sites that use Shopify (Shopify, n.d.-b) and WooCommerce (WooCommerce, n.d.) software. The two CSV files were provided free of charge (regular users pay a fee) by Wappalyzer (Wappalyzer, n.d.), a platform that identifies the technologies used on any website, after reaching out to them via email. However, even when using a Python Selenium script (static HTML analysis did not work since the add-ons are injected), examining 2 million websites could take up to 65 days (on our machine, examining one result took three seconds on average). So, to narrow down the dataset, the websites using countdown-timers on product- and front pages gathered by Mathur et al. (2019) was compared (intersection) with the Shopify and WooCommerce CSV files. Because manually examining was needed, researching all results from Mathur et al. (2019) would take too long and broadening the corpus would not add significant value. The final list consisted out of 59 websites that both actively use Shopify or WooCommerce, and have used countdown timers in the past. At the time of examining, seven out of the 59 websites still contained countdown timers, thus were added to the corpus.

Although seven websites might seem like a low number compared to 59 websites in 2019, one must take into account that websites experiment a lot (Kohavi & Longbotham, 2017). Hence, the results gathered from the three methods mentioned earlier may vary over time. Furthermore, the goal of this corpus is not to be complete or find all existing countdown timers, but to gain a better understanding of the usage of countdown timers in online shopping. Therefore, we stopped broadening the corpus at 60 entries, as this was deemed sufficient enough.

4.1.1 Analysis

In total, we observed 60 websites actively using countdown timers on several characteristics: deceptiveness, location, discounts, low-stock messages, and the time indication and duration of the countdown timer.

Deceptiveness

Out of the 60 observed countdown timers, at least 27 were confirmed deceptive. A countdown timer is labeled deceptive in three cases. First, if the same webpage is opened on another device or after resetting cookies, and the countdown timer starts from the original time again (i.e., the timer starts over), the countdown timer is deceptive. Deceptiveness was tested by refreshing pages, cookie deletion, and using Google Chrome incognito windows to check for inconsistencies. In total, eight instances were found deceptive because of refreshing. Second, a countdown timer is deemed deceptive if the timer reaches zero, but the discount or deal remains in place. Such instances were manually examined by revisiting the websites one to two weeks after the initial visit. In addition, instances that re-instantiated the countdown timers (i.e., timers that start over again) are also labeled deceptive. In total, 18 instances were found deceptive when revisiting the websites. Third, a Countdown Timer is labeled deceptive if the deal or offer does not change after the timer resets. For example, Countdown Timers used on 'daily deals' webpages (e.g., figure 4), should also assure that the products on sale are refreshed the next day. Often, such Countdown Timers are in a 'grey area', as the product or deal changes just so slightly. For example, if only one out of 20 'daily deal' products change after one day, or if the offer changes from 15 to 20 percent. We found such an example can on *www.leesa.com* (Leesa, n.d.) where the special offer remains the same but the discount 'reason' changed from 'Extended Presidents Day Sale' (22-2-2022, top offer) to 'March Mattress Sale' (10-3-2022, bottom offer).

Figure 18 - The offer on *www.leesa.com* (Leesa, n.d.) changed slightly over the course of several weeks. Only the discount 'reason' changed from 'Extended Presidents Day Sale' (top offer) to 'March Mattres Sale' (bottom offer)

We tested for such instances using *TimeTravel* for Windows (Ginkgo LLC, n.d.), which easily lets users change the system time on their Windows device. After changing the system time, we would observe how the offers and Countdown Timers in our corpus would change.

Regarding this third category, we should mention that the total number of non-deceptive countdown timers is still likely to contain false negatives. We could not verify all instances, for example, if the webpage used server-side timing for the Countdown Timer. On the contrary, we should also mention that we could have observed some false positives. For example, if the web pages would change when the actual time would have passed, but did not so when time traveling.

Location

Regarding the location of the countdown timer: 26 were placed on front pages, out of which nine were deceptive; 23 on banners, of which 12 were deceptive; six on product pages, of which five were deceptive; and five on product overviews, of which none were deceptive. However, these are not the only places countdown timers are used in online shopping, as Countdown timers in checkout pages and online shopping carts (Mathur et al., 2019) were not included in our corpus.

The offer

One of the goals is to discover what most countdown timers have to offer, for example, a discount, flash deals, or free shipping. In our data, we observed 46 instances of countdown timers that referred to a discount percentage, discount codes, flash sales (i.e., certain products with discounts), or some combination. Other instances usually indicated free shipping, free items, discounts without mentioning the actual discount itself, low stock messages, and high demand messages. However, in several cases multiple offers are combined, as illustrated in the example below.

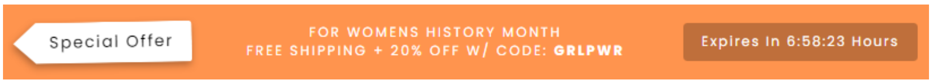

Figure 19 - Countdown Timer on *www.dermaclara.com*. (Dermaclara, n.d.) The special offer includes both a discount and free shipping.

Timer duration and characteristics

Most countdown timers are different, and so are their durations. So, it was decided to categorize the duration of each countdown timer into four groups:

Group	Deceptive	Non-deceptive / unclear	Total
< 02:00 hours left	6	2	**8**
02:00 – 12:00 hours left	9	7	**16**
12:00 – 24:00 hours left	7	14	**21**
> 24:00 hours left	5	10	**15**
Total	**27**	**33**	**60**

Table 2 – Number of Countdown Timers categorized per duration and deceptiveness.

When going into more detail on the deceptive countdown timers from website revisits, it was noticed that out of the 18 in total, seven had such significant time differences that the revisit would categorize them differently. However, for many websites, this depends on the time of visit since many offers imply 'daily deals' or 'daily flash sales'. Furthermore, eight of the 21 deceptive countdown timers display days, even though the deadline is less than 24 hours.

Characteristic of a countdown timer

As can be concluded from the corpus, a large portion of the countdown timers go hand in hand with discounts or any similar deal made by the webshop. Almost half of the observed countdown timers were found to be deceptive, marking a clear distinction between 'just a countdown timer' and a dark pattern (Gray et al., 2018; Luguri & Strahilevitz, 2021). Furthermore, most countdown timers are placed on banners and front pages and are less frequent on product pages and overviews. Regarding deceptive countdown timers, their location is diverse, but not common on product overviews. Timewise, deceptive countdown timers tend to set deadlines between zero and less than 24 hours and do not display any dates. So, for the Countdown Timer used in this experiment, we chose the following characteristic: the Countdown Timer is placed on a front page, next to a specific product, offering a discount. When the product is clicked from the front page or via the product overview, the product details will be displayed, accompanied by a Countdown Timer. Also, our Countdown Timer is deceptive and will restart when the page is refreshed.

4.2 Research Questions

As described in the previous section, it is known how Countdown Timers appear 'in the wild'. However, little is known about the effects of Countdown Timers, which raises a set of research questions that can be aggregated into one main research question:

MQ *What are the effects of deceptive countdown timers on customers' online shopping experience and behavior?*

The main research question is composed of multiple sub-research questions, where our main focus will be on the urgency to buy. The following sub question will be answered using an online experiment, in which participants are visiting a webshop, and depending on which condition they are assigned to, asked to choose between either two products without any special offers (*control* group), one regular product and one discounted product (*discount* group), and one regular product and one discounted product displaying a countdown timer (*timer* group).

SQ1 *What is the effect of discounts and deceptive countdown timers on consumers' product choice?*

After completing the online experiment, participants are asked to fill in a questionnaire. Using questionnaire results in combination with metadata recorded during the online experiment, we attempt to answer the following sub questions:

SQ2 *What are the most important factors that influence the product choice of consumers?*

The following three questions all address urgency to buy, and are divided in three constructs: fear of missing out, perceived time pressure, and feeling steered towards a certain product.

SQ3 *What is the effect of discounts and deceptive countdown timers on consumers' fear of missing out?*

SQ4 *What is the effect of discounts and deceptive countdown timers on consumers' perceived time pressure?*

SQ5 *What is the effect of discounts and deceptive countdown timers on consumers' feeling of being steered towards a certain product?*

Finally, we are interested in how people think and feel about dark patterns and deceptive countdown timers in general. Participants will be asked questions about this in the questionnaire. These exploratory questions serve to answer the final sub question:

SQ6 *How do individuals think and feel about deceptive countdown timers and dark patterns in general?*

4.3 Hypothesis

Following the previously stated sub-research questions, we formulated the following hypotheses (the numbering of the sub-research questions corresponds with the numbering of the hypotheses):

H1 Product choice distribution:
Participants are more likely to choose a product over a similar, equally priced alternative if the product is accompanied by a discount (H1a) or a countdown-timer (H1b).

H2 Product choice reason:
Participants who do not encounter any special offer select a product based on product specifications (e.g., color, looks). If participants do encounter a discount (H2a) or countdown timer (H2b), participants' product choice will (in addition) be motivated by the discount/countdown timer.

The next three hypothesis all deal with the concept of urgency. The hypothesis regarding fear of missing out differs from the other two urgency-related hypotheses: time pressure and steering towards a certain product. Time pressure and steering towards a certain product both concern the *product choice* a consumer faces when having to select a certain product. For instance, the time pressure of a countdown timer is applied on the choice consumers face, they have to decide quickly what product to select.

Regarding fear of missing out, this is different. When participants choose between a (limited-time) discount option and a product without discount, and choose the latter, there is no fear of missing out. Put more simply, when the consumer chooses a product without a discount, there is no missing out on any discount, because there is no discount to 'miss out from'. Therefore fear of missing out should be measured not regarding the *choice* participants face, but with respect to the *product* they chose. Hence, the construct of fear of missing out is compared amongst participants that chose the (limited-time) discount option (in our experiment, the grey office chair).

H3 Fear of Missing Out:

Participants who have selected a product on a discount (H3a) or with a countdown-timer (H3b) will report greater fear of missing out than those who selected a similar product without any discount or countdown timer. Those who encountered a countdown timer will report greater fear of missing out than those who encountered a discount (H3c).

H4 Perceived time pressure:

Participants who have encountered a discount (H4a) or countdown-timer (H4b) will report greater perceived time pressure than those who did not encounter any discount or countdown timer. Those who encountered a countdown timer will report greater perceived time pressure than those who encountered a discount (H4c).

The hypothesis above about perceived time pressure is based on the suggestion that participants that face time pressure conditions (e.g., a countdown timer) experience more time pressure than participants that do not face such conditions (Godinho et al., 2016). For our last hypothesis about product choice influence we expect that the discount and deceptive countdown timer steer people towards the product associated with these special offers, in this case a grey chair, in comparison to the control group.

H5 Product choice influence:

Participants who have encountered a discount (H5a) or countdown-timer (H5b) will feel more steered towards a certain product than those who did not encounter any discount or countdown timer. Those who encountered a countdown timer will feel more steered towards a certain product than than those who encountered a discount (H5c).

In addition to the stated hypotheses above, we have some expectations about the behavior of the control group. First, we expect the products chosen by participants in the control group to be distributed closely to a 50/50 distribution. We expect a near 50/50 distribution because we chose two extremely similar office chairs as the product to select. We chose office chairs because it suited the cover story (see chapter 5.4), , and because we thought that product specifications such as color, brand, or name would not play a significant role for the product selection.

Second, we expect participants in the control group to experience little to no fear of missing out, little to no perceived time pressure, and feel a little to not steered towards a certain product, because participants in the control group do not encounter either a discount or a deceptive countdown timer.

Furthermore, we also have expectations about the impact of this study as a whole. Our goal is not only to test the effects of deceptive countdown timers but also to create awareness of dark patterns. Hence, these expectations are also directly related to a questionnaire statement: “If I encounter Dark Patterns again in the future, I will behave differently”. We expect that participants in this study are more aware of dark patterns in the future, especially those who encountered a deceptive countdown timer during the experiment, since people who experience certain situations are aware of any consequences (Given, 2012).

5 Methodology

This section describes the experiment we conducted to answer our research questions and test our hypotheses. The study has been independently reviewed by the Research Ethics Committee (REC) of the Faculty of Science (FoS) of the Radboud University, which approved the research project. Before the main experiment, we conducted a pilot study with $N = 10$ participants to verify that the experiment was working as intended. After this pilot study, we made minor changes (e.g., bug fixes regarding database issues) and ran the main experiment until we had ten responses. We did some final verifications and did not find any errors, and thus proceeded to collect the remaining 250 responses.

5.1 Experimental Design

This study collected data using an online experiment. A between-subjects (also called between-groups) study design was employed to test the research hypotheses. There were a total of three experimental conditions: (1) the control group (i.e., no discount or dark pattern), (2) the discount group, and (3) the timer group. The conditions are explained in further detail in the materials section.

5.2 Participants

A total of $N = 260$ participants were recruited using Prolific, a crowdsourcing platform tailored for research (Prolific, n.d.). The sample size of this study was calculated using the G*Power tool, an application designed to compute statistical power analyses for many different tests (Erdfelder et al., 2009; Faul et al., 2007). The original G*Power calculation indicated a sample size of 237 participants. In order to account for unusable data, the number of participants was increased by 10%, based on the study results of Grassl et al. (2021), who used a similar experimental design.

For Prolific users to participate, specific criteria were implemented. First, all participants should feature an approval rate[1] between 80 and 100 on Prolific. Second, all participants should participate in the experiment from a country within the European Union. Third, participants who participated in the pilot study ($N = 10$) were not eligible to participate in the main study. This exclusion was implemented because secondary participation might feel less realistic to the participants and could lead to biased data. Finally, participants could only complete the online experiment successfully by participating using a laptop or desktop computer.

[1] The approval rate (0 – 100) is the percentage of studies for which the participant has been approved, versus the number of experiments participated in (Prolific, n.d.).

Participation was estimated to take approximately 13 minutes, and participants were rewarded £1.74 (£8.03/hour). Participants that did not finish the experiment were excluded from the final results.

After filtering out participants who failed to answer the control questions/attention checks and any corrupted data, 245 participants were included in the final sample size. Out of the 245 participants, 96 identified as female (39.2%), 143 identified as male (58.4%), five identified as other (2%), and one participant preferred not to say. The total sample had a mean age of 26.58 years old (SD = 8.30), ranging from 18 to 65 years old. In terms of education, the highest degree or level of education completed was high school for 115 participants (46.9%), 83 participants (33.9%) completed a bachelor's degree. 38 participants (15.5%) a master's degree, five participants (2%) a Ph.D. or higher, two participants (0.8%) completed some high school, and two participants (0.8%) preferred not to say.

Participants were recruited from all across the European Union, with 77 participants (31.4%) from Portugal, 55 participants (22.4%) from Poland, 23 participants from Italy (9.4%), 18 participants from Greece (7.3%), 17 participants from Germany (6.9%), and all other participants participated from other countries (<5% per country). Furthermore, 95 participants (38.8%) indicated to already to know about dark patterns before participating in this study, 119 participants (48.6%) did not know about dark patterns, and 31 participants (12.7%) were not sure. Finally, all participants shop online, and most participants shop online, as indicated by answers to a Likert-type question (Mean = 4, on a 7-point Likert-type question ranging from 1 = 'I never shop online' to 7 = 'I buy everything online').

5.3 Apparatus and Materials

Each participant entered the online experiment on their own device via the Prolific platform. The only requirement to participate in the experiment in terms of hardware was a laptop or desktop computer. Other devices such as mobile phones or tablets were labeled as unsupported devices. However, Prolific only indicates what type of device should be used and cannot screen out participants based on the device used.

Down below, the online experiment is covered in detail. Therefore, this section is divided into three parts: visual stimuli, in which the online experiment conditions are covered; The questionnaire, in which the follow-up questions of the online experiment are described; Finally, the behavioral measurements, in which the behavioral measurements of the online experiment are described.

5.3.1 Visual Stimuli

The online experiment consisted of a webshop, designed to look as realistic as possible using a W3Layouts bootstrap template (W3Layouts, 2018). The webshop, called ‘Electro Store’, fictionally sells office supplies such as electronics, desks, and office chairs. Three versions of the webshop were created, one version for each experimental condition. The webshop was visually identical for all participants, only the conditions differed across groups regarding the exact choice participants faced. A complete overview of the webshop can be found in the Appendix (9.1). The back-end of our fictional webshop was based upon the work of Geels (2021), which is publicly available at: *https://gitlab.socsci.ru.nl/G.Geels/thesis-project/-/tree/master.*

The webshop offered two types of office chairs that differ in color. We chose office chairs because we believe office chairs are an office product where product specifications such as color, brand, looks, or any similar perk would not play a major role in the distribution, especially when compared to other office supplies such as a mouse or laptop. Both chairs are from the product family called the ‘ARGON office chair’, where ‘ARGON’ represented a fictional brand name. All groups saw the same two office chairs, one grey and one black, whose product names were displayed as ‘ARGON <*color*> – Office chair’. Below, all three conditions are described in further detail.

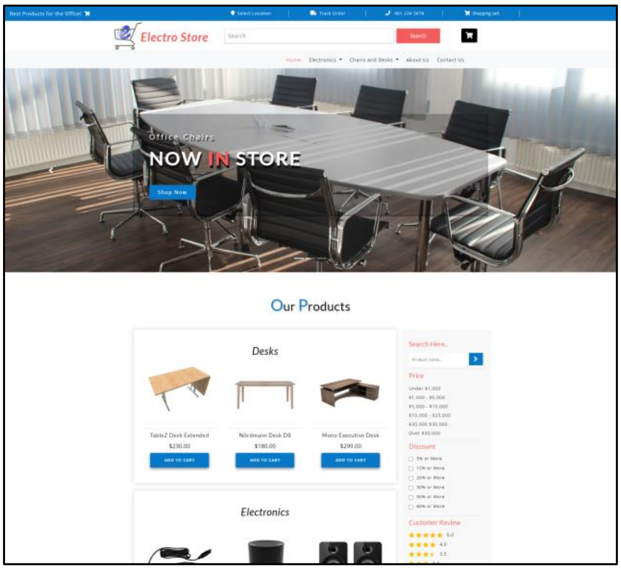

Figure 20 - Partial screenshot of the landing page of Electro Store, the fictional webshop used in the online experiment.

Control Group

As mentioned, participants were invited to select an office chair and faced a different choice depending on their group. The control group saw both chairs offered without additional differences other than the color and product name of the office chairs, as depicted in the image below. The purpose of the control group is to provide results while there are no other influencing factors present and to serve as a baseline to compare other groups to.

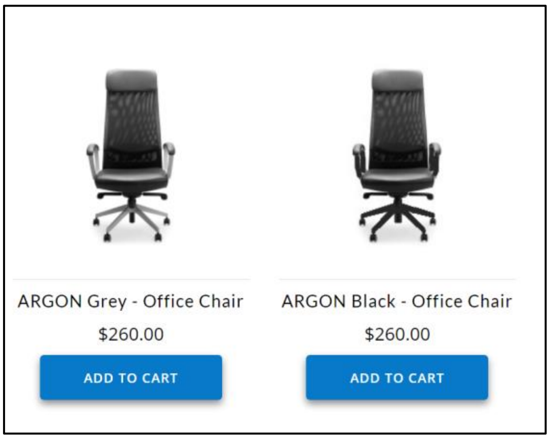

Figure 21 - The condition of the control group. All product details (including price) are identical, except for the color and product name of the chair.

Discount Group

Compared to the control group, the discount group is shown not only a difference in color, but also a reduced price for one of the chairs. The discount is a $60 reduction on the 'ARGON Grey – Office Chair'. The price of both products remains $260.00, but the grey office chair has its original price set at $320.00, as shown in the image below. The function of the discount group is to evaluate the effect of a discount in order to determine if the potential effects of a limited time discount (i.e., countdown timer) are due to the limited time offer or the discount.

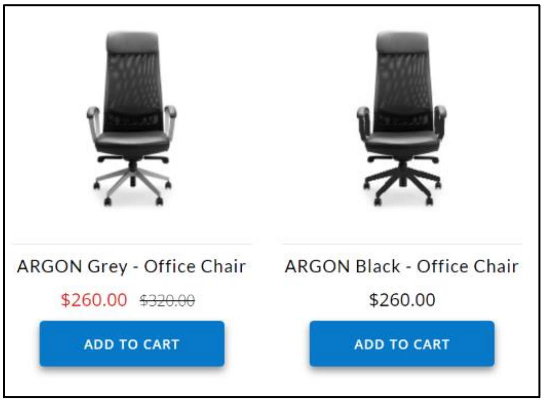

Figure 22 - The condition of the discount group. The grey office chair is on sale for $260.00 instead of the original $320.00.

Timer Group

The timer group is shown another additional difference other than the discount group: a deceptive countdown timer. Similar to the discount group, the grey office chair is on sale. However, the offer is now paired with a deceptive countdown timer to put the participant under additional time pressure. The deceptive countdown timer indicates how much time is left on the offer by displaying 'Offer expires in: <*hours*>h <*minutes*>m <*seconds*>s'. The original countdown time is seven minutes, counting down to zero. Although seven minutes is a duration not seen most often, it suits the time participants need to finish the experiment (13 minutes on average as determined by assessing the initial pilot study). In addition, the countdown timer is deceptive, and if timer group participants refresh webpage or navigate between webpages, the countdown timer resets to seven minutes. We do not expect all participants to notice the deceptive nature of the countdown timer, but it could be noticed. Hence, we keep track of the number of page refreshes to study possible relations between the product choice and participants that may have noticed the deceptive countdown timer. The purpose of the timer group is to evaluate the effect of a (deceptive) countdown timer with respect to the regular product and the control- and discount group.

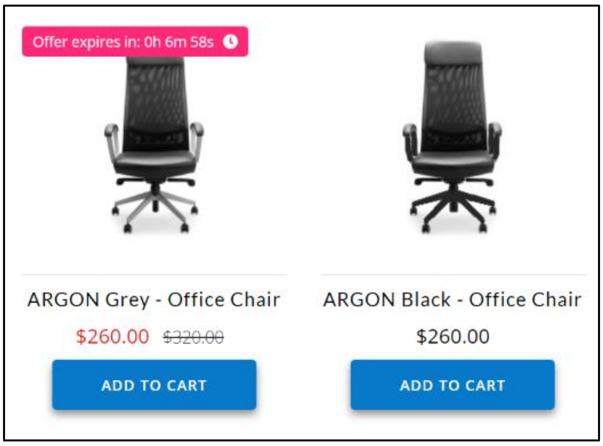

Figure 23 - The condition of the timer group. The grey office chair is on sale and paired with a deceptive countdown timer.

5.3.2 Questionnaire

After the online experiment, participants were asked to fill in a questionnaire. The questionnaire consists of five sections, each covering a different aspect of the experiment or dark patterns in general. The complete questionnaire can be found in Appendix (9.2). Below, each section of the questionnaire is described in more detail.

Recall and Attention Checks

After the participants finish their task (i.e., complete the purchase) and proceed to the survey, they are asked to fill in two attention check questions. The participants are asked what product they bought, and if the purchase was made using a working budget. Both questions should be easy to answer if a participant paid attention during the experiment. We used these attention checks to filter out participants who rushed the experiment and randomly filled in the questionnaire (i.e., participants who did not answered all recall checks correctly).

Reason for Product Selection

In the following section, the 'selection', participants are asked *why* they selected one specific chair. This question is used to determine what factors influence consumer choices (in this case, the participants are the consumers) and should be interesting to compare with other questionnaire results such as the 'urgency' section. Answers to this open question were be coded and analyzed using ATLAS.ti Windows (Version 9.1.7.0; ATLAS.ti, 2021). A detailed description of the analysis can be found in the Appendix (9.3).

Urgency

Participants are asked multiple questions related to urgency to buy, where retailers steer consumers in a certain direction while putting the consumer under time pressure (Childs & Jin, 2020; Gupta, 2013), and exploit the scarcity bias (Gray, Chen, et al., 2021; Mathur et al., 2019; Mittone & Savadori, 2009). First, participants were asked about the fear of missing out regarding a deal or offer, which relates to the scarcity bias. Existing studies (J. Kim et al., 2020; Zhang et al., 2020) about consumers and fear of missing out did feature FOMO-related questionnaires, but those found were targeted toward personal FOMO and feelings (often based on Przybylski et al., 2013), and not about FOMO on offers or deals. Therefore, participants were presented with three newly created statements. Participants should indicate how much it applied to them on a Likert scale[2] ranging from 1 (Not at all) to 7 (Very much). Statements provided were "I feel would have missed out on a great offer if I waited a couple of hours." [3](1 = Not at all to 7 = Very much); "I feel like if I did not buy the product right away, I would regret it later." (1 = Not at all to 7 = Very much), and "I feel that if I did not buy the product right now, the product would become more expensive." (1 = Not at all to 7 = Very much).

[2] A Likert scale is a psychometric scale ranging from two points (e.g., 'not much' – 'very much') from which respondents choose to indicate their opinions, attitudes, or feelings about a particular issue (Joshi et al., 2015; Nemoto & Beglar, 2014).

[3] Unfortunately, this statement had a missing word, but is still expected to be understandable.

Second, participants were asked to indicate the perceived time pressure during the experiment through an existing 9-point Likert scale (Godinho et al., 2016). Questions asked were "Do you believe you had enough time to make a good choice?"(1 = Not at all to 9 = Very much); "Do you believe you had enough time to carefully evaluate each item available?"(1 = Not at all to 9 = Very much), and the extent to which they felt time pressured to decide "How pressured did you feel while making your decision?"(1 = Not pressured to 9 = Highly pressured) (Godinho et al., 2016).

Finally, participants were asked about manipulation and steering of their product choice, as dark patterns are known for steering people's behavior and choices (Brignull, n.d.; Graßl et al., 2021; Mathur et al., 2019). Again, no existing questionnaire suited the questionnaire of this study. Hence, a new statement for a 7-point Likert scale was created: "I felt steered towards selecting one of the two products" (1 = Not at all to 7 = Very much).

Dark Patterns in general

Next, participants were informed about dark patterns and the goals of dark patterns in general. After reading the information, participants were asked what they think about dark patterns in general. Following this question was an informatory piece about deceptive Countdown Timers and the notion that some participants (the timer group) encountered such a deceptive Countdown Timer during the online experiment. Participants were then asked open questions on what they think about Countdown Timers; If they feel influenced by Countdown Timers (e.g., in purchasing speed or satisfaction); If they have ever encountered a Countdown Timer. Lastly, participants should indicate if they would regret purchasing a product on a limited-time discount to find out later the discount would never expire on a 7-point Likert scale. All previous questions could offer interesting results indicating how people experience dark patterns and (deceptive) Countdown Timers.

Demographics

Finally, participants were asked about demographics and some general questions. In terms of demographics, participants are asked about the gender they identified with, age, highest level of education, and from which country they are participating in the experiment. After filling in demographic data, participants were asked how often they shop online and if they knew about dark patterns before this study, followed by whether they will behave differently when encountering dark patterns in the future. The questionnaire ended with a question if all websites and questionnaire sections were displayed correctly. In addition, on each questionnaire section, participants could leave additional comments about that specific questionnaire section.

5.3.3 Behavioral Measurements

During the online experiment, it was planned to record different data of the selection process, but unfortunately, some data got corrupted. Solely data that supports answering our research questions were recorded and processed. To begin, we store information about the selection itself. We record what product was selected and how much time was left on the countdown timer (if displayed) at the time of selection. In addition, we record on what webpage the product was selected.

Next, the total time spent on the webshop (solely the online experiment) was planned to be recorded to measure the total purchasing speed measured from the initial visit until checkout. Along with the time spent on the webshop, we would keep track of what webpages (homepage, product overview, single product views) were visited during the selection process to study if the countdown timer had any effect on the participant's browsing behavior (for instance, if participants that see the countdown timer proceed to checkout without visiting any other webpages).

Furthermore, we intended to record the number of page refreshes. The reason for this was two-sided. First, this measure would validate browsing behavior (as described above) in terms of what web pages were visited and how frequent. Second, the number of page refreshes could indicate a participant noticing the countdown timer's deceptive nature. For instance, it is interesting to find out if a participant in the timer group that refreshed the product overview multiple times (thus discovering the deceptive nature of the countdown timer), will deliberately select the non-timer product because of this (which is highly likely to be answered accordingly in the questionnaire). However, due to technical issues, both the timing data and page refresh data are not sufficiently reliable to be used in the following chapter.

Finally, all data collected is also used for verification that the experiment functioned as intended, especially in case we encounter outliers in our data.

5.4 Procedure

The procedure starts with the recruitment of participants through the Prolific platform. Prolific users (i.e., potential participants) browse experiments[4] listed by researchers on Prolific, after which they could decide to participate. Once a participant clicks the 'Start Now' button on Prolific, the participant is redirected to our online experiment hosted on the Radboud University servers.

First, participants were informed about what data would be recorded, their rights, and other privacy notices. Any upfront questions could be sent to the researchers via email or using the Prolific messaging functionality. Also, participants were informed

[4] Only experiments that the participant is eligible to participate in (based on prerequisites defined by the researchers) are listed.

about the experiment itself, but a cover story disguised the real experiment (about deceptive countdown timers and dark patterns). The cover story was used to disguise the true purpose of the online experiment to attempt to achieve more reliable results. Research has shown that individuals that knowingly participate in experiments modify their behavior from what it would have been without the knowledge, better known as the 'Hawthorne effect' (Adair, 1984; Wickstrom & Bendix, 2000). Especially in behavioral economic experiments where participants, for instance, are asked to purchase specific products, acquiring reliable results is challenging. This is mainly because people are more likely to spend unearned money (e.g., prize money) differently and on less basic goods than earned income (e.g., income from work) (Ambler & Godlonton, 2021; Christiaensen, 2012; Imbens et al., 2001). Put more simply, people spend their own and earned money differently than unearned money. However, asking participants to spend their own money to acquire more reliable research results would be unethical.

Therefore, our cover story aims to stimulate natural spending behavior (i.e., that of earned money) as best as possible, although the purchase would be made using unearned money[5]. In order to realize this, participants were asked to select (i.e., 'purchase') an office chair from a fictional webshop using 'working budget', while being informed this was in order to study how people buy products online and what elements influence their buying choices tailored on 'work budget webshops'.

After reading the information letter, participants were asked for consent to participate in the experiment. Next, participants were reminded about their task: selecting and purchasing an office chair for work using a personal work budget of $300. If all was clear, participants could proceed to the webshop using a 'Start Task' button.

Once participants clicked the 'start task' button, they were assigned to one of the three experimental conditions, and redirected to the homepage of the fictional webshop (see figure 20), which consists of a navigation bar, a big slider showing images, featured products (none of which were office chairs), a promotional section and a footer. In order to find the office chairs, participants could either use the navigation bar, click on a slider image, or navigate via the 'category' listed in the site footer. No links other than the redirect link to the product overview page were operational.

After navigating to the product overview for office chairs and desks (see appendix 9.1), participants would see the condition described in the materials section earlier, with desk offers displayed below the condition and fictional filters displayed on the right. On the product overview page, participants could either add an office chair to the online cart or navigate to the product page of one of the two chairs. Both product pages were identical except for the product images and titles (color difference). At all times,

[5] No real purchase is made during the experiment and fictional money is used.

participants could freely browse between the homepage, product overview, or product pages.

When participants added one product to their online cart, the ‘proceed to checkout’ button would appear. Participants could only click this button when their cart consisted of exactly one product. Adding more products to the online cart would result in an error that required participants to remove one or more products. As soon as the ‘proceed to checkout’ button was clicked, participants were redirected to the ‘thanks!’ screen. Participants could then proceed to the questionnaire from this screen as described in the questionnaire section. The questionnaire was divided in to five webpages, each page covering a subset of the questions of the questionnaire. After completing the questionnaire, the participants were debriefed about the experiment and more details on the research were provided. To successfully complete the experiment, and receive payment, participants needed to click the ‘Back to Prolific’ button. This button redirects participants back to Prolific, which Prolific then counts as a successful participation (which is needed to determine how much participants are still needed to meet the required number of participants). Down below, a visual representation of the entire experimental procedure is shown.

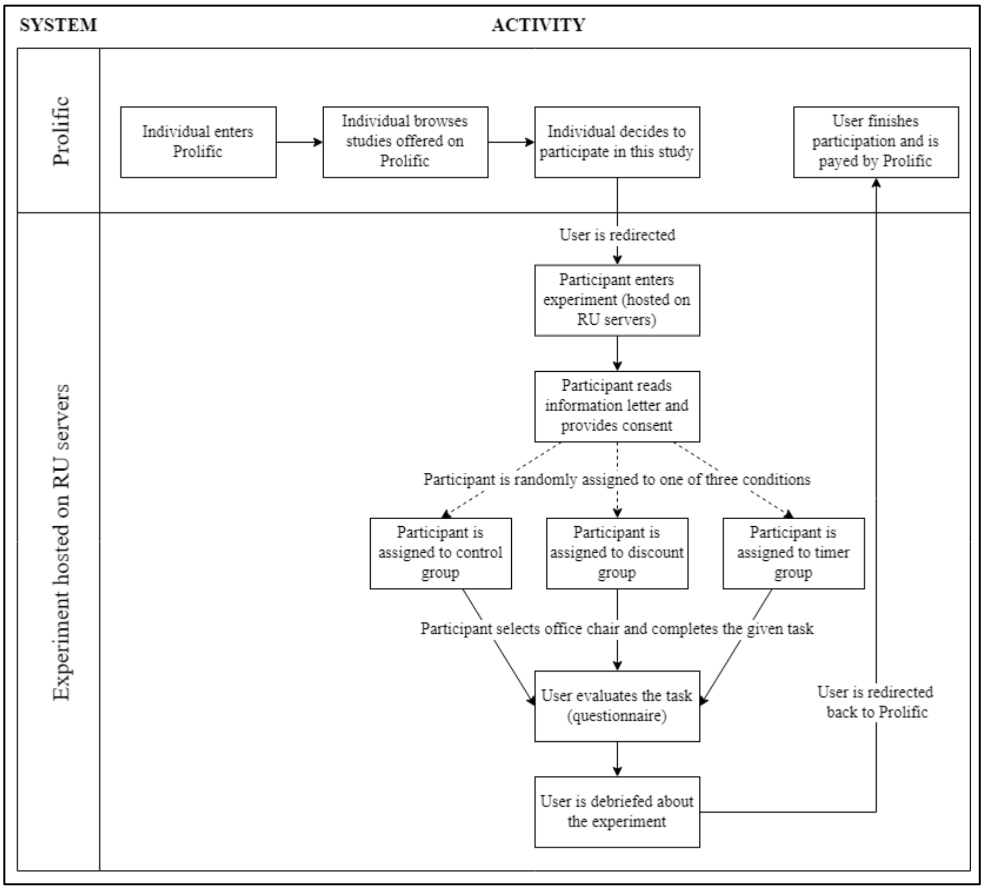

Figure 24 - Experiment flow visualized

6 Results

In this chapter, both the main results and the exploratory results are covered. The main results cover the experimental data used to answer the sub-research questions and test the hypotheses. The exploratory results cover all other data that can be used to support the main results or offer additional interesting insights. Our initial sample size consisted of 260 participants. After filtering, the final sample size consisted of 245 participants, randomly divided into three groups: the control group (N = 75), the discount group (N = 91), and the timer group (N = 79).

6.1 Main results

In this section, all main results are described, including graphical representations. We use the same categorization as in the hypothesis and in chapter five (Methodology) and distinguish between product selection on the one hand and urgency on the other hand.

6.1.1 Product Selection

Participants were asked to select an office chair from a fictional webshop during the experiment. Two aspects of this product selection were documented: what chair was selected, and the reason for this selection (obtained with an open question in the questionnaire). Below, the results of each aspect are described.

Product selection

As seen in figure 25 visualizing product choice among participants, 62 participants (82.7%) in the control group chose the black chair, versus 13 participants (17.3%) that chose the grey chair. In the discount group, 40 participants (44%) chose the black chair (non-discount), versus 51 participants (56%) chose the grey chair (discount). In the timer group, 43 participants (54.4%) chose the black chair (non-timer/discount), versus 36 participants (45.6%) chose the grey chair (discount and countdown timer), a statistically significant difference in proportions, $p < .001$.

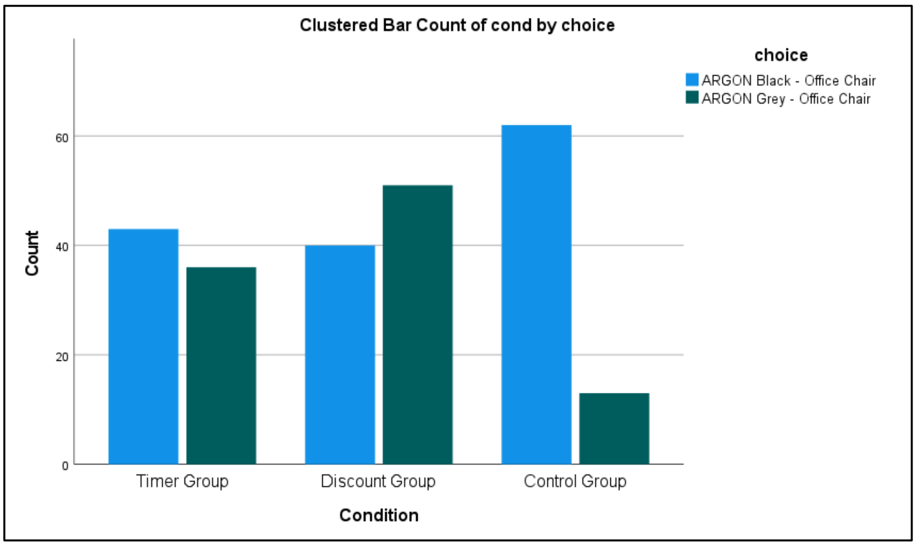

Figure 25 - Product choice distribution per group

First, a chi-square test of homogeneity was conducted between conditions and product selection. All expected cell counts were greater than five. Post hoc analysis involved pairwise comparisons using the z-test of two proportions with a Bonferroni correction. The proportion of participants that chose the grey chair (discount or discount and timer) was statistically significantly lower in the control group than in the other groups, $p < .05$. The proportion of product selection was not statistically significantly different between the discount and timer group, $p > .05$.

Reason for product selection

The reasons for participants' product selection was documented through an open question in the questionnaire. After coding of all results, we found the following reasons for selection (please note that participants can provide more than one reason): *because of the color of the product* (144 instances), *because of the discount or offer* (53 instances), *because it fit within the specified work budget* (9 instances), *because the chair seemed comfortable* (10 instances), *because discount seemed fake* (6 instances), *because of the looks (other than color) of the chair* (34 instances), *because it was the only sort of chair to choose from* (18 instances), and *because of the perceived value of the product* (16 instances). Any other reason was coded as *other* (14 instances). Specific reasons were found more often in certain groups than in others. Down below, we present the results per group.

In the control group, *product color* was the most prevalent reason for product selection (56 instances). For instance, one participant mentioned: *"Because it is black and I prefer that color over grey"*. Another participant mentioned: *"There weren't many differences between the two chairs and I thought the black chair looked better"*, which is representative for many similar provided reasons. In addition, other aspects regarding the *looks* of the chair (other than color) (14 instances) and its perceived *comfortability* were mentioned as reasons for selection (6 instances). Furthermore, participants mentioned that the type of chair was the *only option* offered by the webshop (11 instances) and that it fitted the *budget* of $300 (3 instances). Finally, no participants in the control group mentioned reasons related to price, offers, or perceived value of the product.

Similar to the control group, the discount group also mentioned *product color* as most often as the reason for product selection (48 instances). However, *discount* (i.e., offer/sale/deal/price reduction) was also mentioned by many participants (29 instances). For example, one participant mentioned: *"They're the same chair, but I feel like I'm saving money by buying the one with a discount".* Additionally, some participants also mentioned that the chair on sale must be of greater value because of its price reduction (10 instances). Occasionally, this is mentioned with the discount: *"Because it costed 320 and now its price is the same as the cheaper one, so I'm buying a more valuable chair for the same price as a cheap chair".* Other reasons for the product selection within the discount group were that this type of office chair was the *only type available* (4 instances), one product *looked* better (11 instances), and the chair seemed *comfortable* (1 instance). One participant mentioned that the chair fitted their *budget*. Finally, it was interesting to see that one participant mentioned that the discount was *"fake",* and therefore that participant chose the non-discount option.

The timer group also provided *product color* (39 instances) as the main reason for product selection, followed by the *discount* (i.e., offer/sale/deal/price reduction) (24 instances). In addition to this *discount*, some participants mentioned the *perceived value* of the product with limited-time discount was higher than the non-limited-time discount option (6 instances). Of all participants, no one explicitly mentioned the countdown timer as a reason for choosing the product with the limited-time discount. In contrast, five participants mentioned having chosen the non-timer product because the special offer seemed *sketchy* or *fake* (6 instances). For instance, one participant mentioned: *"It was the same chair so I chose the less "sketchy" one",* as another participant also mentioned to have chosen the other chair *"Because of the fake offer!".* Another portion of participants selected the product because it fitted their *budget* (5 instances). Again, participants also mentioned *comfortability* (3 instances), *looks* (9 instances), and because it was the *only option* available (1 instance) as reasons for selection.

6.1.2 Urgency

A questionnaire was employed to measure different, urgency-related constructs: perceived fear of missing out, perceived time pressure, and feeling of being steered towards products. The three constructs are separately examined, as combining all constructs was not possible due to two reasons. First, fear of missing out is different from the other two constructs. Second, feeling steered towards products is measured using a single Likert-type question, which will result in ordinal data, and therefore it should not be combined with the other constructs[6]. Below, the results of each construct are described.

Fear of Missing Out

The construct 'fear of missing out' was assessed with three Likert-type questions (see Appendix 9.2.3). As mentioned in section 4.3, FOMO is measured using a subset of our sample including only participants that selected the grey chair, because FOMO is related to a *product*, and not the *product choice* participants face. As displayed in figure 26, perceived fear of missing out focused on participants that chose the grey chair, increased from the control group (M = 2.69, SD = 1.40) to the discount group (M = 3.86, SD = 1.68), and timer group (M = 4.44, SD = 1.73), in that order.

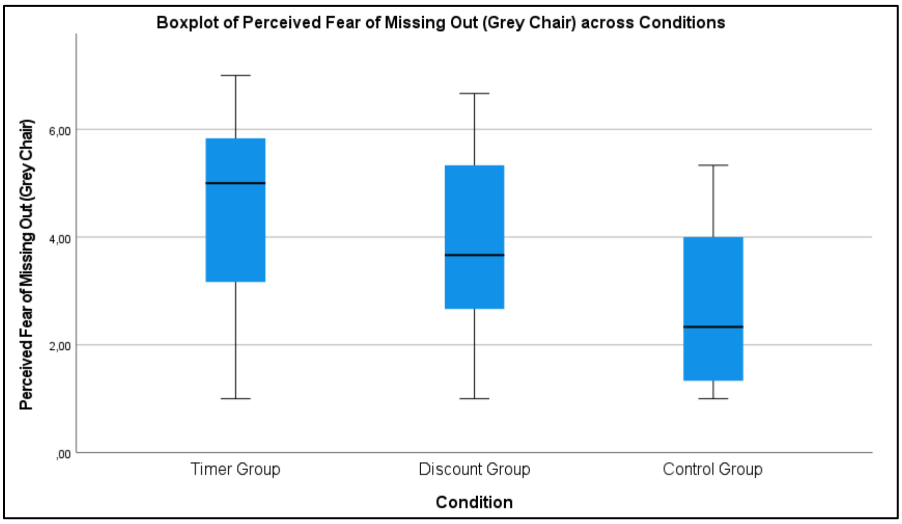

Figure 26 - Boxplot of Perceived Fear of Missing Out (Grey Chair) across Conditions

To determine the difference in the fear of missing out for the participants that chose the grey chair (special offer) across conditions, a one-way ANOVA was conducted. The same three groups were used: the control group (n = 13), discount group (n = 51), and the timer group (n = 36). There were no outliers and the data was normally distributed for each group, as assessed by boxplot and by Normal Q-Q Plot[7]; and there was homogeneity of variances, as assessed by Levene's test of homogeneity of variances (p = .457). Data is presented as mean ± standard deviation. Fear of missing out was statistically significantly different between conditions, $F(2, 97) = 5.266$, $p = .007$, $\omega 2$ =

[6] While some controversy exists about data obtained with Likert-scales (which combine several Likert-type questions into one score), we treat this as interval data in this study.

[7] Our sample size is higher than 50 participants (*N* = 100), hence, a Shapiro-Wilk test was not suitable and replaced by assessment of a Normal Q-Q Plot.

0.08. Tukey post hoc analysis revealed that the mean increase from the control group to the timer group (1.74, 95% CI [0.46, 3.03]) was statistically significant ($p = .005$), but no other group differences were statistically significant.

Perceived time pressure

The construct 'perceived time pressure' consisted of three questions (see 5.3.2). As depicted in figure 27, perceived time pressure increased (a lower mean indicates higher perceived time pressure) from the control group ($M = 6.82$, $SD = 1.64$) to the discount group ($M = 6.73$, $SD = 1.75$), to the timer group ($M = 6.20$, $SD = 2.24$), in that order.

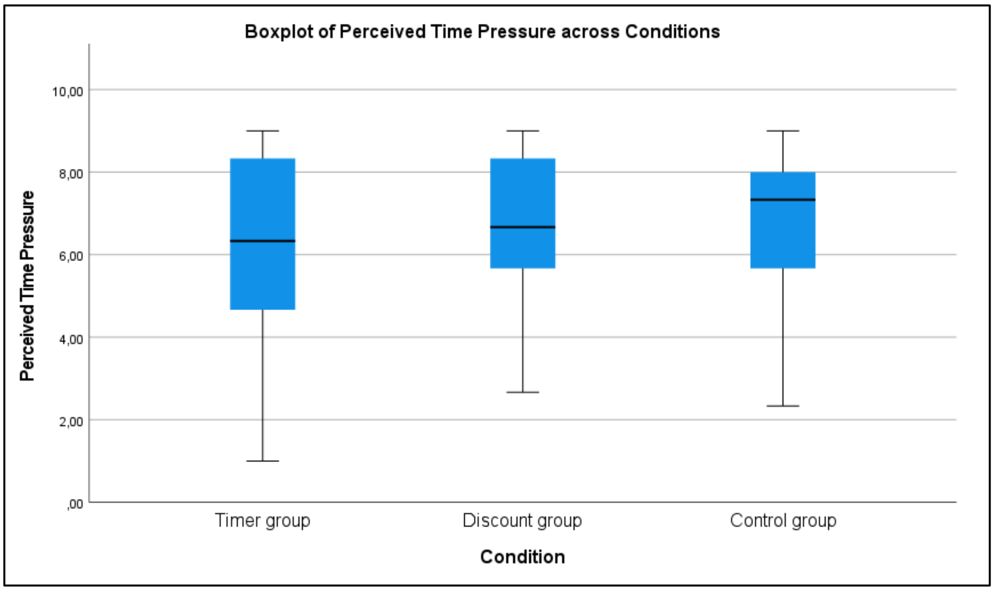

Figure 27 – Boxplot of Perceived Time Pressure across Conditions (please note: a lower score indicates more perceived time pressure)

The scale had a high level of internal consistency, as determined by a Cronbach's alpha of 0.822. There were no outliers and the data was normally distributed for each group, as assessed by boxplot and Normal Q-Q Plot[8], respectively. Homogeneity of variances was violated, as assessed by Levene's Test of Homogeneity of Variance ($p = .002$). The differences between the three groups were not statistically significant, Welch's $F(2, 156.658) = 2.049$, $p = .132$.

Feeling steered towards a certain product

The construct 'steering towards products' was measured using a single Likert-type question (see Appendix 9.2.3). As illustrated in the figure below, feeling steered towards

[8] Again, a Shapiro-Wilk test was not suitable and replaced by assessment of a Normal Q-Q Plot.

a certain product increased from the control group (Mdn = 4), to the discount group (Mdn = 5) and timer group (Mdn = 5).

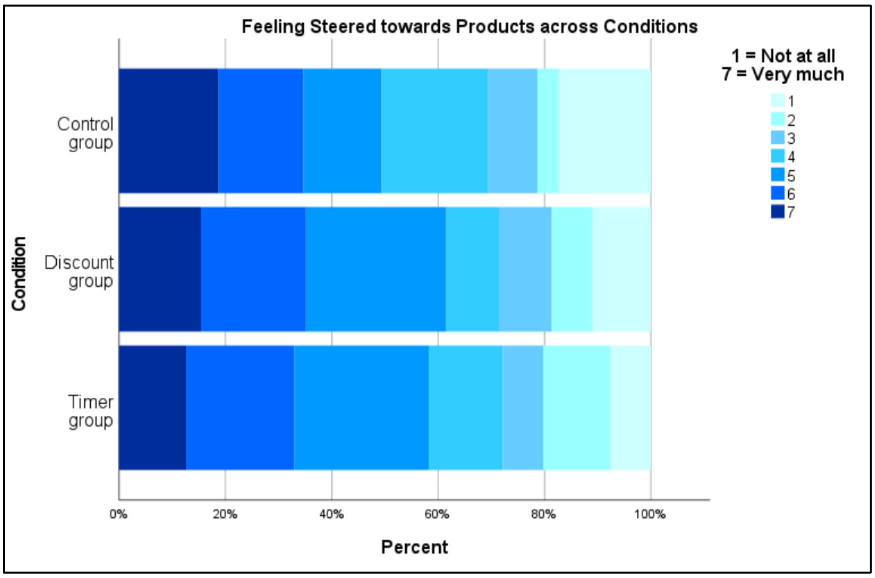

Figure 28 - Stacked bar chart of Feeling Steered towards Products across Conditions

A Kruskal-Wallis H test was conducted to determine if there were differences in participants' feeling of being steered towards a certain product across conditions. Distributions of feeling steered towards a certain product were similar for all groups, as assessed by visual inspection of a boxplot. The differences in Median scores were not statistically significant, $H(2) = .421$, $p = .810$.

6.2 Exploratory results

In this section, we cover the exploratory results. This section is split up as follows. First, responses about dark patterns in general are qualitatively analyzed. Next, the feeling of regret when dealing with dark patterns is analyzed using a Kruskal-Wallis H test, followed by an analysis of the participants' behavior when dealing with dark patterns in the future using the same method. Finally, the time left on the countdown timer at the time of selection is analyzed.

6.2.1 Dark Patterns in general and Deceptive Countdown Timers

After the experiment, participants were informed about dark patterns in general (what dark patterns are, how dark patterns work, and examples), followed by information about deceptive countdown timers. Afterward, we asked participants how they felt about dark patterns in general and deceptive countdown timers in particular. Responses were coded and categorized.

Dark Patterns

Overall, participants stated they are aware of dark patterns and mentioned that dark patterns are *manipulative* (23 instances), *unethical* (18 instances), *immoral* (6 instances) and *unfair* (4 instances). For instance, one participant mentioned: *"I think it is highly manipulative and unethical"*. Another participant mentioned: *"It is an unethical and immoral practice. I would avoid shops that are using this"*. In addition, some participants (6 instances) mentioned that dark patterns should be deemed illegal and banned by policymakers: *"They are a way to convince people to buy and spend money in things that maybe without the dark pattern they wouldn't buy. It should be illegal to say things that are not real just to sell more! Because you are convincing people of the false"*. In contrast, there are participants who do not mind dark patterns (1 instance), or see it as a simple marketing trick (31 instances): *"It's just another marketing strategy, and if/since it works it must mean it's a pretty good one. I don't see anything morally wrong with it"*. A few participants (5 instances) also mentioned not only to be aware of dark patterns (before they participated in this study), but also to actively *avoid* the effects of dark patterns when shopping online. For instance, participants reported: *"I am aware of such practice and I try to avoid retailers that do it"; "I am aware of them and try to avoid"; "I try to avoid falling for these tricks and always ask myself whether I need a certain product, regardless of its price"*.

Deceptive Countdown Timers

When asked about deceptive countdown timers, most responses provided by participants were similar or related to their answers provided at the previous question. A relatively great amount of participants deemed deceptive countdown timers *unethical* (14 instances), *unfair* (7 instances), *immoral* (3 instances) and *manipulative* (12 instances). For some participants, deceptive countdown timers mark the line between what is acceptable marketing (12 instances) and what is manipulation, as elucidated by one participant: "*fake countdown timers is where I draw the line, its misinformation to force the user buy them and force a decision on them"*. Furthermore, many participants extended their view on dark patterns and deceptive countdown timers specifically by mentioning aspects related to urgency such as the *pressuring, stressing,* or *rushing* element (69 instances) of the deceptive countdown timer. For instance, participants mentioned: *"I think they are useful for businesses but put customers under stress and maybe do not leave them enough time to make the decision that is best for them"; "I think they are designed to stress out the consumer, so that they do not think much about their choice"; "they pressure people into rushy decisions"*. Additionally, one participant mentioned avoiding countdown timers because of this *pressuring* nature: *"They exploit the fear of missing out that some people have. For me, I think it has the opposite effect. I get stressed when I see a timer, and I tend to avoid anything related to it. I don't like feeling pressured like that"*.

6.2.2 Influence of Countdown Timers

In addition to the previous two questions, we asked participants if they felt influenced by a countdown timer (open question) when purchasing a product online. Answers were coded and analyzed. Out of the 245 answers, four subgroups were created: influenced, somewhat influenced, not influenced, and no answer provided.

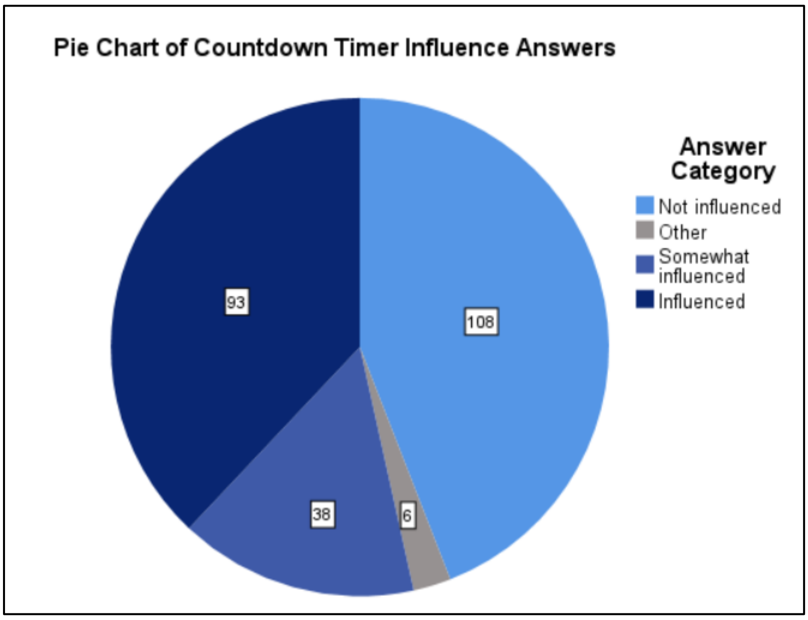

Figure 29 - Countdown Timer Influence answers visualized

To start, 93 participants indicated that countdown timers do influence them. Several reasons mentioned for this are *time pressure* or *rushing*. The following two responses illustrate this: "*Yes absolutely, it makes you feel that if you miss the discount moment the price will be much more expensive*"; *"It makes me panicked, it makes me feel overwhelmed and even if I needed the product, the fact that there's now a (fake) time pressure behind it makes it so that regardless of if it is the best deal out there, I will feel stupid or even regret the purchase after I've paid for it".* Some participants feel influenced in a way that conflicts with the goal of the countdown timer. For example, some participants report leaving the website when encountering a countdown timer: *"In my experience I respond negatively (e.g. leaving the site) to such timers".* A smaller number of participants (38 participants) did feel somewhat or sometimes influenced, dependent on the situation the countdown timer would be presented in. For example, one participant mentioned: *"It depends. If it's an item that I'm currently looking to purchase then yes, as I may regret not purchasing it later. If it's not an item that I'm currently looking to purchase then no".* Conversely, a large group (108 participants) does report not feeling influenced by countdown timers. For instance, one participant mentioned: *"No, I don't take these things seriously. And if it is gone, it is gone. I am not going to buy something* *just because the offer will expire in 10 min. I don't like being pressured".* The main reason for not feeling influenced is the aversion to countdown timers' manipulative and pressuring nature, as mentioned by several participants: *"I don't think I would feel very influenced by them because I wouldn't believe the timer to be true, anyway"; "I don't like to be pressured so I would leave the site. It's a cue for the seller to be not honest".* Finally, a small portion of participants (6 participants) did not answer the question properly and were coded as 'other'.

6.2.3 Regret

In the exploratory section of the questionnaire, a Likert-type question (see Appendix 9.2.4) was included to measure the extent of regret if a participant would have purchased a product on a limited-time discount to find out later that the discount never expired. The feeling of regret was similar across all groups: the control group (Mdn = 5), the discount group (Mdn = 5), and the timer group (Mdn = 5).

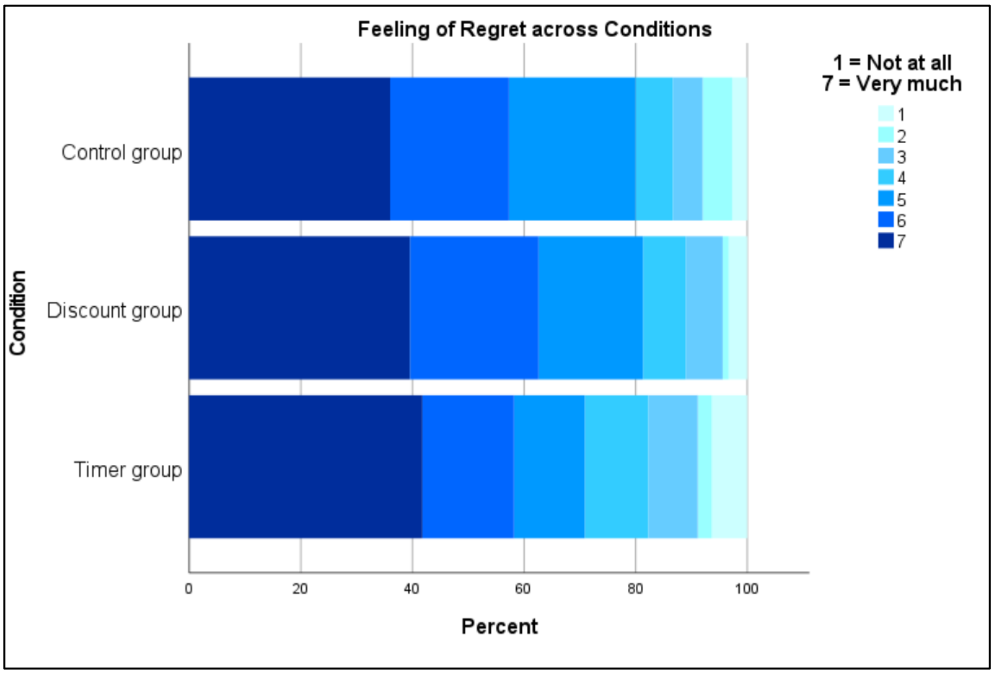

Figure 30 - Stacked bar chart of Regret across Conditions

A Kruskal-Wallis H test was conducted to determine if there were differences in participants' regret across conditions. Distributions of regret were similar for all groups, as assessed by visual inspection of a boxplot. The differences in Median feeling of regret was not statistically significant, H(2) = .464, p = .793.

6.2.4 Countdown Timer analysis

Out of all participants in the timer group, 36 selected the office chair on a limited-time offer. We analyzed the time that was left on the countdown timer at the moment of selection (the countdown timer started at seven minutes). However, since the countdown timer is deceptive, the timer resets when the page is refreshed. Hence, the results are not necessarily related to the total duration of the selection.

Out of the 36 participants in total, 32 selected the product while the countdown timer was above six minutes and 30 seconds, three participants selected the product while the countdown timer was above six minutes, and one participant selected the product while the countdown timer passed the six-minute mark.

6.2.5 Future Behavior

At the end of the experiment, participants were asked to indicate if they would behave different if they would reencounter dark patterns using a 7-point Likert-type question (1 = Strongly disagree to 7 = Strongly agree). Most participants indicated they would behave different when encountering dark patterns in the future (Mdn = 5).

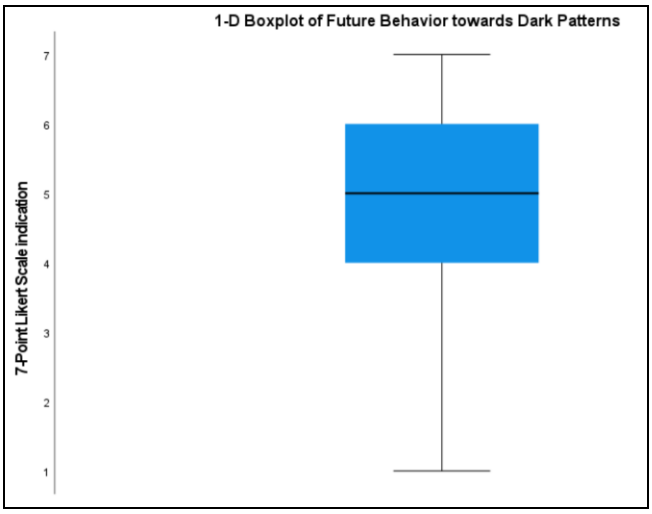

Figure 31 - 1-D Boxplot of Future Behavior towards Dark Patterns

In order to discover if participants' future behavior towards dark patterns differed per condition, a Kruskal-Wallis H test was conducted across conditions. Distributions of future behavior were similar for all groups, as assessed by visual inspection of a boxplot. Future behavior indications were similar across all groups: the control group (Mdn = 5), the discount group (Mdn = 5), and the timer group (Mdn = 5). The differences in Median feeling of regret was not statistically significant, $H(2) = 2.044$, $p = .360$.

7 Discussion and Conclusion

The previous section covered all results of the conducted online experiment. This chapter discusses the main and the exploratory results, followed by the limitations of this study. Finally, future research possibilities will be provided.

7.1 Main Results

In the following subsections, we will discuss the results with respect to our hypotheses regarding product selection and urgency. Product selection is divided into two aspects: product choice (H1) and the reason for product selection (H2). Urgency is divided into three aspects: fear of missing out (H3), perceived time pressure (H4), and feeling steered towards a certain product (H5).

7.1.1 Product choice

We wondered how discounts and deceptive countdown timers would affect consumers' product choices. Our first hypothesis (H1) stated that participants are more likely to choose a product over a similar, equally priced alternative if the product is accompanied by a discount (H1a) or a countdown-timer (H1b). In other words, this means participants in the discount or timer group are more likely to select the grey chair than participants in the control group.

In addition to the hypothesis, we expected a near 50/50 distribution for the control group. However, the actual product choice distribution of the control group was not near a 50/50 distribution but nearly an 80/20 distribution in favor of the black chair. So, color and looks do seem to make a difference regarding product selection, as we see a strong preference for the black chair.

Next, the product choice distribution of the discount group shows that participants in this group selected the discounted product (grey chair) significantly more than participants in the control group, consistent with our hypothesis H1a. What is interesting to see here is that the distribution of the discount group, a near 45/55 distribution in favor of the discounted chair, indicates that the discount reduces the preference for the black chair. In this case, our findings seem to align with consumer choice theory, which describes that people always aim to figure out the best choice regarding the options presented, but can be influenced in the process (Bettman et al., 1998; Bordalo et al., 2013; R. Thaler, 1980).

Lastly, the product choice distribution of participants in the timer group shows that significantly more participants selected the limited-time discount product compared to the control group, which is consistent with our hypothesis H1b. When analyzing the distribution, we see a near 55/45 distribution in favor of the non-limited-time discount product, the black chair. It is interesting to see that the discount and countdown timer reduce the preference for the black chair and thus affect product choice. Although not significant, solely the discount seems slightly more successful in reducing the black chair preference than the discount and deceptive countdown timer combined. Results of our qualitative analysis (see following sections) support this interpretation, as several participants showed an averse reaction to the limited-time offer. Following this interpretation, it seems that the countdown timer diminishes the effect of the discount incentive, as described by other studies (Godinho et al., 2016; Hanna et al., 2016). Our results are in line with the study of H. Kim et al. (2020) indicated that time pressure (e.g., in the form of a countdown timer) is associated with an increased intention to buy. However, based on our results we believe that it is more likely the discount associated with the timer rather than the countdown timer itself that is causing the increase. Furthermore, we found no evidence that indicates that a limited-time offer is more effective than a discount in changing peoples' product preference.

7.1.2 Reason for Product Choice

When analyzing the product chosen by participants, one of the essential areas is understanding why this choice is made (Birdwell, 1968). Hence, we were curious about the most important factors that influence the product choice of participants. We expected that participants that did not face any special offer to select a product based on product specifications such as color or looks. If participants did encounter a discount (H2a) or a countdown timer (H2b), participants' product choice would be additionally motivated by the discount/countdown timer.

We found that participants in the control group selected the product based on *product color, looks* (other than color), *comfortability,* and because it was the only type of chair offered. No participants in the control group mentioned price, discounts, or perceived value, which is in line with our expectations and experiment design.

Participants in the discount group provided the same reasons as mentioned earlier, but additionally, *discount* (i.e., offer/sale/price difference) was also mentioned by almost one-third of that group. Furthermore, participants mentioned that the perceived value of the selected chair was higher due to the price difference. Hence, this was consistent with our hypothesis H2a.

Finally, participants in the timer group provided reasons such as *color, looks, comfortability,* and *budget*, as seen in the other groups. Like the discount group, almost one-third of the participants also mentioned the *discount* as a reason for product selection. Inconsistent with our hypothesis H2b, no participant in the timer group mentioned the countdown timer regarding the product selection, although putting the consumer under time pressure could influence their product choice (Mathur et al., 2019; Reutskaja et al., 2011).

Additionally, participants mentioned choosing the non-limited-time discount product because of the *sketchy* and *fake*-looking countdown timer, which was also not foreseen in our hypothesis. This latter effect of participants deliberately avoiding the non-countdown timer option seems to confirm the reasoning of some studies (Godinho et al., 2016; Hanna et al., 2016) that countdown timers can either enhance or, what also has been reported by participants in this study, diminish the effects of discount incentives. This 'skepticism' about countdown timers, but also applicable to dark patterns in general, would be interesting to research in the future, as such research could showcase the non-effective side of dark patterns. To summarize, product specifications such as color and looks and discounts are the most important factors that influence a product choice. No evidence was found that countdown timers play an important role regarding product choice motivation.

7.1.3 Fear of Missing Out

In order to determine the relation between countdown timers and urgency to buy, we started by asking what the effects of discounts and deceptive countdown timers on consumers' fear of missing out are. We expected that participants who have selected a product on a discount (H3a) or with a countdown-timer (H3b) would report a greater fear of missing out than those who selected a similar product without any discount or countdown timer. In addition, we expected that participants who encountered a countdown timer would report greater fear of missing out than those who encountered a discount (H3c).

Although the mean of the discount group ($M = 3.86$) is higher than the mean of the control group ($M = 2.69$), the increase from the control group to the discount group was not statistically significant, which is inconsistent with our hypothesis H3a. The mean of the timer group ($M = 4.44$) is higher than both the control group and the discount group, but only the increase from the control group to the timer group was significant ($p = .005$). Hence, the significant difference we found between the control group and the timer group is consistent with our hypothesis H3b. Thus, the deceptive countdown timer seems to have an effect on the fear of missing out perceived by consumers that encounter one compared to those who do not encounter any special offer.

As mentioned above, the increase from the discount group to the timer group was not statistically significant, which is inconsistent with our hypothesis H3c. A possible reason we did not find an effect is that discounts typically are not endless. As such, we expect participants to still perceive some fear of missing out when encountering a discount, since most participants also realize discounts typically do not last forever, and therefore perceive some fear of missing out. Adding a countdown timer probably increases this effect, enough to create a significant difference between the control group and the timer group, but not enough for us to find a significant difference between the discount group and the timer group. We would suggest that future studies that examine fear of missing out of special offers should verify this lacking significant difference.

Our findings show an increase in fear of missing out amongst participants that encounter a deceptive countdown timer, a result similar to what is described in two studies (Gray, Chen, et al., 2021; Mathur et al., 2019)

7.1.4 Perceived Time Pressure

We wondered what the effects of discounts and deceptive countdown timers were on consumers' perceived time pressure. We expected participants who encountered a discount (H4a) or countdown-timer (H4b) to report greater perceived time pressure than those who did not encounter any discount or countdown timer. In addition, we expected that participants who encountered a countdown timer would report greater perceived time pressure than those who encountered a discount (H4c).

The perceived time pressure of the discount group (M = 6.73) is higher (a lower Mean indicates higher perceived pressure) than the control group (M = 6.82), but no significant difference was found, which is inconsistent with our hypothesis H4a.

Although the perceived time pressure of the timer group (M = 6.20) is higher than the control and discount groups, the differences between all groups were non-significant. Surprisingly, this is inconsistent with our hypothesis H4b and H4c, as the study of Godinho et al. (2016) did find a significant difference in perceived time pressure when comparing non-time-pressured and time-pressured groups.

We expect that the reason for these results are related to the time pressure participants felt during the experiment as a whole. In Prolific, participants are paid per experiment, which is calculated using the average time taken for the experiment (Prolific, n.d.). Hence, participants often aim to complete the experiment in time, potentially as fast as possible, resulting in additional time pressure regardless of the experiment.

Another possible reason for not finding a significant difference is that some participants deliberately avoid the discount and countdown timer and thus selected the other product. As a result, those participants experienced no time pressure related to the product choice since the choice was already made due to the skepticism about the deceptive countdown timer. These two reasons mentioned earlier might explain why our findings are not in line with those of Godinho et al. (2016).

7.1.5 Product Choice Influence

We were curious about the effect of discounts and deceptive countdown timers on consumers' feeling of being steered towards a certain product. We expected that participants who have encountered a discount (H5a) or deceptive countdown timer (H5b) would feel more steered towards a certain product than those who did not encounter any discount or deceptive countdown timer. In addition, we expected that participants who encountered a countdown timer would feel more steered towards a certain product than those who encountered a discount (H5c).

When focusing on the control group, the feeling of being steered towards a certain product was moderate (Mdn = 4), and not no- or little steering as we expected. The feeling of being steered towards a certain product increased from the control group to the discount group and timer group, where both groups account for the same median score (Mdn = 5). However, differences in Median scores were not statistically significant, which is inconsistent with our hypotheses H5a, H5b, and H5c. This lack of a significant difference means that we, in this our study, did not find any evidence to believe that discounts or countdown timers steer consumers towards a certain product when facing a product choice.

What is interesting here is that the Median of the control group (Mdn = 4) is relatively high on a 7-point Likert-type question ranging from 1 (Not at all) to 7 (Very much). A possible explanation could be that participants felt steered towards a certain product (the office chair) since this was the imposed task. In that case, we have to conclude that our experimental setup might not have worked as we thought it would. Our setup might have introduced a strong sense of steering participants towards office chairs, which might have overshadowed the feeling of being steered by the discount or countdown timer in the product choice of the office chairs themselves.

Furthermore, though not significant, the relatively high Median scores (5 on a 7-point Likert-type question) of the discount and timer groups show that participants in those groups felt steered toward a certain product. These high Median scores could indicate that the special offers do steer consumers towards a certain product, as described in consumer choice theory (Birdwell, 1968; Ge et al., 2009; Reutskaja et al., 2011). However, as our results are not significant, future research should investigate this in more detail.

7.1.6 Urgency

The three previous subsections relate to urgency to buy, where retailers steer consumers in a certain direction (7.1.5) while putting the consumer under time pressure (7.1.4) (Childs & Jin, 2020; Gupta, 2013), exploiting the scarcity bias (7.1.3) (Gray, Chen, et al., 2021; Mathur et al., 2019; Mittone & Savadori, 2009). When examining all results concerning urgency, we only see a difference in results between the control group and the timer group with regard to the FOMO construct. Regarding the other two constructs, we did not find any significant difference. Also, there seems to be no clear difference in results when comparing the discount and timer groups. One logical explanation for not finding this difference would be that there is no difference in urgency to buy with respect to discounts and deceptive countdown timers. This lack of a clear difference could make sense, as most discounts are typical of a temporary nature.

Unfortunately, our result is solely based on the results from the questionnaire since our timing data became corrupted due to technical difficulties. Therefore, it would be interesting to see future research that does manage to gather experimental timing data to verify our findings.

7.2 Exploratory Results

In this section, we discuss the exploratory results. This section is split up as follows. First, responses about dark patterns in general are discussed. Next, the feeling of regret when dealing with dark patterns is discussed, followed by the participants' behavior when dealing with dark patterns in the future. Finally, we discuss the findings regarding the time left on the countdown timer at the moment of selection.

7.2.1 Dark Patterns in general and Deceptive Countdown Timers

Besides the experimental questions, we wondered how participants think and feel about deceptive countdown timers and dark patterns in general. We expected participants to have a negative attitude toward deceptive countdown timers and dark patterns in general, as seen in other studies (Bongard-Blanchy et al., 2021; Luguri & Strahilevitz, 2021).

Dark patterns in general

Our findings were similar to the findings of other studies (Bongard-Blanchy et al., 2021; Luguri & Strahilevitz, 2021) who asked participants about how they think and feel about dark patterns, as almost a quarter of our participants mentioned that they think dark patterns are *manipulative, unethical, immoral, unfair* and that they should be *illegal*. However, it was also interesting to see that out of all participants (N = 245), 31 participants do not mind dark patterns and see it as a simple *marketing trick*. Furthermore, five participants mentioned avoiding dark patterns when shopping online.

Deceptive countdown timers

Regarding the feelings about deceptive countdown timers, attitudes were similar to those above. Still, there were some fascinating findings. First, participants mentioned also to find deceptive countdown timers *unethical, unfair, immoral,* and *manipulative* (36 instances in total). As one participants elucidated, there is a clear line between deceptive countdown timers (i.e., unethical practices) and what they see as a simple *marketing trick*. It is possible that the *fake* and *sketchy* looks of the offer, as reported in 7.1.2 (reason for product choice), make people notice that they are being manipulated, and thus make them draw that clear line between marketing and manipulation.

Finally, many participants (69 instances) mentioned the *pressuring, stressing,* or *rushing* element of the deceptive countdown timer. These instances tell us that many participants recognize the pressuring nature of the deceptive countdown timer but do not necessarily feel pressured by it (as derived from the results in the questionnaire). A possible explanation for this could be the influence countdown timers have on consumers, which is described in more detail in the following subsection.

7.2.2 Influence of Countdown Timers

We hoped to determine whether participants were affected by (deceptive) countdown timers. In addition to measuring possible effects (see previous sections), we also asked participants whether they felt influenced in any way by a countdown timer, but most participants answered this question regarding the product choice. A little over half of the participants indicated that the countdown timer would (somewhat) influence them, primarily because of the *pressuring* nature of the timer.

However, as already found in the previous section, fewer than half of the participants indicated they do not feel influenced by countdown timers. Surprisingly, one of the main reasons for this was also the *pressuring* nature of the countdown timer, as some participants indicate they dislike being pressured and therefore will not select a certain product on purpose. So, even though some participants mention not to be influenced by a countdown timer to buy a certain product, they are still influenced by the countdown timer in their product choice itself. We could have prevented this ambiguity by not asking a broad open question, but by formulating the question more precisely.

Still, participants seem to recognize and experience the pressuring nature of the countdown timer, but the effect of the countdown timer either diminishes or enhances the intention to buy the discount offered (Godinho et al., 2016; Hanna et al., 2016). We did not find any particular pattern regarding the diminishing or enhancing effect, as it seems dependent on individual cases.

7.2.3 Regret

Dark patterns are UI elements that make people undertake actions they might not wish to do (Brignull, n.d.; Gray et al., 2018; Mathur et al., 2019). We applied this definition to our study about countdown timers: we asked participants about their feeling of regret when purchasing a product on a limited-time offer to find out later that offer would never expire. Our results show that over half of the participants showed a high feeling of regret (a score of six or seven on the 7-point Likert-type question), and over 80 percent indicated moderate or higher regret (a score of four or higher). There was no significant difference across groups.

These results illustrate that participants' feeling toward deceptive countdown timers is quite negative when purchasing a product on a limited-time discount to find out later that the discount never expired. Furthermore, we believe such regret could diminish the experienced fear of missing out countdown timers on future purchases. Additionally, this regret could increase participants' awareness and avoidance behavior towards countdown timers, as discussed in other studies (Bongard-Blanchy et al., 2021; Luguri & Strahilevitz, 2021) as well. As previously discussed, employing deceptive countdown timers could backfire on the wanted result (e.g., an increase in sales) of the retailer that employs the deceptive countdown timer (Godinho et al., 2016; Hanna et al., 2016), especially when compared to using discounts only.

7.2.4 Countdown Timer analysis

We analyzed the time left on the countdown timer for participants in the timer group that chose the limited-time discount product. As a result, 32 out of 36 participants selected (i.e., proceeded to checkout) the product within 30 seconds with regard to when the countdown timer (re)started. This finding indicates that the interaction that follows after encountering the timer (also after refresh), does not take very long: within 30 seconds. Although this result does not relate to the total speed of the product selection, it suggests that participants who face a countdown timer actively click around on the webpage and seem to make decisions quickly.

7.2.5 Future Behavior towards Dark Patterns

Finally, we asked participants if they would behave differently (compared to their situation before participation in this study) if they encountered dark patterns in the future. We asked this question to assess if this studies like this raise awareness of dark patterns and whether informing people about dark patterns might help to prevent people from falling for them. The Median score (Mdn = 5) looks promising across all participants, indicating that most participants would behave differently when re-encountering dark patterns compared to their earlier situation. Hence, raising awareness seems to help change people's behavior towards dark patterns in a protective way.

When comparing groups, we expected the timer group to score higher since they had just experienced a dark pattern encounter during the experiment. However, we did not find a significant difference that indicates that lived experience helps raise awareness even better, contradicting the work of Given (2012). Still, it could be the case that some participants have had a lived experience with deceptive countdown timers in the past, and therefore were already aware of the effects. At the same time, this indicates that creating awareness using information and examples, as seen in our questionnaire (see Appendix 9.2), could protect people from the influence of dark patterns. We believe exploring how to effectively protect people from the influence of dark patterns is an important field for future studies.

7.3 Limitations

This study has limitations, and some are already mentioned in the previous chapters. First, the study's core limitation is the experimental setup. Studies in which participants should behave as naturally as possible can be challenging since participants behave differently when they know they are being observed (Adair, 1984; Wickstrom & Bendix, 2000). In order to minimize this effect as much as possible, we used the cover story about working budgets to ensure an ethical study. In comparison, setting up our fake webshop would provide more accurate results since participants would spend their own money instead of fictional money, but this would also be unethical.

Second, we allowed participants to re-enter the study if the first attempt was not finished. Participants who aborted the study, especially after the general questionnaire about dark patterns (in which the cover story ‘confession’ was made), could re-enter and deliberately choose a different product. As a result, some data of re-entered participants may not align with their initial visit.

Third, due to technical issues regarding the time spent on the selection process and the number of page refreshes, this data got corrupted. This incident is regrettable, as it would have supported claims made about the urgency to buy and browsing behavior of participants in the experiment.

Fourth, the experimental setup might not have worked entirely as intended. For instance, some participants in the control group felt steered towards a certain product and experienced time pressure similar to the timer group. Most likely, these results relate to the experiment itself, where participants had the task of selecting an office chair (steering towards a certain product), which was economically most efficient to do within a specified timeframe, as shown on Prolific (time pressure).

Fifth, our sample group should resemble the population of ‘online shoppers’ or ‘internet users’. Different studies (Brandtzæg et al., 2011; Kau et al., 2003; Lokken et al., 2003) have researched the characteristics of this population. When comparing demographics such as age (most online shoppers/internet users range from 18 – 45) and gender (females tend to shop online more often), those demographics are not completely in line with our sample (see section 5.2). For instance, our sample included more males (58.4%) than females (39.2%), and only participants between 18 and 65 years old (although most online shoppers are included in this range, there are people younger and older who shop online). Furthermore, online shoppers also exist in the Northern-America, Asia, and other regions. Our sample only included individuals based in Europe, and thus not completely resemble the population of online shoppers.

Finally, participants could only participate in the study via laptop or desktop. However, many consumers shop online via mobile devices nowadays. Therefore, the generalizability of the results is slightly limited by this constraint.

7.4 Future research

This study offers some propositions about future research opportunities. Some opportunities are already mentioned throughout the previous chapters. First, our study contributes to answering a gap in research: the effects of dark patterns. This study focused on deceptive countdown timers, yet there are many more dark patterns from which their effects remains unknown. Future research should conduct similarly experimental studies that test other dark patterns' effects, as this experimental setup is suitable for re-use (source code of the experiment: https://gitlab.science.ru.nl/jtiemessen/thesis-project-darkpatterns). In our questionnaire results, we found multiple participants that mentioned the deceptive low stock message example on the information page (to inform participants about dark patterns, see PDF mentioned in Appendix 9.1), a dark pattern they would fall for more likely than the countdown timer. Hence, we consider the deceptive low stock message a good candidate for investigating next.

Second, to determine the looks and contents of our deceptive countdown timer, a corpus of 60 instances was constructed. However, building a corpus of a specific dark pattern could be done at a much greater scale. For instance, it would be interesting to see an extensive corpus of countdown timers, analyzing different perks such as time left, position on the webpage, technology used, deceptiveness, et cetera. Such 'corpus studies' would help create a better understanding of how specific dark patterns work and what their prevalence is in more detail.

Third, some participants mentioned in the questionnaire that deceptive countdown timers and dark patterns in general make them avoid (e.g., due to skepticism) certain products or websites. We find this very interesting and are curious about the 'backfiring' effects dark patterns may have on those who employ them.

Fourth, our experiment used a single webshop that displayed all conditions. A broader study with more participants, not necessarily bound to deceptive countdown timers, could do a similar study using other webshop designs. Multiple webshops designed differently, displaying different conditions, could determine the additional effect of a webshop' layout, possibly related to the skepticism mentioned by participants.

Fifth, the control group was put in place to compare other groups to it. What stood out was that in the control group, participants had a preference for one of the two products. Future work that uses a similar experimental setup should choose a test product less prone to biases or side effects because this could form a limitation in the following case: When everyone already favors a certain product and the dark pattern makes this preference stronger, the actual effect of the dark pattern cannot be measured anymore, because everyone was selecting this product already.

Finally, as future work should determine the effects of other dark patterns, actions should be undertaken to combat the dark patterns whose effects are most worrying. Similar to a suggestion mentioned by Mathur et al. (2019), it would be interesting to see, for example, a web browser extension that recognizes deceptive countdown timers, as shown in the picture below.

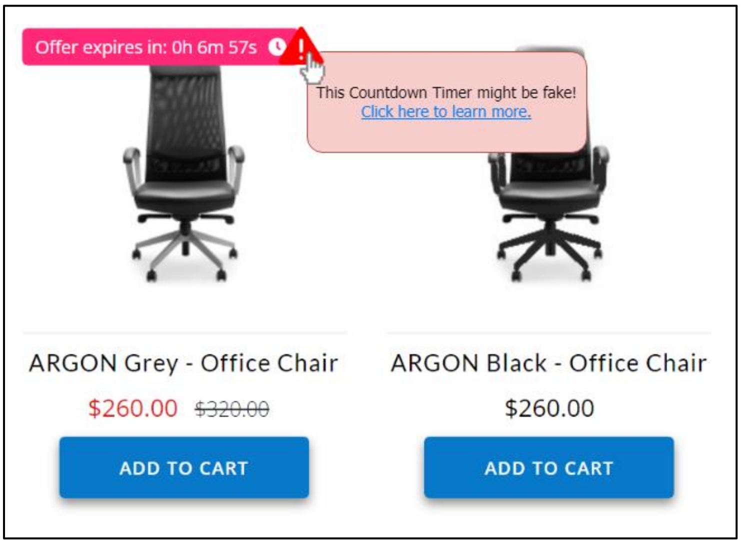

Figure 32 - Countdown Timer warning example, inspired by Mathur et al. (2019)

7.5 Conclusion

Our results show that deceptive countdown timers, like discounts, can affect product choice, but also induce a variety of responses ranging from participants mentioning they do not mind countdown timers to participants that deem them manipulative, deceptive, and feel negatively impacted by them.

When zooming in on how effective deceptive countdown timers are in increasing customers’ urgency to buy, this study has shown that deceptive countdown timers have increase customers’ urgency to buy compared to customers who do not experience any special offer, especially regarding the perceived fear of missing out. However, discounts not accompanied by a deceptive countdown timer seem more successful in luring customers into buying a certain product, as seen in our qualitative data. In addition, deceptive countdown timers potentially make the customer more aware that they are being manipulated or make customers perceive too much time pressure. For these two reasons, some customers intentionally avoid websites/offers with a countdown timer, resulting in a diminishing effect of the discount incentive. Deceptive countdown timers are a clear example of a manipulative dark pattern that is not necessarily more successful than a discount, and could negatively impact consumers' online shopping experience.

7.6 Implications

This study focuses on dark patterns, a concept that goes hand in hand with ethical dilemmas, manipulation, and deceptiveness. Taking our findings into account, we have some final implications for users, policymakers, designers, and companies that strive to act ethically.

7.6.1 Users

We would advise users (i.e., visitors) of online shopping websites to take care when dealing with countdown timers. As this study has shown, countdown timers could very well be deceptive and negatively impact a consumer's shopping experience. In addition, a user could test this by opening the website in incognito mode, and assess if the countdown timer is deceptive. Although this method will not guarantee that a countdown timer is legitimate, it can still help to spot deceptive countdown timers.

7.6.2 Policymakers

Recent developments (Adhya, 2022; EDPB, 2022; European Commission et al., 2022) show that policymakers are undertaking actions to combat dark patterns. Our advice to policymakers is to use studies such as this to determine the effects of dark patterns in a legal context. Based on this study, we recommend including deceptive countdown timers in the list of illegal dark patterns, as they are a clear example of what could be a marketing practice (regular countdown timer) and a manipulative dark pattern (deceptive countdown timer).

However, we would also like to address that unlawful manipulation is not only the side of the dark patterns that matter. As this study shows, deceptive countdown timers also harm consumers regarding their experience and behavior towards online shopping in general, as also mentioned in other studies (Bongard-Blanchy et al., 2021; Gray, Chen, et al., 2021; Luguri & Strahilevitz, 2021).

7.6.3 Designers and Ethical Companies

Our advice for designers and companies that strive to act ethically is as follows: Although deceptive countdown timers are not deemed illegal (yet), the manipulative nature of such practices is manipulative and worrying. Therefore, we would advise designers and companies not to employ deceptive countdown timers on their online shopping platforms, as it not only ruins the shopping experience of customers but is also an unethical practice.

8 References

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9 Appendix

9.1 Online Experiment

All files used for our online experiment can be accessed at https://gitlab.science.ru.nl/jtiemessen/thesis-project-darkpatterns. This repository contains all files for the main experiment. Additionally, the full experiment can be downloaded in PDF format from here (condition = timer group).

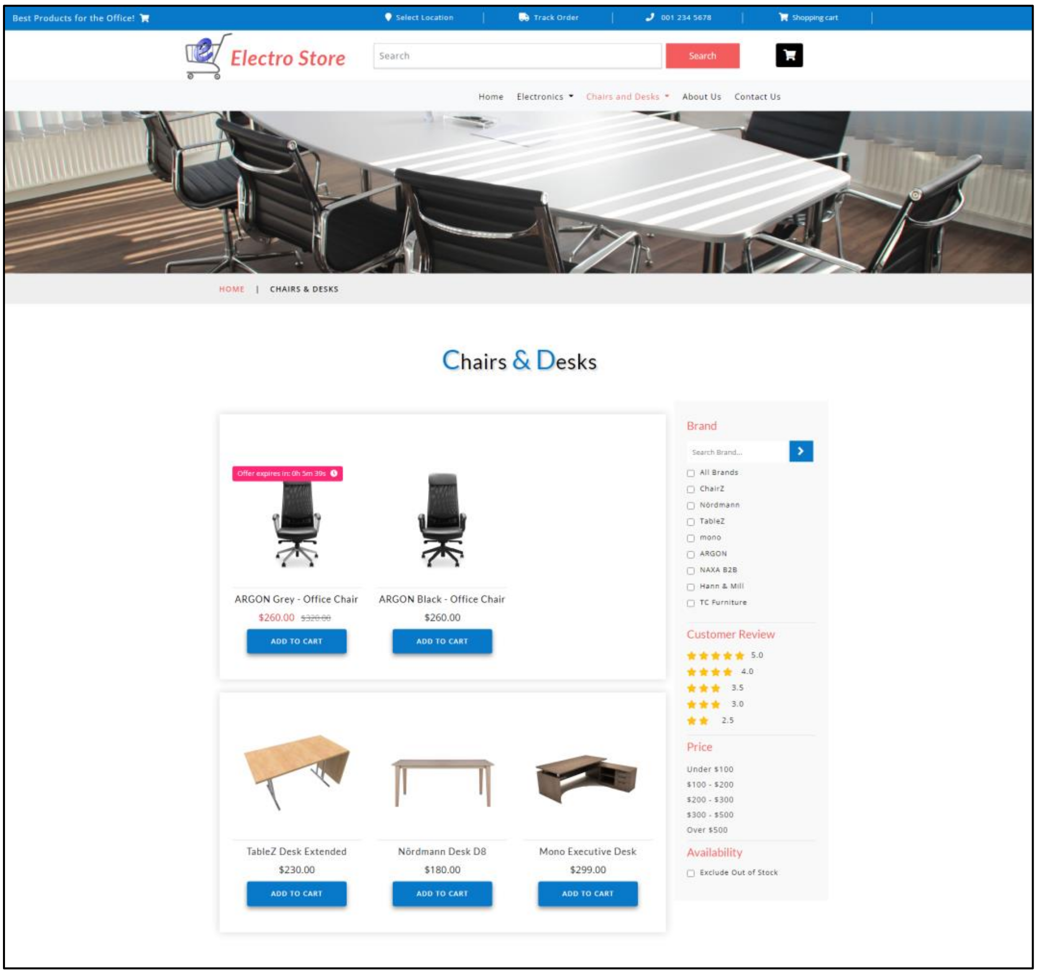

Figure 33 - Snippet of the Chairs & Desks overview on our fictional webshop 'Electro Store'.

9.2 Questionnaire

The questionnaire can also be found in PDF format on https://gitlab.science.ru.nl/jtiemessen/thesis-project-darkpatterns. The questionnaire consisted out of five segments, each segment regarding different questions. Below, all questions are written out per segment.

9.2.1 Control

1. What product did you purchase?
   a. Keyboard
   b. Desk
   c. Speakers
   d. Office Chair
   e. Not sure
2. Was the purchase made using a work budget?
   a. Yes
   b. No
   c. Not sure

9.2.2 Product Selection

1. Why did you select this chair? (open question)

9.2.3 Urgency

Fear of missing out

Questions regarding fear of missing out needed to be answered using a 7-point Likert scale consisting out of three questions, ranging from 'Not at all' to 'Very much'.

1. I feel I would have missed out on a great offer if I waited a couple of hours.
2. I feel like if I did not buy the product right away, I would regret it later.
3. I feel that if I did not buy the product right now, the product would become more expensive.

Time Pressure

Questions regarding perceived time pressure needed to be answered using a 9-point Likert scale consisting out of three questions, ranging from 'Not at all' to 'Very much' for the first two questions, and 'Not pressured' to 'Highly pressured' for the third question.

4. Do you believe you had enough time to make a good choice?
5. Do you believe you had enough time to carefully evaluate each item available?
6. How pressured did you feel while making your decision?

Steering towards a certain product

The question regarding being steered towards a certain product needed to be answered using a 7-point Likert-type question ranging from 'Not at all' to 'Very much'.

7. I felt steered towards selecting one of the two products.

9.2.4 Dark Patterns in general and Deceptive countdown timers

1. What do you think about Dark Patterns? (open question)
2. What do you think about fake countdown timers? (open question)
3. Do you feel influenced by a countdown timer? (E.g., in purchasing speed, decision, satisfaction) (open question)
4. Have you ever encountered countdown timers before this experiment?
    a. Yes
    b. No
    c. Not sure
5. I would regret it if I purchased a product on a limited-time discount, to find out later the discount never expired. (7-point Likert-type question ranging from 'Not at all' to 'Very much')

9.2.5 Demographics

1. As what gender do you identify?
    a. Female
    b. Male
    c. Other
    d. Prefer not to say
6. What is your age?
7. From which country are you participating in this experiment?
8. What is the highest degree or level of education you have completed?
    a. Some High School
    b. High School
    c. Bachelor's Degree
    d. Master's Degree
    e. Ph.D. or higher
    f. Prefer not to say
9. I shop online… (7-point Likert-type question ranging from 'Never' to 'I buy everything online')
10. I knew about Dark Patterns before this study.
    a. Yes
    b. No

    c. Not sure
11. If I encounter dark patterns again in the future, I will behave differently. (7-point Likert-type question ranging from 'Strongly disagree' to 'Strongly agree')
12. Were all websites and questionnaires of the study displayed correctly?
    a. Yes
    b. No

9.3 Qualitative analysis

In this study we qualitatively analyzed answers participants provided on the open questions. Below, we will explain briefly how these results were analyzed using using ATLAS.ti Windows (Version 9.1.7.0; ATLAS.ti, 2021). Please note that in most searches we made use of ATLAS.ti it's function to include inflected forms.

In order to code documents that mentioned the 'offer', we analyzed for 'offer', 'discount', 'deal', 'sale', or 'promotion'. We searched for color using: 'color', 'colour', 'grey', or 'black'. To find reasons mentioning the 'only option' we used the former and 'option' or 'available'. To find comments regarding perceived value, we used the search terms: 'value', 'better', 'quality', 'perceived value', and some manual adjustments were made. Finally, most other queries issued used single terms and most results were manually examined.