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"JUST LET ME BUY MY THING!"

A SURVEY STUDY ON CONSUMERS' PERCEPTIONS OF SOCIAL INFLUENCE IN E-COMMERCE

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ABSTRACT

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This study aimed to shine a light on social influence-based patterns in E-Commerce. Influencing consumer behavior online is nowadays commonplace, but research on when a persuasion attempt becomes an attempt at manipulation has been scarce. This thesis used the concept of online customer experience (OCE) as a start-off point to explain why commonly used social influence-based patterns can rarely be unanimously categorized as digital nudges or dark patterns. According to OCE, each consumer forms a highly subjective perception of a service provider and their experience when shopping online, and this ultimately affects how patterns used in E-commerce are perceived. The commonly used social influence-based patterns considered in this study were ratings and reviews, product recommendation systems, product badges, and activity messages. This study used an online survey to determine a) Which patterns are considered digital nudges and dark patterns; and b) Which traits in consumers are linked to their categorization of patterns. Of the patterns considered, ratings and reviews and product recommendation systems were considered as digital nudges, and product badges and activity messages were perceived as dark patterns. Younger, less educated people who score high in neuroticism and uncertainty avoidance are more susceptible to dark patterns, as are people whose persuasion knowledge and advertisement skepticism are low. This thesis provides significance to both E-Commerce retailers and policymakers by providing information on how consumers perceive attempts at influencing their behavior.

Keywords: E-Commerce, digital nudges, dark patterns, social influence, social proof

TIIVISTELMÄ

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Tämän tutkielma tutki sosiaalisen vaikuttamisen keinoja verkkokaupassa. Kuluttajien käyttäytymiseen vaikuttaminen on nykyään yleistä, mutta se ei ole saanut kaipaamaansa huomiota tutkimusmaailmassa. Etenkin tutkimus siitä, milloin kuluttaja kokee vaikuttamisyritykset manipulointiyrityksinä, on ollut harvassa. Tämä tutkielma käyttää asiakaskokemuksen muodostumista verkkokaupassa (online customer experience, OCE) lähtökohtana selittämään sitä, miksi yleisiä vaikuttamisen keinoja on usein vaikea luokitella vaikuttamis- tai manipulaatioyrityksiksi. OCE:n mukaan jokainen kuluttaja muodostaa subjektiivisen näkemyksensä kuluttajakokemuksesta vieraillessaan verkkokauppojen sivuilla, ja tämä vaikuttaa siihen, miten kuluttaja kokee hänen käyttäytymiseensä kohdistuvat vaikuttamisyritykset. Tässä tutkimuksessa yleisesti käytetyistä sosiaalisen vaikuttamisen keinoista perehdyttiin arvosteluihin, tuote-ehdotuksiin, badgeihin, ja aktiivisuusilmoituksiin. Tutkimusmetodina oli verkkokysely, jonka avulla pyrittiin selvittämään A) Mitkä näistä vaikuttamisen keinoista koetaan digitaalisina tönäisyinä (vaikuttaminen) ja mitkä synkkinä suunnittelumalleina (manipulaatio); sekä B) Mitkä tutkittavien piirteistä vaikuttivat heidän arviointeihinsa vaikuttamisen keinoista. Arvostelut ja tuote-ehdotukset koettiin digitaalisina tönäisyinä, ja badget ja aktiivisuusilmoitukset synkkinä suunnittelumalleina. Nuoremmat, vähemmän koulutetut vastaajat, joilla oli korkeampi neuroottisuus ja epävarmuuden välttely, olivat alttiimpia synkille suunnittelumalleille kuin vastaajat, joilla oli korkea suostuttelutietämys ja skeptisyys mainontaa kohtaan. Tämä tutkimus hyödyttää sekä verkkokauppatoimijoita että päättäjiä ymmärtämään, miten kuluttajat kokevat heihin kohdistuvat vaikuttamisyritykset verkkokaupassa.

Asiasanat: verkkokauppa, digitaaliset tönäisyt, synkät suunnittelumallit, sosiaalinen vaikuttaminen, sosiaalinen todiste

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1 INTRODUCTION

Shopping online has become so commonplace that we rarely start to think about what pushes us to shop at certain E-Commerce retailers over others. This preference, however, is very important from an E-Commerce retailer's point of view. It is what distinguishes a successful, profitable business from an unsuccessful one (Bonastre, 2014). For an E-Commerce business to be lucrative, it needs to provide its users with a satisfying online customer experience and persuade them to make purchases online.

Designers who work in E-Commerce often use patterns to help them to provide an online customer experience that is both enjoyable and persuading. **Patterns** are replicable design solutions to specific problems (Bösch, 2016). In the context of E-Commerce, patterns can manifest as solutions to problems such as how to increase a click-through rate on a product page, or how to increase customers' order values in the last steps before going through the checkout.

These patterns persuade consumers by making use of known psychological vulnerabilities (Mirsch, 2017). We as humans are social animals, constantly searching for cues about the social presence of others. Even the implied social presence of others can influence our actions (Messer, 2017). The (alleged) behavior of others acts as social proof and guides our behavior. Knowing this, many E-Commerce retailers proudly boast their best-selling products. By showcasing the popularity of a product, it appears more attractive to customers. Implied scarcity of a product boosts the effect of social proof. If there are only a few items left in stock, it must mean that the product is of good quality – why else would others buy it?

These small enhancements in the E-Commerce site's user interface – showcasing popular products or implying that there are only a few items in stock are called **digital nudges**. They are minor changes on the site that persuade the consumer toward a choice that aims to benefit both the consumer and the E-Commerce retailer (Mirsch, 2017). Introducing the customer to the bestselling products might help them avoid experiencing choice overload. Stating that a product has only one item left in stock helps consumers not to miss out on an item that they consider purchasing.

Sometimes, these attempts at persuasion cross a line and become attempts at manipulating the consumer. These manipulative user interface patterns are called **dark patterns.** Dark patterns not only make use of known psychological vulnerabilities but exploit them to undermine consumers' conscious decision-making (Mathur, 2019). Their use benefits the E-Commerce retailer at the expense of the consumer. Customers might be subjected to false reviews or intrusive activity notifications to push them toward purchases that they would not have made, if not exposed to dark patterns.

As competition in E-Commerce grows, so does the use of digital nudges, and their unethical alternative, dark patterns (Narayanan, 2020). Still, little is known about a specific type of patterns – digital nudges and dark patterns that are based on social influence. Social influence is powerful in changing human behavior, and marketers have used it in their campaigns for years (Friestad, 1994). Nevertheless, studying its use in patterns and in the context of E-Commerce has not yet gained traction.

Previously, literature on digital nudges and dark patterns has largely focused on the phenomena in general (Gray, 2018; Gray, 2021), their regulation (Calo, 2014), and ethical debate about the use of persuasion and manipulation in E-Commerce in general (Spencer, 2020). The "gray area" between clear digital nudges and dark patterns has not been a topic of interest in the research literature. The empirical part of this study aims to shine a light on how consumers categorize patterns that are not distinctly digital nudges or dark patterns.

This study resulted in a research model that utilized Kemppainen's (2020) model of **online customer experience** (OCE). This model was seen as a good fit for the study, as according to it, OCE is a highly subjective phenomenon in which the consumer is an active agent, creating a mental image of their own experience. This subjectivity of OCE can help us understand why many patterns cannot clearly be classified as digital nudges or dark patterns, but that their categorization is dependent on the consumer and their traits and experiences.

This thesis aims to answer the following research questions:

1. What is known about digital nudges and dark patterns based on social influence, in the context of E-commerce?
2. Which traits in respondents are related to how patterns are categorized into digital nudges and dark patterns?

To answer the first research question, a literature review was conducted. The literature review aimed to research digital nudges and dark patterns based on social influence, specifically in the context of E-Commerce. Due to the relatively new interest in digital nudges and dark patterns in E-Commerce, the literature used in this thesis was not limited to that context but often focused on the use of digital nudges and dark patterns in general. Literature was searched using Google Scholar. The following keywords were combined and used to find relevant literature:

dark patterns, digital nudges, nudging, persuasion, social proof, scarcity, social impact theory, social presence, online customer experience, user experience, E-Commerce.

This thesis aims to combine research from behavioral economics, social psychology, and information systems, to help understand social influence-based digital nudges and dark patterns in E-Commerce. The focus of this thesis is on B2C E-Commerce, in which the purchasing decision is made online. Thus, B2B E-Commerce and "webrooming" is outside of the scope of this thesis.

The literature review of this thesis consists of three main sections. In the first section, the ever-growing interest in E-Commerce is explored. One of the most important factors for E-Commerce success, online customer experience (OCE) is discussed. The factors that drive persuasion and manipulation in E-Commerce are considered.

The second section of the thesis focuses on how human behavior can be influenced. The vulnerabilities of human psychology that are used in persuasion and manipulation attempts are described. The latter part of this section tries to examine the difference between digital nudges and dark patterns.

Finally, in the last section, digital nudges and dark patterns in E-Commerce are looked at in practice. From there, the thesis moves onto its empirical part: studying patterns identified in the literature review, and people's perceptions of them.

2 E-COMMERCE AND ONLINE CUSTOMER EXPERIENCE

When was the last time you ordered something online? Probably very recently. According to research on online shopping habits conducted by Posti (Posti, 2021), 60% of Finns have ordered something online within the past month. This figure has grown considerably, 22% from the year 2019 (Posti, 2021).

The rising popularity of online shopping is not only limited to Finland. In the last ten years, the number of consumers who have bought products online has grown from 54% to 71% in the EU area (Lupiáñez-Villanueva, 2022). This rapid growth of E-Commerce has generated competition in the market, as more and more service providers are taking their business online.

A good customer experience has become a competitive requirement for E-Commerce vendors to succeed and overtake their competition (Bonastre, 2014). Online customer experience, its components, and its formation are discussed in the next chapters.

It is to be noted, that research on **user experience** (UX) is used to complement research on online customer experience (OCE) in this thesis. This is due to the similar nature of UX in the context of E-Commerce, and OCE. The concept of online customer experience is often used in the retail literature, referring to the cognitive and emotional experience of shopping online, which is affected by factors like perceived ease of use, perceived usefulness, and enjoyment (Rose, 2011). All these factors also tie into the concept of user experience.

Patterns and their use in OCE design are also discussed. Patterns are replicable user interface designs that can be adapted into different contexts to improve the OCE of an E-Commerce site (Bösch, 2016). A good pattern helps designers to improve the site to provide an effective, satisfying, and efficient online customer experience (Karagoel, 2021). The competitive nature of E-Commerce has unfortunately led to the development of dark patterns – patterns whose primary goal is to create profit for their deployer, at the expense of the consumer (Gray, 2018). These dark patterns, and their more ethical alternative, digital nudges, are discussed throughout this thesis.

2.1 Online Customer Experience in E-Commerce

The simplest definition of OCE is the experience that the E-Commerce site creates for the customer (Garrett, 2010). The ISO standard adapted for UX on E-Commerce sites, and thus OCE, states that OCE consists of all those customer perceptions and responses that result from the use or anticipated use of the E-commerce site. This includes the customer's feelings, beliefs, observations, reactions, and behaviors that occur before use, during use, and after using the site. (ISO, 2010).

Having a good online customer experience is critical for E-Commerce site success (Bonastre, 2014). Positive OCE is linked to enhanced customer loyalty toward the online shop (Kujala, 2011), higher customer satisfaction and repurchase intention (Rose, 2012), and even heightened trust in online shopping (Rose, 2011). Improving the E-Commerce site's OCE therefore not only advances customers' satisfaction but helps businesses to be profitable (Petre, 2006). Negative OCE, on the other hand, can lead to loss of customers and profit as consumers move to other vendors (Garrett, 2010).

The research of OCE has traditionally focused on the outcomes of a good or bad customer experience. In the past, OCE has been seen as a mere transactional process: the customer is seen as a passive actor whose role and activities can be managed, and experiences tailored and altered. Recent studies on OCE have stressed the importance of a customer-centric interpretation of OCE. Customers should be seen as the creators of their own subjective experiences, and their motivations, psychology, social relations, and environment, play an active part in how a customer forms a mental picture of their customer experience while using an E-Commerce site. (Kemppainen, 2020)

To improve an E-Commerce site's online customer experience, one can make use of heuristics to aid the design process. Petre et al. (2006) suggest a customer-centered approach that encourages providing quality information to customers to assist them in their purchasing process, building customers' trust using cues, and creating user interfaces that make the use of the site efficient and easy. Bonastre et al. (2014) stress the importance of fostering a long-term relationship with customers by providing transparent information throughout the purchasing process.

2.1.1 Patterns in Online Customer Experience Design

Good user interface (UI) design aims to create user interfaces that help users reach their goals by being self-explanatory and easy to learn. The information must be presented in a way that is accessible and easy to navigate (Maier, 2020). A good OCE design aims to create effective, satisfying, and efficient experiences, prioritizing customers' goals (Karagoel, 2021). Designers can use heuristics (Petre, 2006; Bonastre, 2014) to ensure that the site's design encourages good OCE.

To help designers continuously create good UI designs and online customer experiences, the design world has adopted the use of patterns. Patterns in the design world have been created to easily apply "best practice" solutions to common problems. They are built from a solution that has been created to fit a specific

problem, and then abstracted and generalized to be reused in similar scenarios (Bösch, 2016).

A good pattern captures a well-established and feasible solution to a known design problem. It works by persuading the customers to take predefined actions on the website, helping them to reach their goals. This in turn makes it efficient and easy to use the site and improves online customer experience. Good patterns are meant to be used and replicated by other designers. (Bösch, 2016)

These good patterns are known as digital nudges in the persuasion literature. Digital nudges use knowledge about human psychology to aid customer decision-making in an environment that has a multitude of choices for a customer to choose from. (Mirsch, 2017)

An anti-pattern on the other hand is a solution that is proven to represent bad practice and should be avoided. No pattern is born as an anti-pattern – these are design solutions that were created to improve online customer experience, but in practice have resulted in a poor OCE or even harm to the consumer. Anti-patterns are still important in their role of raising awareness of subpar solutions. (Greenberg, 2014)

A dark pattern is an established solution for exploiting and manipulating users. Unlike anti-patterns, which are unintentionally bad for the online customer experience and the consumer, dark patterns are intentionally created to push consumers to act in a way that is unaligned with their own goals and best interests (Gray, 2018). The working mechanism of dark patterns is the manipulation of customers. Dark patterns are used for the manipulator's gain, not the consumers' benefit (Lupiáñez-Villanueva, 2022).

The different types of patterns, their working mechanisms, intents, and outcomes are described in the table below.

Table 1: Types of patterns

Type of Pattern	**Working Mechanism**	**Intent**	**Outcome**
Good pattern (digital nudge)	Persuasion	Improve OCE	Good OCE
Anti-pattern	Accidental manipulation	Improve OCE	Bad OCE
Dark pattern	Manipulation	Benefit the designer deploying the pattern	Bad OCE

2.2 Factors that Drive Persuasion and Manipulation in E-Commerce

For an E-Commerce website to be successful, it needs to build customers' trust, engage them to use the site, and persuade them to buy its products. Persuasion

and manipulation are thus natural phenomena in the E-Commerce space (Fenko, 2017).

Some characteristics of E-Commerce make it especially prone to persuasion and manipulation attempts when compared to traditional brick-and-mortar stores. Some of these traits are related to the economic pressure that derives from the heightened competition in the E-Commerce field, and others to the digital nature of E-Commerce stores. These traits, outlined in Table 2, are now discussed in detail.

E-Commerce businesses like brick-and-mortar stores alike have economic pressure to maximize their profit. Knowledge about vulnerabilities of human decision-making has led some designers and developers to take advantage of this knowledge. According to Calo (2014): "*Once one accepts that individuals systematically behave in nonrational ways, it follows from an economic perspective that others will exploit those tendencies for gain*"; and Spencer (2020): "*The susceptibility to manipulation produces an opportunity for manipulation that no profit-maximizing manufacturer can ignore*". If other players on the market engage in manipulative practices, those that do not are in a poor competitive position. This raises the pressure for E-Commerce stores to deploy manipulative dark patterns on their site to match the practices of their competitors.

The economic pressure of E-Commerce stores has led professionals working in the E-Commerce environment to start to focus on short-term sales metrics more than the long-term customer experience. To generate more profit, persuasive and manipulative strategies are used to encourage consumers to spend more money on the site, often very impulsively (Maier, 2020). This effect is further heightened by E-Commerce stores' ability to finetune and alter each step of the purchasing process to improve sales metrics (Calo, 2014).

As technology develops, information systems have become more and more complex. The advances in technology have made it possible to create persuasion and manipulation attempts that can easily go undetected by consumers (Lembcke, 2019). On the other hand, as people use IS for completing their day-to-day tasks, they gain a false sense of security about their abilities to spot manipulative practices, risks, and threats online. Many indeed believe that they are immune to online exploitation and manipulation (Nong, 2019). This makes consumers on E-Commerce sites vulnerable to dark patterns. Many dark patterns are so subtle that they are difficult to spot, especially for consumers who believe that their behavior cannot be manipulated (Nong, 2019).

Advancements in technology have made it possible to easily implement persuasion and manipulation attempts on a large scale and low cost, with unprecedented personalization (Bongard-Blanchy, 2021). Companies can aim their manipulation attempts at consumers who would be the most affected by them, at a point in time when their willpower is depleted (Spencer, 2020). Multiple versions of the same website can be presented to customers to test which minuscule differences in the UI of the site best boost sales metrics. This first-hand information about consumers' behavior on the site can be combined with third-party data to create a personalized, even more effective form of manipulation (Calo, 2014).

Even if the companies were not intentionally trying to implement dark patterns on their site, they may accidentally discover manipulative anti-patterns with the help of A/B testing. These patterns are more likely to be adopted if testing only focuses on measuring short-term success with metrics like click-through and conversion rates. (Maier, 2020)

Table 2: Trends increasing persuasion and manipulation in E-Commerce

General Trends in E-Commerce	**Results in practice**
Economic pressure to maximize profit	- Focus on short-term profit has led to the adoption of persuasive and manipulative tactics to boost sales - Retailers that use persuasive and manipulative tactics force others to adopt these practices as well to not end up in a poor competitive position
Technological advancements	- Every step of the buying process can be altered, which might encourage persuasion and manipulation of customers - More developed technology allows persuasion and manipulation attempts to go undetected by customers - Increased use of IS systems has created a false sense of security for customers - A/B testing can be used to generate designs that persuade or manipulate customers most effectively

3 HOW TO INFLUENCE BEHAVIOR IN E-COMMERCE

As stated before, the success of an E-Commerce retailer depends on their ability to persuade their customers to purchase items on their site (Fenko, 2017). How can E-Commerce retailers influence us to purchase products, even items that we originally did not consider when first entering the site? By using persuasion tactics.

Persuasion is based on the knowledge that humans are not always rational decision-makers, but that our behavior is constantly affected by our feelings, experiences, the people around us, and the context in which we make our decisions. These psychological vulnerabilities which are discussed more in detail in the next chapters are something that persuaders can make use of to influence our behavior to make us act according to their goals (Drossos, 2019).

By understanding our psychological vulnerabilities, designers and developers can create online customer experiences to purposefully influence human behavior – for better or worse (Maier, 2020). We are however not powerless when facing these persuasion attempts – our persuasion knowledge helps us to try to resist attempts at influencing our behavior.

3.1 Persuasion Knowledge and Advertisement Skepticism

Due to the sheer amount of persuasion we as consumers and users of technology face daily, humans have developed ideas about it. **Persuasion knowledge** refers to the ability to recognize when we are being persuaded of something, and to activate a defensive reaction against the persuasion attempt (Lupiáñez-Villanueva, 2022) if we wish to resist it (Fenko, 2017). Our persuasion knowledge helps us to identify exactly how, when, and why marketers are trying to influence us and to respond to these persuasion attempts in a way that aligns with our own goals (Friestad, 1994).

Whereas persuasion knowledge refers to the knowledge consumers have about persuasion techniques and coping strategies, **ad skepticism** refers to a

consistently negative response tendency toward advertising. As an individual's persuasion knowledge develops, so does their ad skepticism. Consumers with high persuasion knowledge can be difficult to persuade due to their more controlled response to marketing communications, but consumers with high ad skepticism may prove impossible to persuade because they simply would not believe any marketing statements. (Obermiller, 1998).

Persuasion knowledge is activated when we start to suspect the marketers' motives and develop skepticism toward the persuasive messaging (Fenko, 2017). The activation of persuasion knowledge thus requires an active, conscious realization that one is being persuaded. What about those times when we are in a state of flow, autopiloting our way through tasks? This is when persuasion is at its most powerful (Fenko, 2017).

In online interactions, the design of the user interfaces is intentionally created to put us into a state of mindless scrolling (Lupiáñez-Villanueva, 2022), to encourage us to browse through categories of products and click through different items. The online user experience is designed to be so satisfying that individuals are absorbed into it, and their persuasion knowledge becomes neutralized (Lupiáñez-Villanueva, 2022). At that point, marketers can tap into our unconscious, non-rational decision-making, and get us to sign up for a newsletter to get a discount, or to buy more products to score a free delivery. These are things (giving up private information, spending more money than one planned), that one might not have consciously decided to do, but due to being persuaded into doing, did.

How do marketers target these vulnerabilities to induce non-rational decision-making, thus influencing our behavior? These tactics are discussed in the next chapters.

3.2 Vulnerabilities of Human Psychology

Human decision-making is rarely fully rational. Due to our limited cognitive resources, our judgments and decisions are strongly influenced by emotions, social influence, the use of heuristics (mental shortcuts in decision-making), biases, and the context in which we make our decisions (Lembcke, 2019). Even our willpower is a finite resource that depletes throughout the day. The less willpower one has, the more likely they are to use heuristics in their decision-making or trust their autopilot mode of thinking (Calo, 2014).

Marketers know this and take advantage of our limited capacity to process complex information. Information is often presented in a form that makes it difficult for consumers to grasp the true cost of their decisions (Spencer, 2020), whether it is giving up information or purchasing a product or a service.

To influence people's behavior in an effective way, marketers must find a way to tap into consumers' unconscious, automated mode of thinking. This type of thinking, called **System 1 thinking**, and its more rational counterpart, **System 2 thinking**, are first looked at in detail. By activating consumers' System 1 thinking, consumers are more prone to making hasty or impulsive decisions due to

different psychological vulnerabilities, such as the tendency to look for cues for others' social presence, or susceptibility to social proof or scarcity. These factors and their effect on consumers' behavior on E-Commerce platforms are discussed in the following chapters. An overview of these psychological vulnerabilities is presented in Table 3.

3.2.1 Conscious and unconscious decision-making

If our cognitive resources and willpower are limited, how can we make countless decisions each day? Psychologists have sought to answer this question for decades, and one prevalent theory is that human cognition is divided into two systems of thinking, System 1, and System 2 (Spencer, 2020). This dual process theory, first proposed by Kahneman (2011), argues that to save cognitive resources, humans have two systems for decision-making, one to manage simple tasks and one to solve more complex ones.

System 1 can be characterized as a fast, automatic, and largely unconscious way of thinking. It requires only little energy and attention and is thus used to handle the large number of seemingly mundane decisions that we make daily (Spencer, 2020). Due to its automatic nature, it is prone to biases and systematic errors. Marketers can trigger this type of thinking when it benefits them (Spencer, 2020), by creating a message that unconsciously pushes the person toward automatic decision-making.

System 2 in contrast is a controlled way of thinking. Conscious decisions are made slowly and with effort, and due to their more taxing nature, it is reserved for decisions that are more complicated and cannot be automated (Spencer, 2020).

Both systems interact with each other. System 1 might offer suggestions to System 2 to ease decision-making. On the other hand, context cues, increased motivation during the task, or the nature of the environment in which the decisions are made might trigger a more conscious, System 2 form of thinking. The task, the specific context, and the person's cognitive capacities at that point in time determine which system will predominantly be addressed in a decision (Lembcke, 2019).

None of us see the world in an objective light. Our previous experiences and subconscious thought patterns shape the way we see the world around us and thus affect the decisions that we make. These errors in judgment are called **biases**. Because biases are unconscious, they affect both our System 1 automatic thinking, as well as System 2 controlled thinking (Acquisti, 2017).

Biases relevant to the social influence on consumers in the context of E-Commerce are the **bandwagon effect**, **scarcity bias**, and **loss aversion**. According to the bandwagon effect, people are eager to follow the example of others as to how to behave in specific situations. Scarcity bias states that people tend to value things that are scarce more than those that are abundant. Loss aversion refers to the preference people have for avoiding losses and disadvantages (Mirsch, 2019).

These errors in judgment are often taken advantage of when designers create user interfaces on digital platforms. For example, in E-Commerce, customers' bandwagon effect, scarcity bias, and loss aversion can be triggered all at once by displaying a badge on a product that says: "High in Demand – Only 10 Left in Stock!". The first part of the badge implies that the product is popular with other consumers, taking advantage of the influence of social proof, whereas the second part of the badge triggers a person's scarcity bias to create a feeling of superior quality due to the scarcity of the product. The part that stresses that there is only limited availability of the product also provokes a person's loss aversion bias. Consumers value not missing the product higher than using their financial means to buy the product, so they end up purchasing the product.

3.2.2 Social Impact Theory

Humans are social animals and are always on the lookout for cues that indicate the presence of others (Messer, 2017). The effect of other people on our behavior can be explained with **social impact theory**. According to it, the "*real, implied, or imagined presence or actions of other individuals affects our physiological states and subjective feelings, motives and emotions, cognitions, beliefs and values, and behavior*" (Messer, 2017). Thus, even a cue for the social presence of others can affect our behavior. These social cues can be generated or altered by marketers to try to change consumer behavior (Nong, 2019), and they play a significant role in the consumption process (Argo, 2005).

According to the social impact theory, the magnitude of social impact is affected by the strength of the social presence, the immediacy of the social presence, and the size of the social presence (Messer, 2017). The immediacy of others can be physical, temporal, or social (Xue, 2019).

In E-Commerce, social cues of varying degrees are used. The size of social presence on the E-Commerce platform can be implied with badges that state that a product has been purchased ten times during the last hour. The temporal immediacy of social presence can be inferred from activity notifications that alert the user whenever a product that they are looking at is added to another consumer's shopping basket.

3.2.3 Cialdini's Influence Techniques

Research into influencing human behavior has resulted in the theorization of six universal principles that can be used to influence people's attitudes or behaviors. These principles, which make use of knowledge of human psychology and its vulnerabilities, are **reciprocation, consistency, social proof, liking, authority,** and **scarcity** (Cialdini, 2009). According to Cialdini (2009), people's automatic decision-making process can be activated by anyone with the knowledge of how to make use of the vulnerabilities of human psychology (Cialdini, 2009), without the one who is being persuaded even being aware of it (Spencer, 2020). To better understand the power of social influence on people's behavior in an E-Commerce environment, only the principles of social proof and scarcity are discussed in this thesis.

According to the principle of social proof, our behavior, thoughts, attitudes, and feelings are shaped by the others around us (Fenko, 2017). The more a behavior is performed, the more correct we deem it (Cialdini, 2009). Simply implying or informing a person that many others have complied with something can stimulate a person's compliance (Cialdini, 2009). Social proof is inherently linked to herd behavior – we as humans are prone to do what everyone else around us is doing (Huang, 2006).

Marketers are aware of our natural tendency to imitate others and use the principle of social proof in many ways. A product might be marketed as a best seller to trigger the principle of social proof, which in turn results in a higher likelihood of purchase (Fenko, 2017).

Why do people almost automatically believe that popular is always better? First, people tend to select popular items because they believe that a product is popular due to its better quality (Huang, 2006). Second, people believe that large groups of people possess more information and are less prone to making poor decisions. By following their example, individuals believe that they too will make better decisions (Messer, 2017).

Some people are more prone to the effect of social proof than others. Psychological characteristics, like the person's Big 5 traits or orientation on the individualistic-collectivistic scale, explain some of the differences. People who score high in neuroticism, low in openness, and low in conscientiousness are more susceptible to social proof (Oyibo, 2019). People who are more collectivistic on the personal individualistic-collectivistic orientation are also more prone to look to others' behavior as to how to act in different situations (Cialdini, 2010).

Social proof is at its most powerful in situations where there is a lot of uncertainty (Cialdini, 2009), or too much information (Huang, 2006). In unclear or ambiguous situations, when we lack the mental model of how to correctly behave in that situation, we are more likely to look to and accept the actions of others as the right way to act in that situation (Cialdini, 2009). An information overload can trigger the imitation of others, to try to save one's cognitive resources and minimize the effort of decision-making (Huang, 2006). Lastly, when the people we observe are like us, the strength of social proof grows (Cialdini, 2009).

Thus, one might argue that an E-Commerce platform is an ideal context to use the social proof principle. When entering an E-Commerce platform that is unfamiliar to us, we look at others' behavior as an example of how to act. The platform provider might use that information to showcase best-selling products right on the home page of the site, as a symbol of how others behave. This can also serve as a shortcut in an environment, where information is abundant. When we land on a product page, the similarity of others to us might be highlighted by a product recommendation system that tells us that consumers like us also bought the following set of items.

The next principle that will be looked at in more detail is the scarcity principle. One might not instantly see the connection between social influence and scarcity, but scarcity often acts as a cue for social proof. According to the scarcity principle, what is scarce is good. The scarcity of something acts as a cue for its quality – scarce products are perceived as better than those that are easier to obtain (Fenko, 2017).

Like the principle of social proof, the principle of scarcity affects some more than others. People who score high on uncertainty avoidance tend to show a more pronounced purchase intention when they are subjected to the scarcity principle. These individuals rely heavily on heuristics in their decision-making to avoid uncertainty. (Fenko, 2017).

There are three types of scarcity: time scarcity, quantity scarcity, and demand-related scarcity (Sin, 2022). Demand-related scarcity acts as a cue for social proof – if something is in high demand, it must be something that many others value as well. This type of scarcity is often implied in E-Commerce. Messaging about a product's high demand creates a signal to consumers, that the product is likely to sell out soon (Mathur, 2019), creating a sense of urgency and pushing the consumer to quickly decide to buy it (Lupiáñez-Villanueva, 2022).

Table 3: Psychological vulnerabilities targeted by persuaders

Psychological Vulnerability	**How E-Commerce Retailers Use It**	**Individual Factors that Increase the Effectiveness**	**Contextual Factors that Increase the Effectiveness**
Tendency to trust social proof	Trigger bandwagon effect to make customers buy products others are buying, and direct them to consider other popular items in the store	- High personal collectivist orientation - High neuroticism, low openness, and low conscientiousness	- High uncertainty - Information overload - Observing people like us
Tendency to value scarcity	Trigger loss aversion bias to encourage more impulsive shopping	- High uncertainty avoidance	- Information overload
Falling into automatic thinking	Trigger System 1 thinking to enhance the effect of social proof and scarcity		- High uncertainty - Information overload

3.3 Digital Nudges – an Ethical Form of Persuasion

Persuasion has gained a lot of attention in different scientific disciplines. Behavioral economists and designers have adopted the idea of a persuasion attempt and condensed it into a replicable design pattern – a **nudge**. Nudges are created to persuade a consumer of something. They are based on the aforementioned knowledge about human psychology and decision-making (Mirsch, 2017), attempting to guide consumers toward better choices.

Nudges are "*any aspect of the choice architecture that alters individuals' behavior in a predictable way*" (Mirsch, 2017). They do not limit consumers' choices, allowing them to go their way if they so wish (Mathur, 2021). The goal of a nudge is to encourage the user to make a certain decision in the given choice architecture, but not coerce them to.

Nudges are meant to improve the choice architecture people encounter so that they can make wiser decisions that benefit the person and the party deploying the nudge (Thaler, 2018). The objective is to increase both individual and societal welfare (Mathur, 2021). Nudges work by either encouraging people to make certain decisions or by triggering a reflective way of thinking when people are prone to making hasty, automatic decisions (Lembcke, 2019).

One might see nudges as an inevitable phenomenon – there is no neutral way to present the consumer with different choices, they are always "nudged" toward one option or another (Gray, 2021). Nudges always have an effect – even when a person notices a nudge and decides to ignore it or act against it, it takes a cognitive toll on that person (Lembcke, 2019). Small and seemingly insignificant modifications, like changing the boldness of a text, or the order of the choices, have a strong impact on human decision-making (Lembcke, 2019).

The number of decisions people make daily in digital environments is on the rise, as is the significance of those decisions on people's lives (Lembcke, 2019). There is a clear need for digitally supported decision-making to protect customers from malicious persuasion attempts, or even from themselves. This is where **digital nudges** come in (Mathur, 2021). Digital nudges use different user interface (UI) design elements to persuade the user into beneficial choices from individual and societal points of view. (Mirsch, 2017).

An example of nudging in E-Commerce could be displaying reviews left by other consumers. Relevant information about the quality of the item or the speed of the delivery can aid the consumer in their purchasing decision, as well as benefit the service provider by boosting sales.

Even though the premise of digital nudging is noble, in practice, nudges are increasingly used for the detriment of the user (Jesse, 2020). These unethical nudges, or dark patterns, cause excessive friction for the user, cost them time or money and make the choice environment difficult to navigate (Mathur, 2021). **Dark patterns** work by discouraging behavior that is in a person's best interest or encouraging self-defeating behavior (Thaler, 2018). The emergence of dark patterns has raised ethical concerns about nudging. Dark patterns and their ethically questionable nature are considered in the next chapters.

3.4 Dark Patterns

Dark patterns were first identified by Brignull in 2010, as "*tricks used in websites and apps that make you do things that you didn't mean to*" (Brignull, n.d.). They quickly gained interest from other researchers, which has led to multiple categorizations of dark patterns, and studies on their prevalence. Studying dark patterns in different contexts, like E-Commerce and mobile apps, has gained

traction recently (Narayanan, 2020). Increased interest in people's digital well-being has also played a role in the ever-growing research into dark patterns (Roffarello, 2022).

The origin of dark patterns can be traced back to three trends in the commercial and technological landscape. Narayanan (2020) argues that retail's deceptive practices, digital nudging, and lastly, growth hacking, have led to an increase in dark patterns.

Deceptive practices, like flash sales that go on for days, have become so normalized that consumers have accepted them. As discussed in the previous chapter, nudging has inevitably led to the formation of ethically questionable nudges, some of which can be classified as dark patterns. Growth hackers have used knowledge of design and humans' psychological vulnerabilities to increase customer bases and product adoption rates with tools that do not always pass the morality check. Growth hacking is not inherently deceptive or manipulative, but as the pressure to gain an advantage in a competitive market grows, the more likely growth hackers are to use morally ambiguous practices. (Narayanan, 2020)

3.4.1 Definitions of Dark Patterns

Defining dark patterns is hard since they often share qualities that are not equally present in all dark patterns. Some dark patterns are deceitful in nature, while others covertly manipulate or coerce consumers into making decisions against their wishes (Narayanan, 2020). Some people might see a design pattern as a dark pattern, and some as a legitimate practice (Geronimo, 2020).

Based on the research on dark patterns and their characteristics, the following definition is proposed. Dark patterns are intentional design patterns (Sin, 2022) that undermine user autonomy (Bongard-Blanchy, 2021), by either forcing (Gray, 2018), steering (Mathur, 2021), coercing (Mathur, 2021), or manipulating (Maier, 2020) the user to act against their own goals. The strength of a dark pattern is magnified by its deceptiveness or ability to mislead the consumer (Mathur, 2021). Dark patterns are created to benefit the party that employs them (Bongard-Blanchy, 2021), at the expense of the user (Mathur, 2021).

3.4.2 Prevalence of Dark Patterns

Dark patterns are becoming more common on different digital platforms, like E-Commerce, mobile apps, and social media (Mathur, 2019). Yet, estimating their prevalence is difficult, as they are often covert by nature and hard to recognize for many. Another challenge is the blurred line between digital nudges and dark patterns (Sin, 2022). This aspect is considered in the last section of this chapter. Lastly, dark patterns rarely exist on their own – many dark patterns are often combined with several others to magnify their effect (Lupiáñez-Villanueva, 2022).

These factors are good to keep in mind when reading reports about the prevalence of dark patterns. A study aiming to study the prevalence of dark patterns in the EU area found that 97% of the most popular websites in the EU deploy at least one dark pattern (Lupiáñez-Villanueva, 2022). According to the estimates of Karagoel et al. (2021), 45% of all consumers are affected by dark

patterns. In the context of E-Commerce, Mathur et al. (2019) found that over 11% of E-Commerce websites include dark patterns. Interestingly, the more popular an E-Commerce site was, the more likely it was to use dark patterns. According to the authors, this 11% figure is on the lower end of the ballpark since their approach was automated and only recognized overt, text-based dark patterns. Many covert and visual dark patterns were thus not taken into consideration (Mathur, 2019).

3.4.3 Dark Patterns or Digital Nudges?

If both dark patterns and digital nudges aim to influence consumers' decision-making toward a predefined choice, how can ethical nudges be distinguished from unethical dark patterns? Digital nudges work by persuading a consumer to autonomously make a choice that aligns both with the E-Commerce retailer's and consumer's goals. Dark patterns, on the other hand, work by manipulating the consumer into taking an action that benefits the retailer at the expense of the consumer. (Maier, 2020)

One core characteristic of manipulation is its hidden nature – manipulation tries to bypass the individual's conscious decision-making by exploiting known cognitive, emotional, or other decision-making vulnerabilities (Lupiáñez-Villanueva, 2022). A dangerous aspect of manipulation is that individuals can be falsely led to believe that they are in control of their own decisions, even if those decisions are prompted by manipulation (Mathur, 2021).

Therefore, for nudging to be ethical, it needs to reside on the persuasion end of the persuasion-manipulation spectrum. A nudge becomes a dark pattern when a line between persuasion and manipulation attempt is crossed. This line, however, is not always clear. Distinguishing manipulation from persuasion often proves difficult (Spencer, 2020), even for legislators and scholars who have studied the topic extensively. Therefore, categorizing design patterns into digital nudges and their unethical alternatives, dark patterns, is not always a black-and-white matter. Between clear attempts at persuasion or manipulation exists a gray area, that consists of morally ambiguous patterns. In this area, the classification of a pattern as a digital nudge or a dark pattern is dependent on the consumers' subjective online customer experience, and their way of forming a mental model of the pattern they encounter (Kemppainen, 2020). This gray area is represented in Figure 1 below.

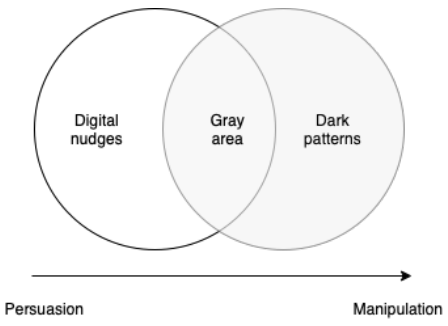

Figure 1: Digital Nudges and Dark Patterns on a Spectrum

Even the existence of dark patterns can be debated. Some argue that dark patterns are not that dark, they are just behaviorally driven marketing strategies (Sin, 2022). This statement is further cemented by the sheer number of distinct types of dark patterns. It is hard to argue that all dark patterns are a danger to both consumers and society if many of them simply inconvenience consumers or annoy them. Some common distinguishing features of digital nudges and dark patterns, that can help in their categorization, are outlined in Table 4.

Others claim that even seemingly persuasive nudges can be categorized as dark patterns if their truthfulness cannot easily be verified by consumers (Sin, 2022). Experts advise to always err on the side of caution – if a pattern can be considered both a nudge and a dark pattern, it should be categorized as the latter to best protect consumers (Sin, 2022).

Even if the practice of nudging can seem prone to manipulation for some, nudges are an important part of our digital environment. Complex and ever-changing digital environments often by nature provoke irrational and hasty decision-making (Meske, 2020a), which can be countered with digital nudges. Let us, therefore, consider guidelines that help us create digital nudges, and not their manipulative counterparts, dark patterns.

Manipulation works by bypassing our conscious decision-making process (Spencer, 2020), by taking advantage of our psychological vulnerabilities. When nudging consumers, it must be ensured that consumers are aware that their behavior is being influenced (Meske, 2020b). Consumers' freedom of choice must be preserved, and they must be able to make autonomous decisions for themselves (Meske, 2020b).

Manipulative practices always have the intent of manipulation (Spencer, 2020). Accidentally manipulative patterns found during A/B testing count as anti-patterns, not as dark patterns (Bösch, 2016). Manipulation is done at the expense of the consumer that is being manipulated (Spencer, 2020). Designers of nudges must therefore make sure that the nudges also benefit the consumer that is being manipulated, and that it does not trigger them to act against their wishes (Michels, 2022).

When nudging consumers, the use of manipulative strategies like coercion or deception is not allowed (Meske, 2020b). Nudges should always be based on truthful information that is verifiable by customers (Sin, 2022).

Table 4: Digital nudges versus dark patterns

Type of Pattern	**Triggered Decision-making**	**Intent**	**Strategies**
Digital Nudge	Conscious, autonomous (System 2)	Persuasion	Providing relevant, truthful information to aid decision-making and to avoid choice overload
Dark Pattern	Automatic, unconscious (System 1)	Manipulation	Coercion, deception

Considering these guidelines and characteristics that help us differentiate digital nudges from dark patterns, let us analyze an example from the E-Commerce context, product reviews. Product reviews can be used as a tool for persuasion, a digital nudge, to encourage customers to purchase products. Product reviews provide a way for consumers to gain relevant information from verified buyers that aids their purchasing decision and does not coerce them to act.

These reviews can also be manipulative. Designers can hand-pick reviews that trigger consumers' specific psychological vulnerabilities, like the bandwagon effect. Reviews can also be used to create a sense of demand-related scarcity, to provoke the consumer's loss aversion bias. This shows the intent of manipulation from the designer's side. Deceitful, fabricated reviews are commonplace on E-Commerce sites. These kinds of reviews would be categorized as dark patterns due to their false nature. The next chapter of the thesis helps us to better understand social influence-based dark patterns in the context of E-Commerce.

4 DIGITAL NUDGES, DARK PATTERNS, AND SOCIAL INFLUENCE

As seen from Chapter 3, there is a myriad of ways to influence customers' decision-making online, by tapping into the psychological vulnerabilities of the human mind. We as humans are especially prone to the effect of social proof – the actions of others set a precedent for our behavior. This holds especially in situations where we are confronted with too much information or too many options.

Digital nudges and dark patterns often make use of this tendency of consumers to alter their behavior according to that of others. This chapter of the thesis focuses on socially influencing customer behavior in E-Commerce in practice. First, consumers' perceptions and reactions to dark patterns are considered. Then, the effects of dark patterns are discussed from both individual and company points of view.

4.1 Dark Patterns in Practice

As discussed in the previous chapters, dark patterns are becoming an increasingly common form of influencing customers' behavior online. Dark patterns help companies generate more short-term profit in a competitive E-Commerce landscape (Maier, 2020). They might even go unnoticed by customers, as their prevalence has led consumers to accept dark patterns as a normal part of the online experience (Lupiáñez-Villanueva, 2022). This might entice even wary companies to try reaching their business goals with the help of dark patterns.

Even though the use of dark patterns might seem attractive to companies, one must carefully consider them before implementing them on an E-Commerce site. Consumers' perceptions and reactions to dark patterns are rarely positive and can thereby harm companies. These perceptions and effects of dark patterns are now considered more in detail.

4.1.1 Perceptions and Reactions to Dark Patterns

Although people are aware that online designs can manipulate them and shape their decision-making and behavior (Bongard-Blanchy, 2021), they are often not capable of identifying dark patterns when they encounter them (Lupiáñez-Villanueva, 2022). This can be seen even in situations in which people are specifically asked to point them out (Lupiáñez-Villanueva, 2022). The less overt a dark pattern is, the more easily it goes unnoticed (Luguri, 2021), especially by less-educated people and older people (Bongard-Blanchy, 2021). Even worse, people think they are better at recognizing manipulation attempts than they are (Bongard-Blanchy, 2021). This overconfidence might set consumers more susceptible to the effects of dark patterns.

When people do identify a dark pattern, they typically will not point it out as they accept dark patterns as a normal part of the online experience. Another explanation is that a consumer who has been manipulated is embarrassed to admit that they did not notice the manipulation attempt in time, and do not want to draw any more attention to the problem. (Lupiáñez-Villanueva, 2022)

People are generally uncertain whether dark patterns are an acceptable business practice (Bongard-Blanchy, 2021). Nevertheless, many consider the use of dark patterns a "*dishonest way to conduct business*" (Maier, 2020), which is never wanted by consumers (Maier, 2020).

4.1.2 Effects of Dark Patterns

Dark patterns are highly effective at altering human behavior and have long-standing consequences for both consumers and society. Due to the various effects dark patterns have, Mathur et al. (2021) recommend looking at the effects of dark patterns through different lenses to gain a full understanding of their effect. The effects of dark patterns are now considered from an individual and company standpoint. For an overview of these effects, refer to Table 5.

Effects on individuals

From the individual perspective, dark patterns benefit the designer of dark patterns at the expense of the consumer. For a consumer, this might present as concrete financial loss, an invasion of their privacy, or an increased cognitive burden. (Mathur, 2021). This causes varying reactions to dark patterns.

Some consumers simply ignore dark patterns when they face them (Bongard-Blanchy, 2021), while others react with annoyance (Bongard-Blanchy, 2021), frustration (Maier, 2020), or anger (Maier, 2020). The effects are not limited to people's emotional reactions – studies have observed neurophysiological responses as well. Dark patterns cause increased anxiety and alertness in consumers and make completing common day-to-day tasks ineffective (Lupiáñez-Villanueva, 2022).

The most obvious harm caused by dark patterns found on E-Commerce sites is the financial loss that the consumer experiences after being pushed to spend more money than they originally anticipated (Mathur, 2021). Consumers' purchasing behavior can be manipulated with activity notifications that trigger

their loss aversion bias, by highlighting products that are popular right now to take advantage of the social proof and scarcity principles, or with deceitful reviews that the consumer accepts as truth.

Dark patterns might entice consumers to give up more personal information than they would be willing to give if they were using a more neutral user interface (Mathur, 2021). Consumers can be manipulated to join a mailing list by showcasing the number of subscribers that the mailing list already has. Fraudulent reviews and activity notifications can be used to fabricate an impression of a trustworthy and popular E-Commerce store, to encourage consumers to purchase items, and steal their private information.

The effect of increased cognitive burden can also magnify the effects of financial harm and loss of personal information. When a consumer must use unnecessary time, energy, and attention using the E-Commerce store, they might make a seemingly easy choice that ends up benefitting the service provider, not the consumer themself (Mathur, 2021).

Effects on companies

The harmful effects of dark patterns are not only limited to consumers – but they can also be observed from the company's perspective. Dark patterns endanger competition and lower consumers' trust in the market (Mathur, 2021). They also cause financial harm to companies by reducing the number of purchases and returning customers (Costello, 2022).

E-Commerce stores that use dark patterns to manipulate consumers to purchase their products harm healthy competition on the market. The use of dark patterns can increase a company's market power and set those companies that do not use dark patterns at an unfair disadvantage. This in turn might cause more companies to adopt these unethical practices, just to be able to compete with other companies on the market, furthering the effect of harming healthy competition. (Mathur, 2021)

Dark patterns harm consumers' trust in the market. Consumers might be warier about purchasing products online if they have been subjected to dark patterns and the harm they cause for an individual. The loss of trust hurts all companies alike – also those, who engage in legitimate and honest business practices. This loss of trust can slow down the growth of E-Commerce and hurt new businesses that have not yet gained a trusting audience. (Mathur, 2021)

Dark patterns are found to significantly reduce purchasing and recommendation intention (Costello, 2022). They have also been linked to a loss of customer satisfaction, trust, and credibility (Maier, 2020). In the long term, loss of trust and credibility will lead to customers abandoning the companies that deploy dark patterns (Bongard-Blanchy, 2021), or shopping online altogether (Mathur, 2021).

Table 5: Effects of dark patterns on consumers and companies

Perspective	Effect
Consumer	Emotional response (annoyance, frustration, anger)
	Psychological stress (increased anxiety and alertness)
	Neurophysiological reaction (stress)
	Financial loss
	Loss of control of personal information
	Increased cognitive burden
Company	Loss of customer satisfaction, trust, and credibility
	Consumers' reduced purchasing and recommendation intention
	Consumers' decreased trust in the market
	Unfair competition in the market

4.2 Social Presence in E-Commerce

Shopping is fundamentally a social process. Traditionally E-Commerce has been devoid of this aspect, compared to brick-and-mortar stores. As the interest in E-Commerce has grown, many retailers have tried to infuse different social cues in their online stores to replicate the social aspect of traditional shopping (Liew, 2017).

There are two forms of social presence in E-Commerce - an **interactive form of social presence**, and **a non-interactive form of social presence** (see Table 6). An interactive form of social presence includes active social interactions (Argo, 2005) and information exchanges with other users or employees of the company (Messer, 2017). This kind of social presence can be achieved with community forums or chatbots on the site.

A non-interactive form of social presence exposes consumers to the (inferred) social presence of others, without the active social interaction with them (Messer, 2017). Even mere knowledge of the presence of others can impact consumers' shopping behavior. This type of social presence is the focus of this thesis. It can present itself in many ways, which are discussed in Chapter 4.3.

Table 6: Forms of social presence in E-Commerce

Form of Social Presence	Characteristics	Practical Applications
Interactive	Active social interactions and information exchanges with others	Chatbots and community forums
Non-interactive	Cues about the social presence of others	Reviews, product recommendation systems, activity messages, and badges (see Chapter 4.3 for more detail)

Non-interactive forms of social presence can affect purchasing behavior through two routes: **the social proof route**, and **the social pressure route** (Figure 2). In the social proof route, visitor traffic size is a cue for item popularity. This popularity acts as social validation for consumers, making persuasive attempts more effective. In the social pressure route, being exposed to other visitors on the site can trigger a feeling of crowdedness. This in turn raises concerns about the scarcity of the products, which motivates consumers to see others as competition. This activates a stress response, increasing consumers' consumption and impulse spending behavior. (Messer, 2017)

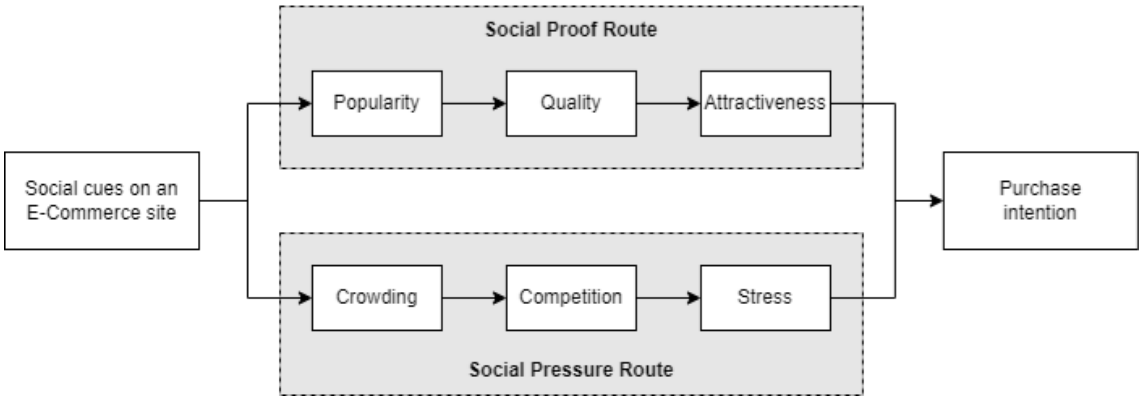

Figure 2: Routes of the Non-interactive Form of Social Presence (adapted from Messer, 2017)

4.3 Summary of the literature review

The heightened competition in the E-Commerce market has led retailers to adopt different strategies to attract more customers and increase their profits. One of these strategies is introducing tried and tested ways of socially influencing customers on an E-Commerce site. Consumers' behavior can be influenced with digital nudges, or their more unethical alternatives, dark patterns. They both make use of known psychological vulnerabilities to influence human behavior. Digital nudges can prompt changes in human behavior by providing relevant

information to aid conscious decision-making or change the choice architecture to help consumers to avoid choice overload (Mirsch, 2017). Dark patterns, on the other hand, aim to bypass the conscious decision-making process and steer or deceive consumers into making decisions that are in the end bad for them (Mathur, 2019).

Social influence-based patterns have varying degrees of effectiveness, based on both individual and contextual factors. People who are more neurotic, have high uncertainty avoidance, low openness, and low conscientious tend to be more vulnerable to these types of patterns (Oyibo, 2019). E-Commerce sites that create a feeling of high uncertainty, purposefully trigger information overload in users, or that stress the similarity of other customers to the user (Huang, 2006), have a higher likelihood of influencing customer behavior with the help of social influence-based patterns.

These patterns have varying effects on the online customer experience (OCE). A good OCE has become a necessity for E-Commerce sites to succeed in a competitive environment. Positive OCE is linked to increased customer loyalty (Kujala, 2011), higher customer satisfaction, and re-purchase intention (Rose, 2012). These factors in turn increase the profitability of a business, and its ability to sustain itself. Digital nudges improve the site's OCE by providing quality information to customers and assisting them in their purchasing process (Petre, 2006). Dark patterns that focus on short-term gains over fostering long-term relationships with customers often do this at the expense of the site's OCE (Bonastre, 2014).

Dark patterns do not only harm the site's online customer experience from the company's point of view – they also cause psychological and neurophysiological harm (Lupiáñez-Villanueva, 2022), an increased cognitive burden, and financial losses to consumers (Mathur, 2021). Their harmful also damage the company using them. Companies that use dark patterns risk the loss of customer satisfaction, trust, and credibility, and a loss of returning customers (Maier, 2020).

If dark patterns are so harmful to consumers, and in the long term, to businesses, why are they used? First, technological advancements have made it easy to implement dark patterns quickly, on a large scale, and on a low budget (Bongard-Blanchy, 2021). The most covert types of patterns often go unnoticed by customers (Lembcke, 2019), which might make dark patterns an attractive solution for companies trying to increase their profits in the short term. Second, the increased use of nudging and attempts at influencing human behavior has inevitably led to the adoption of nudges that cross the line between persuasion and manipulation.

Recognizing when a nudge goes too far can prove difficult, as distinguishing dark patterns from digital nudges is challenging even for legislators and scholars (Spencer, 2020). This gray area between clear digital nudges and dark patterns can be difficult to navigate due to the highly subjective phenomenon of online customer experience. OCE is formed in the mind of each customer, resulting from their rational thinking, past experiences, aroused emotions, and social cues from others (Kemppainen, 2020). Because of this, a pattern that might be deemed as an acceptable digital nudge might be interpreted as a harmful dark pattern according to others.

The research model derived from the literature review can be seen below, in Figure 3. It shows the interplay of individual factors, contextual factors, and subjective OCE on the assessment of patterns found on an E-Commerce site.

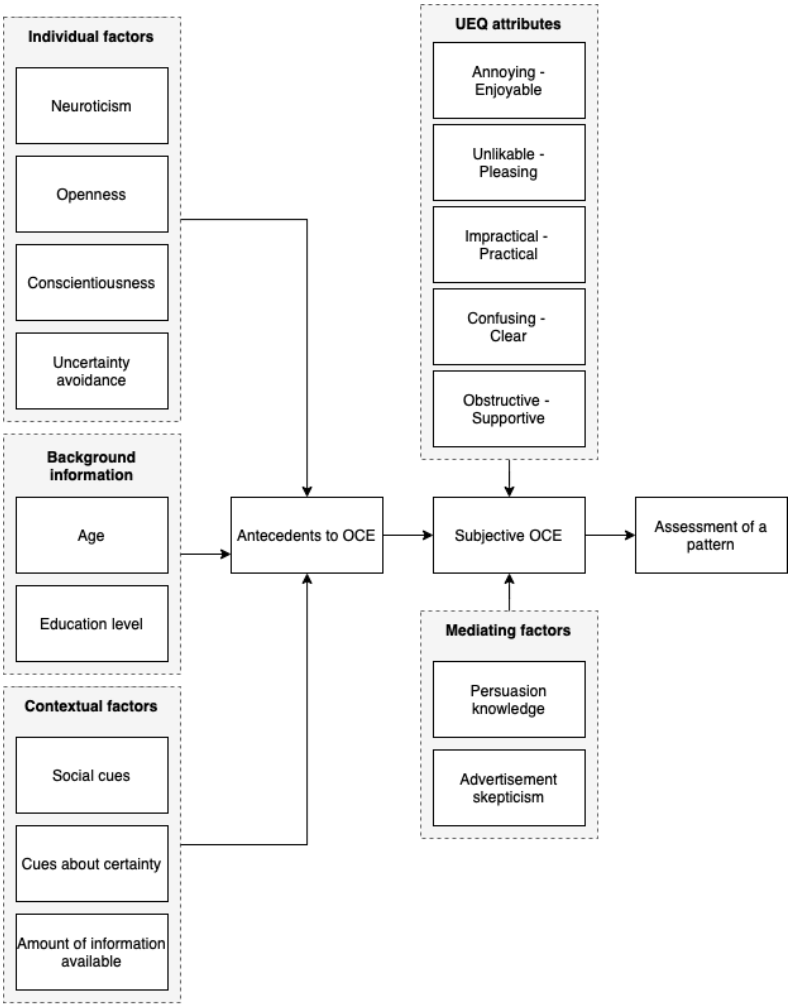

Figure 3: Research model of customers' pattern assessment on an E-Commerce Site

As a general guideline for practitioners considering implementing social influence-based patterns on an E-Commerce site, one must carefully consider the motives behind wanting to implement these patterns. If a pattern is considered only to boost sales, it runs the risk of doing so at the expense of the customer, resulting in a dark pattern. Nudging should always aim to improve both the online customer experience (OCE) and help companies reach their own goals. It is worthwhile to consider both short-term and long-term implications of the design decisions on an E-Commerce site. If these decisions are made based on only short-term metrics, it might result in patterns that in the end cause more harm than good for the consumer.

5 EMPIRICAL PART

This chapter introduces the research method that was used in this study to answer the second research question of the thesis. The research question is as follows:

RQ 2. Which traits in respondents are related to how patterns are categorized into digital nudges and dark patterns?

The first part of this section aims to give practical examples of social influence in E-Commerce. These examples are then used in the survey part of this thesis. The second part of this section explains why a survey was chosen as the appropriate research method for this study. The third part of this section aims to describe the process by which the questionnaire for the survey was constructed.

5.1 Examples of Social Influence in E-Commerce

As discussed in the theoretical part of the thesis, social influence digital nudges and dark patterns can greatly influence consumer behavior in E-commerce stores (Mathur, 2019), and are thus often used to help companies reach their business goals. Many companies choose to utilize patterns that are based on non-interactive form of social influence, as their implementation is often more cost-effective, and companies have more control over them. Some examples of the non-interactive social influence of digital nudges and dark patterns are discussed in this chapter.

The patterns considered in this thesis are all patterns that fall into the "gray area" between digital nudges and dark patterns. The categorization of them into either category is dependent on the consumers' personal online customer experience (OCE), their individual and background factors, and contextual factors. When trying to classify a pattern into a digital nudge or a dark pattern, the intent of the pattern, its truthfulness or deceitfulness, and its way of affecting behavior must be considered. For example, one can argue that patterns that work through

the social proof route are less "dark" in their nature than the ones that work through the social pressure route. The first type of pattern might influence consumer behavior by altering their preferences, the latter tries to emotionally manipulate the consumer into purchasing by inducing a fear of missing out. Therefore, the examples of social influence digital nudges and dark patterns are divided into those that work through the social proof route, and those that work through the social pressure route.

Even though patterns that work through the social proof route can often be less "dark" in their nature, examples of dark patterns can also be found in this category of patterns. See Table 7 for an overview of different types of social influence patterns used in E-Commerce, and what makes them a digital nudge or a dark pattern. Practical examples for each pattern are provided.

5.1.1 Social Influence through Social Proof

Ratings and Reviews

One of the most studied types of social proof forms of social influence is online ratings and reviews (Figure 4). Most E-commerce sites display customer reviews to aid the consumer in their decision-making and to help build trust with new customers. Online ratings and reviews influence awareness of products, customers' expectations, perceptions and attitudes, behavioral intentions, and behavior. (Amblee, 2011)

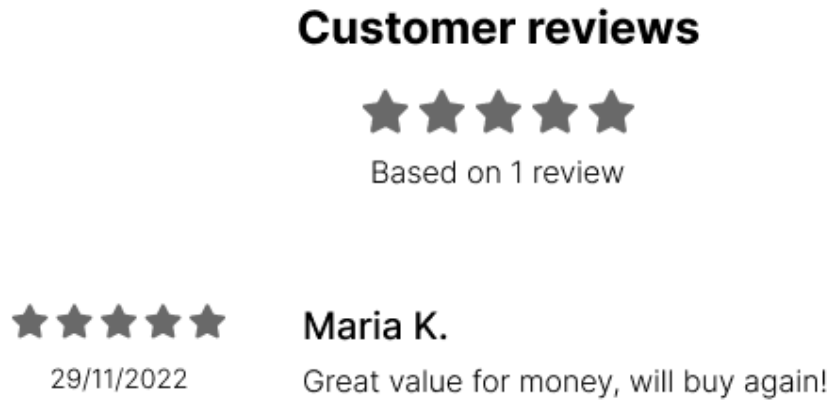

Figure 4: (Artificially created) example of ratings and reviews in E-Commerce

A high rating on a product can act as a cue for product quality, and a high number of reviews acts as a cue for product popularity, affecting the perception of product quality. By displaying customer reviews, an E-Commerce retailer can present concrete proof to consumers that other customers have purchased the

product as well, which can then persuade the consumer to follow suit. A problem arises when the origin of reviews is unknown.

Many E-Commerce retailers have resorted to using fake reviews on their sites to create a misleading impression of trustworthiness and popularity to consumers. Even though some fake reviews might seem apparent even to novice online shoppers, many fake reviews go unnoticed by consumers (Möhring, 2021). Many consumers might believe that they are immune to online manipulation attempts, making them susceptible to manipulative ratings and reviews (Bongard-Blanchy, 2021). Fortunately, for consumers' sake, there is an increasing number of tools available to spot fake reviews when shopping online. (Möhring, 2021).

Product Recommendation Systems

Product recommendation systems (Figure 5) might be the most obvious example of E-Commerce retailers making use of consumers susceptibility to social proof. Other consumers' behavior on the site is used to create an algorithm that informs the consumer that people like them have bought the following items, or that after looking at a specific product, others have looked at the following items. This sets a standard for behavior for the consumer to follow (Mirsch, 2017).

Product recommendation systems are used to help consumers to find items relevant to them and to avoid choice overload (Jesse, 2020). They provide a social reference point to customers on what they should look at next, or what could go well together with their purchase.

Figure 5: (Artificially created) example of a product recommendation system

On paper, product recommendation systems appear beneficial to both consumers and businesses. In practice, their ethical nature can be questionable. Product recommendation systems rarely disclose the logic behind how the recommendations are formed, resulting in an information asymmetry between

the business and the consumer. These systems are designed to trigger impulsive purchasing, which can also be seen problematic from an ethical standpoint.

A more ethical way of utilizing a product recommendation system on the website could be by displaying the logic behind the product recommendation system transparently to the consumer. The products could also be ranked by an attribute that is meant to help consumers to make more informed purchasing decisions, like the return rate of a specific product (Moser, 2019).

Product Badges (Social Proof)
Product badges (Figure 6) are an effective way of nudging consumers to buy specific products. They can act as social proof by implying that a product is a "best seller" or "trending". This can reassure the consumer about their purchase and encourage them to buy that product. (Bansal, 2022).

Figure 6: (Artificially created) example of a Social Proof Badge on a Product

Like with product recommendation systems, the logic behind product badges is often unclear. Bansal et al. (2022) noted in their study that badges are often too permanent to reflect the actual popularity or trendiness of a product (Bansal, 2022). For a badge to be an ethical nudge and not a dark pattern, it should inform the consumer truthfully about the popularity of a product at a given point in time and be updated accordingly. In the future, badges could be automatically generated directly from sales data to transparently reflect the situation at the moment, and not be assigned manually to just boost sales.

5.1.2 Social Influence through Social Pressure

Activity Messages
Activity messages (Figure 7) are recurring and attention-grabbing messages that inform the consumer about the activity of others on the site (Mathur, 2019). A

consumer might receive a notification that someone from their country has just added a product to their basket (physical immediacy), or that the product they are looking at has been bought multiple times during the last hour (temporal immediacy) (Xue, 2019). The immediacy of social presence indicated by these activity messages creates a sense of scarcity and a feeling of stress for the consumer (Lupiáñez-Villanueva, 2022).

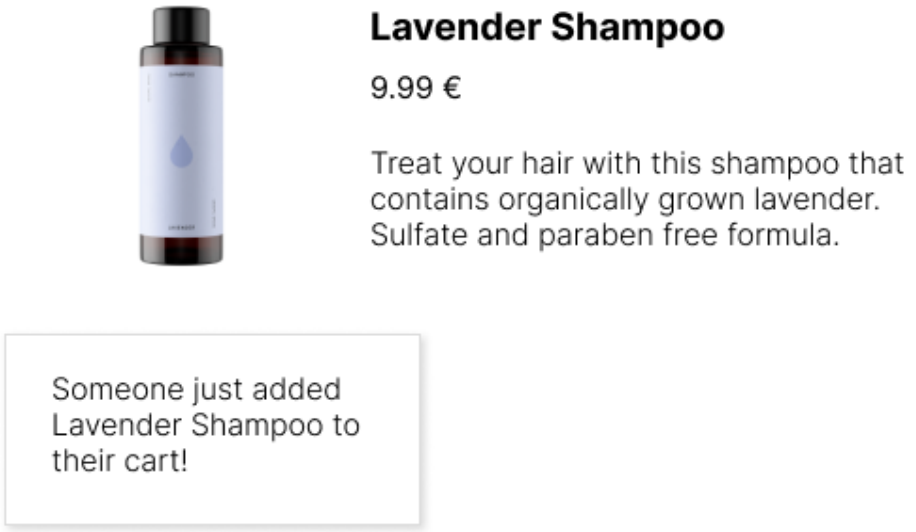

Figure 7: (Artificially created) example of an Activity Notification

In a study conducted by Mathur et al. (2019), it was revealed that many of these activity messages are deceptive. Activity messages about other consumers or numbers of purchases were often generated randomly, to incite a bandwagon effect and push the consumer toward purchasing. (Mathur, 2019)

Even when not deceitful, activity messaging causes stress in users and can create a feeling of information overload, encouraging consumers toward impulsive purchases. Thus, one might wonder if there is an ethical way to nudge consumers with activity messages. One might argue that one such situation arises when a product in question is one-of-a-kind or very limited in inventory. Notifying the consumer that a product they have been looking at was added to another customer's basket might help them not to miss out on the product.

Product Badges

Product badges (Figure 8) can also be used to create pressure on the customer by indicating demand-related scarcity. A badge stating that a product is "trending" or "selling fast" implies that it is likely to sell out soon (Mathur, 2019), creating a sense of urgency for the consumer. This can cause a strong emotional response, an almost panic-like state, pushing the consumer to make impulsive purchases (Bansal, 2022).

Figure 8: (Artificially created) example of a Scarcity Product Badge on a Product

5.1.3 Overview of Social Influence Patterns in E-Commerce

As one can see from the multiple examples of social influence patterns found in E-Commerce, many of them can either act as digital nudges or dark patterns, depending on why and how they are implemented, and how they are perceived by the consumers. The multi-faceted nature of these patterns is described in Table 7.

Patterns that work through the social pressure route are more often dark in their nature, as they encourage impulsive purchases by creating a (false) sense of urgency for the customer. Patterns that work through the social proof route can also be classified as dark patterns if they are deceptive or misleading. The table below aims to describe how a social influence-based pattern can be used both as a digital nudge and a dark pattern, depending on the motives behind its implementation.

Table 7: Social influence patterns in E-Commerce

Ways to Use Social Influence in an E-Commerce Store	Working Mechanism	Considered as a Digital Nudge When…	Considered as a Dark Pattern When…
Ratings and Reviews	Social proof	Information provided in reviews is relevant and truthful	Information provided in reviews is deceitful or intentionally misleading
Product Recommendation Systems	Social proof	Product recommendations are relevant and the logic behind recommendations is disclosed	The logic behind the recommendation system is not transparently disclosed, intentionally encourages impulsive purchasing
Product Badges	Social proof and social pressure	Badges are truthful and reflect the actual sales of products	Badges are assigned to boost sales and do not reflect actual sales data or consumer behavior on the site
Activity messages	Social pressure	Helps consumers not miss out on products that are low in stock	Creates a false notion of scarcity, intentionally encourages impulsive purchasing

The empirical part of this thesis aims to better understand which traits in consumers affect their way of categorizing social-influence based patterns that reside in the "gray area" between obvious attempts at persuasion (digital nudges) or manipulation (dark patterns) of consumers. The four types of patterns described in Table 7 were chosen for the study due to their prevalence in E-Commerce and their subjectively persuasive or manipulative nature.

5.2 Choosing the Research Method

It is important to choose a research method that can provide the right data to answer the research questions one is interested in. This thesis aims to understand the often-used social-influence-based patterns in E-Commerce, and how people perceive them. The empirical research part of this thesis aims to answer the following research question:

RQ 2. Which traits in respondents are related to how patterns are categorized into digital nudges and dark patterns?

After careful consideration of various research methods, an online survey was chosen as the most suitable research method for this study. Surveys offer several advantages – they are an efficient and fast way to gather quantitative data (Laugwitz, 2008), from a large and diverse sample of respondents (Mathur, 2021).

Online surveys allow for anonymous responses, which can make the respondents feel more comfortable answering questions honestly (Couper, 2000). Given that people who have been manipulated by dark patterns in the past are embarrassed to admit that they did not notice the manipulation attempt in time (Lupiáñez-Villanueva, 2022), they might be reluctant to admit this in a non-anonymous setting.

Furthermore, online surveys provide rich data that can be easily analyzed and quantified (Laugwitz, 2008). This data can be used to identify which traits in respondents are related to the way they categorize patterns into digital nudges and dark patterns.

Online surveys do introduce some limitations. Respondents often have difficulties assessing their behavior or attitudes. Even when respondents can assess their behavior and attitudes, surveys are prone to response style bias, non-response bias, and social desirability bias. (Glasow, 2005)

Even though the use of an online survey introduces some limitations, it was chosen as the most suitable research method for this study due to its ability to provide rich and measurable data.

5.3 Constructing the Questionnaire

The main purpose of the survey was to study people's perceptions of different social influence-based patterns that are often used in E-Commerce. These patterns (see Chapter 5.1 for more detail) were identified in the research literature and deemed commonly used in E-Commerce. Four artificial examples of user interfaces were created using Figma to represent the four patterns described in Chapter 5.1 (Ratings and reviews, Product recommendation system, Product Badges, and Activity messages). They were modeled after real-life examples of each pattern and generalized. The style of each pattern was kept the same to minimize the effect of styling choices like fonts and shapes, colors, or wording. The patterns are displayed in the full survey found from Appendix 2.

Respondents were asked about their background information (gender, age, nationality, level of education, and last online purchase). Respondents were also asked about factors that might affect their way of classifying dark patterns. These factors are their personality traits (extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience), uncertainty avoidance, persuasion knowledge, and ad skepticism.

Neuroticism, openness, and conscientiousness were measured using the Ten Item Personality Scale (TIPI) (Gosling, 2003). This scale was used as it has proven to measure the different Big 5 personality dimensions efficiently and reliably despite its briefness. It is an efficient method to use in situations in which

a shorter survey length is more valuable than a deep understanding of the facets of the participants' personalities (Gosling, 2003). Individual level of uncertainty avoidance (UA) was measured using the UA scale designed by Jung et al. (2004). This individual-level measurement of UA has accurately replicated the results of the aggregate level of UA first introduced by Hofstede.

Participants were also asked about their persuasion knowledge and advertisement skepticism. The measurement of persuasion knowledge was adopted from Bearden et al. (2001). The scale has scored high internal consistency reliability and has often been used as a measure of consumers' positive persuasion knowledge (see Ahluwalia, 2004; Aguirre-Rodriguez, 2013). Advertisement skepticism was measured using the skepticism scale (SKEP) designed by Obermiller et al. (1998). The scale's construct validity is strongly supported, and its test-retest reliability is adequate (Obermiller, 1998).

After the background questionnaire, participants were shown the artificially created user interfaces of different social-influence-based patterns, each on their pages, followed by a set of contrasting attribute pairs chosen from the User Experience Questionnaire (UEQ), and a set of questions about the feelings invoked by the pattern. The UEQ attribute pairs were chosen based on the differences between digital nudges (DN) and dark patterns (DP). Half of the attribute pairs were reversed to control for response style bias. The pairs and the reason for including them based on existing research are displayed in the table below.

Table 8: Chosen attributes from UEQ

Attribute pairs (UEQ)	**Reason to include in the study**
(DP) Annoying – Enjoyable (DN)	Dark patterns are considered as annoying (Bongard-Blanchy, 2021)
(DP) Unlikable – Pleasing (DN)	Dark patterns are considered unlikable and unwanted by consumers (Maier, 2020)
(DP) Impractical – Practical (DN)	Digital nudges aim to improve the choice architecture so that consumers can make decisions that benefit them (Thaler, 2018)
(DN) Clear – Confusing (DP)	Dark patterns are by design confusing to disturb conscious decision-making (Meske, 2020a)
(DN) Supportive – Obstructive (DP)	Digital nudges can support consumers in choosing the best choice for them, even if their automated decision-making were to act against their best interests (Meske, 2020a)

Lastly, to capture the emotional and psychological dimension of digital nudges and dark patterns, respondents were asked to rate the pattern on four different aspects: how frustrated, angry, anxious, and alert the pattern made them feel. These feelings were adopted from the results of other studies considering people's perceptions of dark patterns (mainly, Bongard-Blanchy, 2021; Maier, 2020). Respondents were also able to leave a longer comment for each pattern to explain their answer in more detail. Therefore, this thesis provides a multi-dimensional

understanding of these patterns, as the survey measures both feature-focused and feeling-focused appraisals of patterns as digital nudges or dark patterns.

Hypotheses for the study were formed from the literature review. People who are older and less educated are less likely to notice a dark pattern, especially if it is more covert in its design (Bongard-Blanchy, 2021).

Some psychological characteristics make people more vulnerable to being influenced, and thus less likely to spot a dark pattern. People who are more neurotic, less open, and less conscientious are more susceptible to the effects of social proof (Oyibo, 2019), and thus less likely to recognize that a pattern makes use of this vulnerability. People who score high on uncertainty avoidance can more easily be influenced by using the scarcity principle (Fenko, 2017). This might influence their ability to spot a dark pattern when encountered.

People who score high on persuasion knowledge and advertisement skepticism are more likely to view these patterns in a negative light, and thus categorize them as dark patterns. Persuasion knowledge helps consumers to identify when marketers are trying to influence their behavior (Friestad, 1994), and thus respondents with higher persuasion knowledge might better recognize when a pattern aims to alter their behavior in a manipulative way, categorizing them as dark patterns. People with high advertisement skepticism have a consistently negative response tendency toward advertising (Obermiller, 1998). Thus, it is argued that respondents with high advertisement skepticism will more likely categorize patterns as dark patterns.

Thus, the hypotheses of the traits that affect the respondents' assessment of patterns are as follows:

H1): Younger respondents are more likely to categorize patterns as dark patterns than older respondents.

H2): More highly educated respondents are more likely to categorize patterns as dark patterns than less educated respondents.

H3): Respondents with high neuroticism are less likely to categorize patterns as dark patterns than respondents with low neuroticism.

H4): Respondents with low openness are less likely to categorize patterns as dark patterns than respondents with high openness.

H5): Respondents with low conscientiousness are less likely to categorize patterns as dark patterns than respondents with high conscientiousness.

H6): Respondents with high uncertainty avoidance are less likely to categorize patterns as dark patterns than respondents with low uncertainty avoidance.

H7): Respondents with high persuasion knowledge are more likely to categorize patterns as dark patterns than respondents with low persuasion knowledge.

H8): Respondents with high skepticism toward advertising are more likely to categorize patterns as dark patterns than respondents with low ad skepticism.

The survey was shared publicly via the author's social media channels (Instagram, LinkedIn, Reddit), and on Survey Circle. In addition, the survey was shared on the email list of students at the Faculty of Information Technology at the University of Jyväskylä. The full survey can be found in Appendix 2 at the end of this thesis.

6 RESULTS

This chapter discusses the results of the survey. First, the background information of respondents is considered. After this, the perceptions of patterns are looked at in more detail. The four patterns considered in the survey (ratings and reviews, product recommendation systems, product badges, and activity messages) are classified to either digital nudges or dark patterns, based on how most of the respondents perceived them. Then the thesis moves on to consider the hypotheses set in the previous section, to find out more about how traits in respondents are linked to how they categorize the patterns into digital nudges and dark patterns.

6.1 Background information

The survey gathered a total of 633 respondents. After the data was cleaned and duplicates were removed, a maximum of 627 data points (N = 627) were considered. Not all the responses were complete since respondents had the option to not answer any questions they did not want to. Incompletely filled scales were excluded from their respective analyses.

Of all the respondents, 222 (35.4%) identified as female, 389 (62.0%) as male, and 16 (2.6%) as other. The gender distribution of the respondents can be seen in Figure 9.

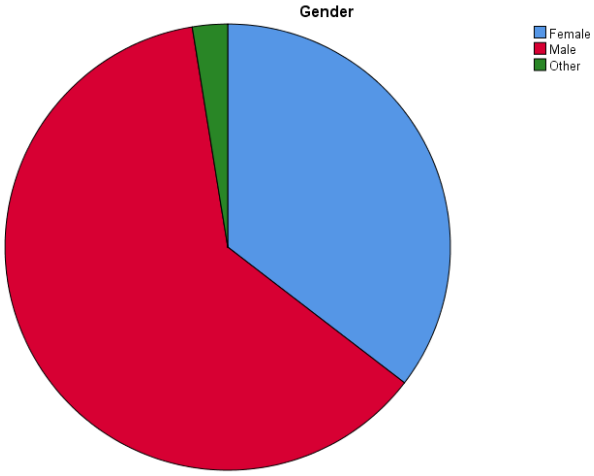

Figure 9: Gender distribution of the respondents

The average age of the respondents was 29.56, with a standard deviation of 7.492. For analysis purposes, respondents' age was categorized into age groups. The categorization was done so that age categories were formed to fit fixed 5-year intervals to balance the overrepresentation of specific ages. Of all the respondents, 136 (21.7%) were 24 or younger, 235 (37.5%) were 25 to 30 years old, 139 (22.2%) were 31 to 36 years old, 52 (8.3%) were 37 to 41 years old, and 70 (10.4%) were over 41 years old. The age distribution of the respondents can be seen in Figure 10.

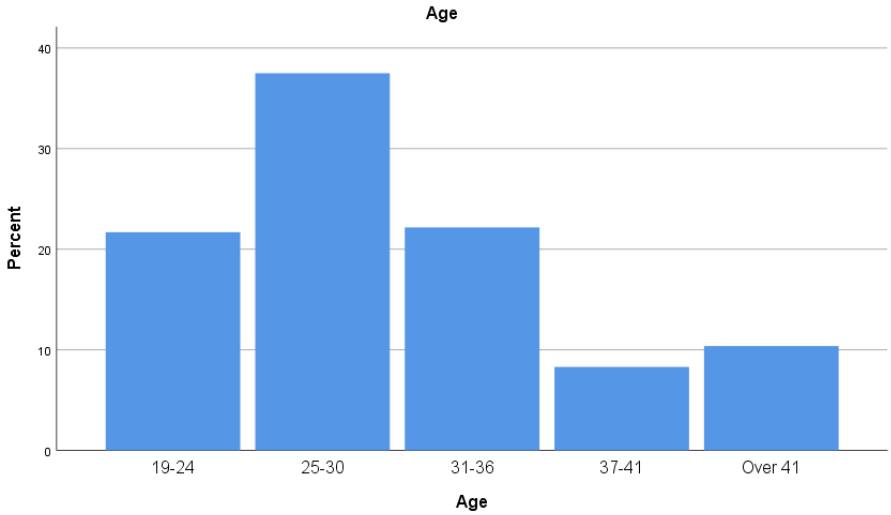

Figure 10: Age distribution of the respondents

Respondents of the survey were mainly Finnish (N = 520, 82.9%). The survey gathered respondents also from other countries, namely: Canada (N = 5, 0.8%), China (N = 5, 0.8%), Croatia (N = 1, 0.2%), Czechia (N = 1, 0.2%), Germany (N = 8, 1.3%), Estonia (N = 1, 0.2%), France (N = 2, 0.3%), India (N = 4, 0.6%), Italy (N = 1, 0.2%), Kosovo (N = 1, 0.2%), Nigeria (N = 1, 0.2%), Russia (N = 1, 0.2%), UK

(N = 6, 1.0%), and the United States (N = 70, 11.1%). Thus, the nationalities most represented in this study are Finnish (82.9%) and American (11.1%). The distribution of different nationalities of respondents can be seen in Figure 11.

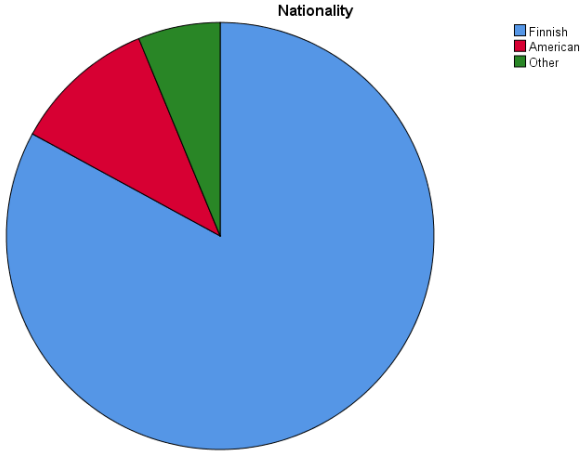

Figure 11: Distribution of different nationalities of the respondents

Respondent's education level was measured by asking them to choose their education level from five options (high school/vocational school, bachelor's degree, master's degree, doctorate, and other). Based on the analysis of the results, one additional option (comprehensive school) was added. Of all the respondents, 4 (0.6%) stated that their highest achieved education level was comprehensive school, 166 (26.5%) responded high school/vocational school, 267 (42.6%) responded bachelor's degree, 161 (25.7%) responded master's degree, and 29 (4.6%) responded doctorate. The distribution of education levels of respondents can be seen in Figure 12.

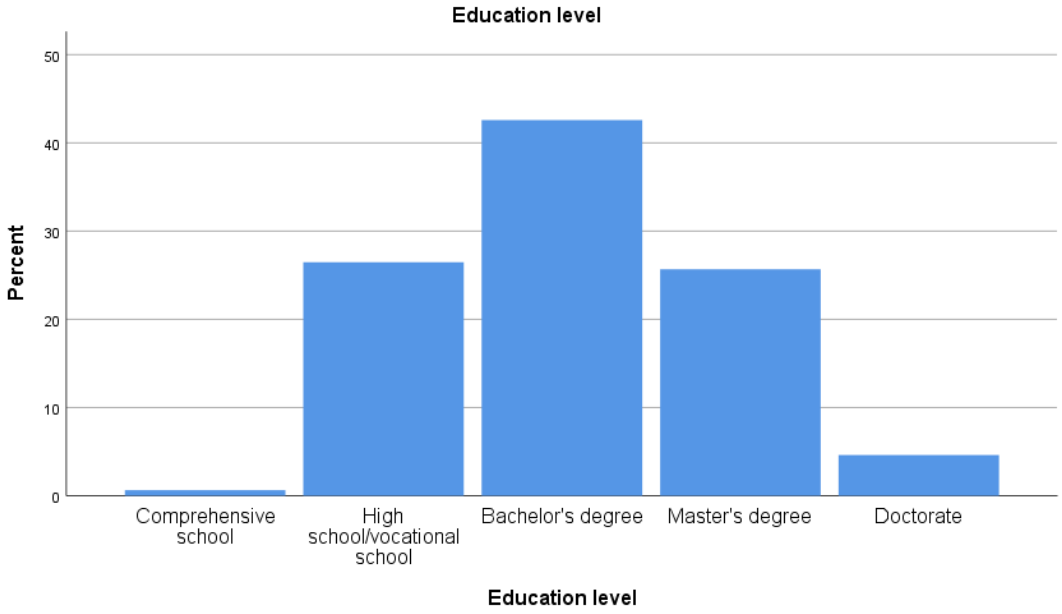

Figure 12: Distribution of education levels of the respondents

Finally, respondents were asked when the last time was that they made a purchase online. 270 (43.1%) of respondents had purchased something online during the last week, 268 (42.7%) had done so during the last month, 78 (12.4%) had done so during the last year, 11 (1.8%) had done so over a year ago, and no respondent replied never having purchased something online. The distribution of respondents' last purchases online can be seen in Figure 13.

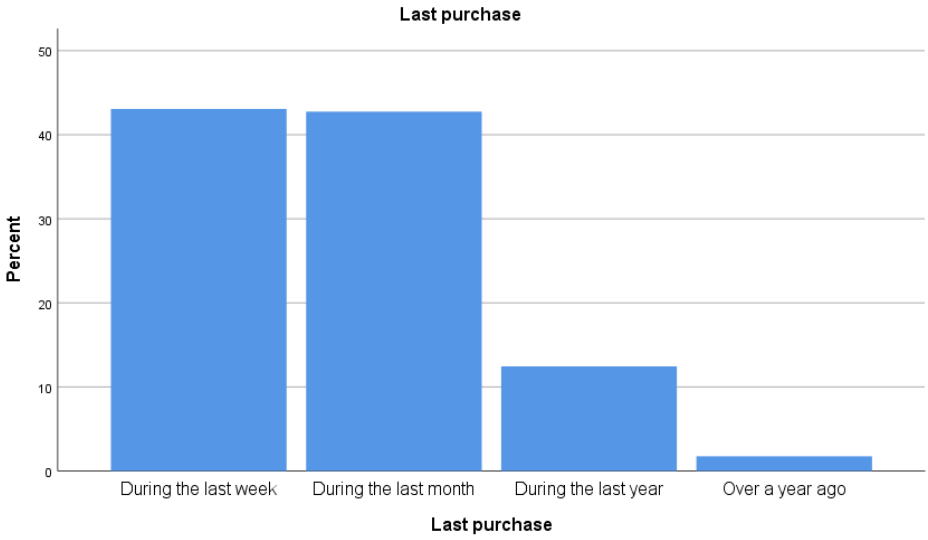

Figure 13: Distribution of the respondents' last online purchase

6.2 Respondents' perceptions of patterns

UEQ score derived from the UEQ inventory used was the basis for classifying the patterns studied in this thesis as digital nudges or dark patterns.

6.2.1 Testing whether patterns differ from each other significantly

Before categorizing the patterns into digital nudges and dark patterns, a Friedman test was conducted for the UEQ scores of patterns to determine whether the patterns differ from each other significantly. As the same respondents rated each of the four patterns, and as the data is not normally distributed, the Friedman test was used.

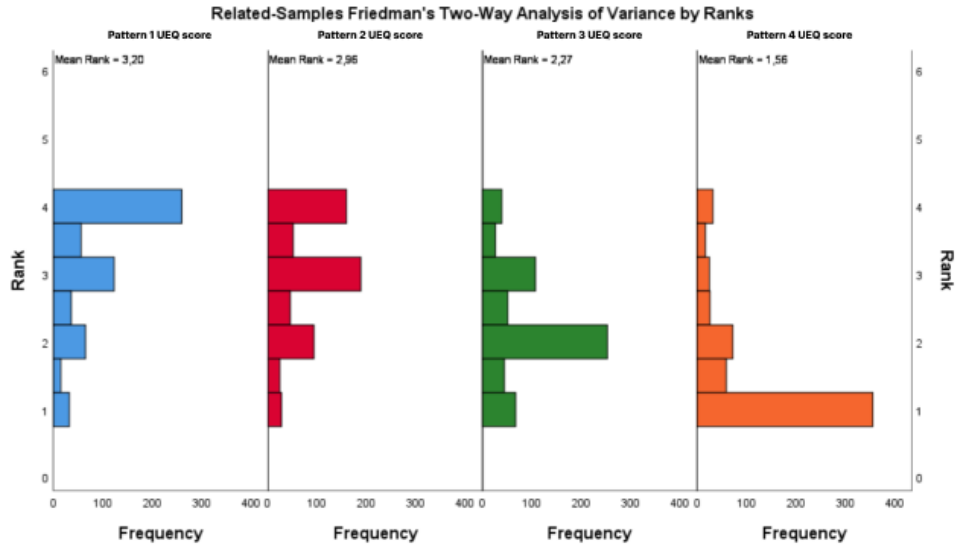

Figure 14: Friedman test for patterns' UEQ scores

Table 9: Pairwise comparisons of patterns' UEQ scores

Patterns compared	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.
1-2	0.238	0.075	3.154	0.002	0.010
1-3	0.928	0.075	12.321	0.000	0.000
1-4	1.641	0.075	21.782	0.000	0.000
2-3	0.691	0.075	9.167	0.000	0.000
2-4	1.404	0.075	18.628	0.000	0.000
3-4	0.713	0.075	9.461	0.000	0.000

As one can see from Table 9 above, all patterns' UEQ scores differ from each other in a statistically significant manner.

6.2.2 Categorizing patterns into digital nudges and dark patterns

As UEQ score was measured on a 5-step Likert scale, a score of under 3 indicated that the average user experience for a pattern was more negative than positive. Thus, a cutoff point of UEQ of less than 3 was used to divide the patterns based on whether they were more negatively or positively perceived overall. For the purposes of this analysis, this split is considered to reflect the line between a dark pattern and a digital nudge. Each pattern and its UEQ score is displayed in Table 10 below. Cronbach's alpha was calculated for each pattern's UEQ score to ensure that UEQ measured the same concept – that pattern's darkness.

Table 10: Patterns and their UEQ scores

Sum variable	Mean	Median	Std. dev.	Cronbach's α
Pattern 1 UEQ	3.4159	3.4000	0.75966	0.744
Pattern 2 UEQ	3.1066	3.2000	0.81141	0.780
Pattern 3 UEQ	2.6120	2.6000	0.80603	0.723
Pattern 4 UEQ	2.0504	1.8000	0.84644	0.771

Based on the classification of pattern categorization outlined above, patterns 1 and 2 can be considered as digital nudges, and patterns 3 and 4 are considered as dark patterns by most of the respondents. These differences in the categorization of patterns are best represented in Figure 15 below, which shows how many respondents considered the pattern a dark pattern, and how many did not.

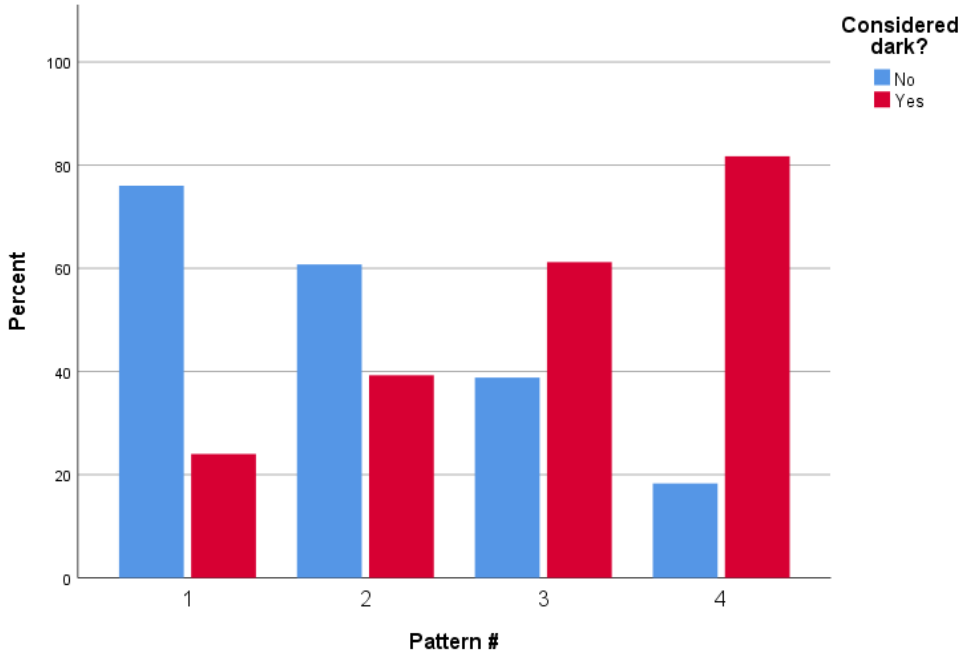

Figure 15: Respondent counts for categorization of the patterns

As one can note from the figure above, pattern 1 is quite clearly considered a digital nudge, and pattern 4 is considered a dark pattern. However, for patterns 2 and 3, the categorization is not as clear-cut. Patterns and their categorizations into digital nudges and dark patterns can be seen in Table 11 below.

Table 11: Patterns and their categorization

	Total	Considered a digital nudge		Considered a dark pattern	
Pattern	**N**	**N**	**%**	**N**	**%**
1	617	469	74.8	148	24.0
2	619	376	60.0	243	38.8
3	616	239	38.1	377	60.1
4	607	111	17.7	496	79.1

6.2.3 Most impactful characteristics that make a pattern dark

Some of the attribute pairs in the UEQ and items in the feeling questionnaire had a bigger impact than others on whether a specific pattern was ranked a digital nudge or a dark pattern. To find out which characteristics had the highest impact on the categorization of a pattern, Mann-Whitney test was used. Respondents

were divided to two groups: considered the pattern a dark pattern (UEQ score under 3) and did not consider the pattern a dark pattern (UEQ score 3 or higher). These two groups were then compared according to their answers to the UEQ attribute pairs and items in the feeling questionnaire to find more about what makes a pattern dark in people's minds. The most impactful item was found by testing which answers were the furthest away from each other in the two groups used.

The UEQ items with the highest impact (defined as the highest standardized Mann-Whitney test statistic) on the subsequent categorization of a pattern as a dark pattern were **item C** (impractical – practical; U = 13661.500, N = 596) for pattern 1 (ratings and reviews); **item B** (unlikable – likable; U = 16881.000, N = 590) for pattern 2 (product recommendations), and **item A** (annoying – enjoyable; U = 18187.500, N = 591 and U = 10759.000, N = 576) for patterns 3 and 4 (product badges and activity messages). Across all features, **item D** (clear – confusing) had the least impact on the subsequent categorization of a pattern as a dark pattern.

The feeling item with the highest impact (defined as the highest standardized Mann-Whitney test statistic) on the subsequent categorization of a pattern as a dark pattern was **feeling A** (frustrated) for each feature.

6.2.4 Insights from open-ended questions

After respondents had rated each pattern, they had the chance to deliberate on their answers in an open-ended question. The open-ended questions aimed to reveal any additional meaningful information that could not be captured in a quantitative format through the scales used.

Answering the open-ended questions was surprisingly popular, and many of the answers submitted were very detailed. The high response rate of the open-ended questions and the detail in the answers indicates that social influence in E-Commerce is a topic that resonates with many, and triggers many (negative) emotions. Table 12 below shows the number of answers to the open-ended question for each pattern.

Table 12: Number of answers to open-ended questions for each pattern

Pattern	N	% of all respondents
1	243	39.4
2	189	30.9
3	207	35.8
4	204	33.6

As one can see from Table 12, the number of replies to the open-ended questions stayed stable, after non-response bias was accounted for. If one is to assume that the fixed order of patterns would have resulted in fewer people wanting to answer the open-ended question in the latter part of the survey, one can see that the negative feelings triggered by the last two patterns, 3 and 4, balanced this phenomenon, and reply percentage rose higher than that for pattern 2.

6.3 Respondents' traits related to the perception of patterns

After considering the patterns featured in the survey on a more general level, the focus is shifted to analyzing which traits in the respondents are linked to the categorization of patterns into digital nudges and dark patterns.

6.3.1 Sum variables

Before considering the hypotheses set in Chapter 5.3, sum variables were formed the independent variables used in the study (TIPI personality traits, uncertainty avoidance, persuasion knowledge, and advertisement skepticism). Cronbach's alpha was calculated to ensure the reliability of the sum variables. The calculated sum variables can be seen in Table 13 below.

Table 13: Sum variables and their Cronbach's α

Sum variable	Mean	Median	Std. dev.	Cronbach's α
Neuroticism	4.45	4.50	1.33	0.589
Openness	4.63	4.50	1.10	0.224
Conscientiousness	4.56	4.50	1.22	0.498
Uncertainty avoidance	4.71	4.86	1.03	0.809
Persuasion knowledge	5.58	5.67	0.85	0.839
Advertisement skepticism	5.19	5.33	1.23	0.938

Uncertainty avoidance (α = 0.809) and persuasion knowledge (α = 0.839) reached a good internal consistency, and advertisement skepticism (α = 0.938) was at an excellent level. For the TIPI personality traits, none of the sum variables reached an acceptable level of internal consistency. No alterations to the sum variable could be made to improve their internal consistency, as each TIPI personality trait sum variable consisted of only two questions. Low alphas for TIPI are recognized in literature and derive from the design of the inventory. Their reliability is thus better measured by considering their test-retest validity, which reaches adequate levels (Gosling, 2003). Further evaluation of using TIPI in this study is given in the discussion section of this thesis.

6.3.2 Testing for normality

To determine the statistical test that will be used to analyze how the respondents' traits are related to how they categorize the patterns, Kolmogorov-Smirnov and Shapiro-Wilk tests for normality were conducted. The results of the tests can be seen in Appendix 1. No variables pass the test for normality, meaning that the statistical tests used in this thesis will not assume normally distributed values.

6.3.3 Testing for hypotheses

Hypotheses were tested by calculating a correlation between an independent variable (sum variables found in Table 13), and a dependent variable (UEQ score). Correlation between an independent variable and each item in the feeling inventory was also calculated to find out more about the emotional dimension of customer online experience (OCE) for each pattern. As none of the independent variables in this study were normally distributed, Spearman's rank correlation coefficient was used.

Hypothesis 1
According to H1, younger people are more likely to categorize features as dark patterns than older respondents. To determine whether respondents' age correlated with the tendency to rate a pattern as a dark pattern, correlation for respondents' age and their UEQ score was calculated for each pattern featured in the survey. The results of this statistical test can be seen in Table 14a below.

Table 14a: Correlations between age and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Age x	ρ	**-0.146****	-0.042	0.015	0.026
UEQ score	Sig. (2-tailed)	0.000	0.300	0.714	0.524
	N	617	619	616	607

A positive correlation between age and UEQ score was expected, but a negative correlation between age and UEQ score for pattern 1 was found (ρ = -0.146**). For other patterns, no statistically significant correlation between age and pattern categorization was found. H1 is not supported – younger people were less likely to categorize pattern 1 as dark pattern than older respondents.

Correlations were also calculated between age and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 14b below.

Table 14b: Correlations between age and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Age x Frustration	ρ	**-0.163****	-0.009	0.055	0.072
	Sig. (2-tailed)	0.000	0.821	0.168	0.075
	N	622	615	623	618
Age x Anger	ρ	**-0.160****	-0.031	-0.032	0.024
	Sig. (2-tailed)	0.000	0.448	0.431	0.554
	N	619	616	618	613
Age x Anxiety	ρ	**-0.087***	-0.051	0.053	0.018
	Sig. (2-tailed)	0.030	0.208	0.188	0.650
	N	619	613	616	609
Age x Alertness	ρ	-0.069	**-0.106****	0.042	0.004
	Sig. (2-tailed)	0.089	0.009	0.299	0.926
	N	615	609	607	605

A negative correlation between age and triggered feelings was found for patterns 1 and 2. For other patterns, no statistically significant relationship between age and triggered feelings was found. Older respondents felt more frustrated, angry, and anxious toward pattern 1, and felt more alert toward pattern 2 than younger respondents.

Hypothesis 2

According to H2, more highly educated respondents are more likely to categorize patterns as dark patterns than less educated respondents. To determine whether respondents' education level correlated with the tendency to rate a pattern as a dark pattern, correlation for respondents' education level and their UEQ score was calculated for each pattern featured in the survey. The results of this statistical test can be seen in Table 15a below.

Table 15a: Correlations between education level and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Education level x UEQ score	ρ	-0.030	0.023	0.027	0.079
	Sig. (2-tailed)	0.450	0.564	0.500	0.052
	N	617	619	616	607

A negative correlation between education level and UEQ score was expected, but no statistically significant correlation was found. H2 is rejected – higher education level does not correlate with respondents' tendency to categorize patterns as dark patterns.

Correlations were also calculated between education level and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 15b below.

Table 15b: Correlations between education level and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Education level x Frustration	ρ	**-0.084***	-0.049	0.011	0.014
	Sig. (2-tailed)	0.035	0.220	0.776	0.726
	N	622	615	623	618
Education level x Anger	ρ	**-0.131****	**-0.109****	-0.044	-0.017
	Sig. (2-tailed)	0.001	0.007	0.280	0.671
	N	619	616	618	613
Education level x Anxiety	ρ	**-0.094***	**-0.126****	-0.064	**-0.082***
	Sig. (2-tailed)	0.000	0.002	0.112	0.042
	N	619	613	616	609
Education level x Alertness	ρ	0.000	**-0.90***	0.066	0.023
	Sig. (2-tailed)	0.991	0.027	0.102	0.576
	N	615	609	607	605

A negative correlation between education level and triggered feelings was found for patterns 1, 2, and 3. For pattern 3, no statistically significant relationship between education level and triggered feelings were found. More educated respondents felt more frustrated, angry, and anxious toward pattern 1; more angry, anxious, and alert toward pattern 2; and more anxious toward pattern 4 than respondents with lower education level.

Hypothesis 3

According to H3, respondents with high neuroticism are less likely to categorize patterns as dark patterns than respondents with low neuroticism. To determine whether respondents' neuroticism correlated with the tendency to rate a pattern as a dark pattern, correlation for respondents' neuroticism and their UEQ score was calculated for each pattern featured in the survey. The results of this statistical test can be seen in Table 16a below.

Table 16a: Correlations between neuroticism and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Neuroticism x UEQ score	ρ	0.031	-0.039	0.052	**0.100***
	Sig. (2-tailed)	0.445	0.338	0.196	0.014
	N	612	614	622	603

A positive correlation between neuroticism and UEQ score was expected and found between neuroticism and UEQ score for pattern 4 (ρ = 0.100*). No statistically significant relationships between neuroticism and UEQ scores for other patterns. H3 is supported – more neurotic respondents are less likely to categorize pattern 4 as a dark pattern.

Correlations were also calculated between neuroticism and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 16b below.

Table 16b: Correlations between neuroticism and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Neuroticism x Frustration	ρ	-0.061	**-0.101***	**-0.136****	-0.032
	Sig. (2-tailed)	0.130	0.013	0.001	0.445
	N	617	610	618	613
Neuroticism x Anger	ρ	-0.060	-0.064	-0.065	0.002
	Sig. (2-tailed)	0.135	0.115	0.109	0.964
	N	614	611	614	608
Neuroticism x Anxiety	ρ	**-0.192****	**-0.163****	**-0.234****	**-0.139****
	Sig. (2-tailed)	0.000	0.000	0.000	0.001
	N	614	608	611	604
Neuroticism x Alertness	ρ	-0.025	-0.005	**-0.092***	**-0.102***
	Sig. (2-tailed)	0.533	0.893	0.024	0.013
	N	610	605	604	602

A negative correlation between neuroticism and triggered feelings were found for all patterns. More neurotic respondents felt more anxious toward pattern 1; more frustrated and anxious toward pattern 2; more frustrated, anxious, and alert toward pattern 3; and more anxious and alert toward pattern 4 than less neurotic respondents.

Hypothesis 4

According to H4, respondents with low openness are less likely to categorize patterns as dark patterns than respondents with high openness. Spearman's rank correlation coefficient was calculated for respondents' openness and their UEQ score for each pattern featured in the survey. The results of this statistical test can be seen in Table 17a below.

Table 17a: Correlations between openness and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Openness x UEQ score	ρ	-0.003	0.055	**-0.139****	**-0.168****
	Sig. (2-tailed)	0.944	0.171	0.01	0.000
	N	609	611	608	600

A negative correlation between openness and UEQ score was expected and found for patterns 3 (ρ = -0.139**) and 4 (ρ = -0.168**). No statistically significant relationship between openness and UEQ scores were found for patterns 1 and 2. H4 is supported – respondents low in openness are less likely to categorize patterns 3 and 4 as a dark pattern.

Correlations were also calculated between openness and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 17b below.

Table 17b: Correlations between openness and feelings triggered by patterns

			Pattern			
Spearman's rho			**1**	**2**	**3**	**4**
Openness x Frustration		ρ	0.068	0.072	-0.079	**-0.093***
		Sig. (2-tailed)	0.093	0.075	0.051	0.021
		N	614	608	616	611
Openness Anger	**x**	ρ	0.060	**0.091***	-0.002	-0.050
		Sig. (2-tailed)	0.138	0.025	0.951	0.222
		N	612	609	611	606
Openness Anxiety	**x**	ρ	0.072	**0.133****	-0.061	0.048
		Sig. (2-tailed)	0.074	0.001	0.130	0.240
		N	612	607	609	602
Openness Alertness	**x**	ρ	0.015	**0.128****	0.035	0.070
		Sig. (2-tailed)	0.718	0.002	0.394	0.088
		N	607	602	601	599

A positive correlation between openness and triggered feelings was found for pattern 2. Less open respondents felt more anger, anxiety, and alertness toward

pattern 2. For pattern 4, a negative correlation was found between openness and frustration. Less open respondents felt less frustration toward pattern 4.

Hypothesis 5

According to H5, respondents with low conscientiousness are less likely to categorize patterns as dark patterns than respondents with high conscientiousness. Spearman's rank correlation coefficient was calculated for respondents' conscientiousness and their UEQ score for each pattern featured in the survey. The results of this statistical test can be seen in Table 18a below.

Table 18a: Correlations between conscientiousness and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Conscientiousness x UEQ score	ρ	0.047	0.056	0.022	-0.052
	Sig. (2-tailed)	0.246	0.167	0.593	0.206
	N	611	613	610	601

A positive correlation between conscientiousness and UEQ score was expected, but no statistically significant relationships between conscientiousness and UEQ scores were found for any of the patterns. H5 gained no support, as no statistically significant relationships were found.

Correlations were also calculated between conscientiousness and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 18b below.

Table 18b: Correlations between conscientiousness and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Conscientiousness x Frustration	ρ	0.056	0.043	**0.129****	0.020
	Sig. (2-tailed)	0.165	0.294	0.001	0.613
	N	616	610	617	612
Conscientiousness x Anger	ρ	**0.089***	**0.286****	**0.112****	0.077
	Sig. (2-tailed)	0.027	0.000	0.006	0.059
	N	613	612	612	607
Conscientiousness x Anxiety	ρ	**0.120****	**0.109****	**0.144****	**0.104***
	Sig. (2-tailed)	0.003	0.007	0.000	0.010
	N	613	607	601	603
Conscientiousness x Alertness	ρ	0.040	**0.081***	**0.113****	**0.082***
	Sig. (2-tailed)	0.328	0.046	0.006	0.044
	N	609	603	601	599

A positive correlation between openness and triggered feelings was found for all patterns. Less open respondents felt more anger and anxiety toward pattern 1; more anger, anxiety, and alert toward pattern 2; more frustration, anger, anxiety, and alert toward pattern 3; and more anxiety and alert toward pattern 4.

Hypothesis 6

According to H6, respondents with high uncertainty avoidance are less likely to categorize patterns as dark patterns than respondents with low uncertainty avoidance. Spearman's rank correlation coefficient was calculated for respondents' uncertainty avoidance and their UEQ score for each pattern featured in the survey. The results of this statistical test can be seen in Table 19a below.

Table 19a: Correlations between uncertainty avoidance and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Uncertainty avoidance x UEQ score	ρ	**0.139****	0.082	**0.177****	**0.173****
	Sig. (2-tailed)	0.001	0.054	0.000	0.000
	N	554	555	554	545

A positive correlation between uncertainty avoidance and UEQ score was expected and found for patterns 1 (ρ = 0.139**), 3 (ρ = 0.177**), and 4 (ρ = 0.173**). H6 is supported – respondents with high uncertainty avoidance were less likely to categorize patterns 1, 3, and 4 as dark patterns than respondents with low uncertainty avoidance.

Correlations were also calculated between uncertainty avoidance and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 19b below.

Table 19b: Correlations between uncertainty avoidance and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Uncertainty avoidance x Frustration	ρ	-0.024	**-0.126****	-0.049	-0.009
	Sig. (2-tailed)	0.567	0.003	0.244	0.825
	N	559	557	560	556
Uncertainty avoidance x Anger	ρ	-0.076	**-0.106***	-0.036	-0.014
	Sig. (2-tailed)	0.072	0.000	0.391	0.737
	N	557	612	557	554
Uncertainty avoidance x Anxiety	ρ	**-0.168****	**-0.149****	**-0.208****	**-0.222****
	Sig. (2-tailed)	0.000	0.000	0.000	0.010
	N	557	554	555	548

Uncertainty avoidance x Alertness	ρ	**-0.123****	-0.063	**-0.126****	**-0.156****
	Sig. (2-tailed)	0.004	0.140	0.003	0.000
	N	554	548	548	544

A negative correlation between uncertainty avoidance and triggered feelings was found for all patterns. Respondents with high uncertainty avoidance felt more anxiety and alertness toward pattern 1; more frustration, anger, and anxiety toward pattern 2; more anxiety and alert toward pattern 3; and more anxiety and alert toward pattern 4.

Hypothesis 7

According to H7, respondents with high persuasion knowledge are more likely to categorize patterns as dark patterns than respondents with low persuasion knowledge. Spearman's rank correlation coefficient was calculated for respondents' persuasion knowledge and their UEQ score for each pattern featured in the survey. The results of this statistical test can be seen in Table 20a below.

Table 20a: Correlations between persuasion knowledge and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Persuasion knowledge x UEQ score	ρ	0.056	-0.003	**-0.106****	**-0.188****
	Sig. (2-tailed)	0.164	0.950	0.009	0.000
	N	609	611	608	599

A negative correlation between persuasion knowledge and UEQ score was expected and found for patterns 3 (ρ = -0.106**) and 4 (ρ = -0.188**). H7 is supported – respondents with high persuasion knowledge were more likely to categorize patterns 3 and 4 as dark patterns than respondents with low persuasion knowledge.

Correlations were also calculated between persuasion knowledge and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 20b below.

Table 20b: Correlations between persuasion knowledge and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Persuasion knowledge x Frustration	ρ	**0.088***	**0.135****	-0.043	**-0.103***
	Sig. (2-tailed)	0.029	0.001	0.290	0.010
	N	614	610	615	611
Persuasion knowledge x Anger	ρ	**0.087***	**0.130****	**0.225****	**-0.113****
	Sig. (2-tailed)	0.031	0.001	0.000	0.005
	N	557	609	618	607
Persuasion knowledge x Anxiety	ρ	**0.182****	**0.191****	**0.152****	**0.175****
	Sig. (2-tailed)	0.000	0.000	0.000	0.000
	N	612	606	609	604
Uncertainty avoidance x Alertness	ρ	0.015	**0.093***	-0.015	0.071
	Sig. (2-tailed)	0.711	0.023	0.710	0.081
	N	610	602	601	600

Persuasion knowledge was positively correlated with triggered feelings for patterns 1, 2, and 3. Respondents with high persuasion knowledge felt less frustration, anger, and anxiety toward pattern 1; less frustration, anger, anxiety, and alertness toward pattern 2; and less anger and anxiety toward pattern 3. For pattern 4, respondents with high persuasion knowledge felt less anxiety, but more frustration and anger than respondents with low persuasion knowledge.

Hypothesis 8

According to H8, respondents with high advertisement skepticism are more likely to categorize patterns as dark patterns than respondents with low advertisement skepticism. Spearman's rank correlation coefficient was calculated for respondents' advertisement skepticism and their UEQ score for each pattern featured in the survey. The results of this statistical test can be seen in Table 21a below.

Table 21a: Correlations between advertisement skepticism and patterns' UEQ scores

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Advertise-ment skep-ticism x UEQ score	ρ	-0.038	**-0.186****	**-0.312****	**-0.460****
	Sig. (2-tailed)	0.351	0.000	0.000	0.000
	N	595	597	594	588

A negative correlation between advertisement skepticism and UEQ score was expected and found for patterns 2 (ρ = -0.186**), 3 (ρ = -0.312**) and 4 (ρ = -0.460**). H8 is supported – respondents with high advertisement skepticism were more likely to categorize patterns 2, 3, and 4 as dark patterns than respondents with low advertisement skepticism.

Correlations were also calculated between advertisement skepticism and each feeling inventory item. This was done for each pattern featured in the survey. The results of this statistical test can be seen in Table 21b below.

Table 21b: Correlations between persuasion knowledge and feelings triggered by patterns

		Pattern			
Spearman's rho		**1**	**2**	**3**	**4**
Advertisement skepticism x Frustration	ρ	**0.168****	**0.082***	-0.070	**-0.195****
	Sig. (2-tailed)	0.000	0.046	0.085	0.000
	N	600	595	602	598
Advertisement skepticism x Anger	ρ	**0.218****	0.142	-0.070	**-0.154****
	Sig. (2-tailed)	0.000	0.001	0.089	0.000
	N	599	596	597	593
Advertisement skepticism x Anxiety	ρ	**0.296****	**0.287****	**0.147****	**0.198****
	Sig. (2-tailed)	0.000	0.000	0.000	0.000
	N	598	594	595	590
Advertisement skepticism x Alertness	ρ	0.036	**0.176****	0.035	**0.110****
	Sig. (2-tailed)	0.381	0.000	0.396	0.008
	N	594	588	587	586

Advertisement skepticism was positively correlated with triggered feelings for patterns 1, 2, and 3. Respondents with high advertisement skepticism felt less frustration, anger, and anxiety toward pattern 1; less frustration, anxiety, and

alertness toward pattern 2; and less anxiety toward pattern 3. For pattern 4, respondents with high persuasion knowledge felt less anxiety and alertness, but more frustration and anger than respondents with low persuasion knowledge.

7 DISCUSSION AND CONCLUSIONS

This study aimed to shine a light on social influence-based patterns in E-Commerce, and which traits in people affect their perceptions of these patterns. The research questions of this thesis were the following:

1. What is known about digital nudges and dark patterns based on social influence, in the context of E-commerce?
2. Which traits in respondents are related to how patterns are categorized into digital nudges and dark patterns?

7.1 Discussing social influence-based patterns in E-Commerce

The first research question is explored in Chapters 2, 3, and 4. A summary of the literature review is provided in Chapter 4.3. To recap: heightened competition in the E-Commerce market has led retailers to adopt digital nudges and their more unethical alternative, dark patterns, to increase their profits and gain a competitive advantage. Digital nudges and dark patterns work by making use of known psychological vulnerabilities to influence human behavior, for better or worse.

Social influence-based patterns are effective due to humans' tendency to view the behavior of others as a guide for their own behavior. Individual traits (such as neuroticism or persuasion knowledge) and contextual factors of the E-Commerce site (amount of information available, perceived similarity to other customers) influence the effectivity of these patterns.

Social influence-based patterns have varying effects on the online customer experience (OCE). Digital nudges improve the site's OCE by providing customers with quality information to assist them in their decision-making. Dark patterns work at the expense of the site's OCE to drive up companies' short-term profit by deceiving or manipulating customers.

Categorizing patterns into digital nudges and dark patterns is difficult even for legislators and scholars due to the highly subjective nature of OCE. A research model was derived from the literature review to help understand the assessment

of patterns in E-Commerce. According to the model, a pattern's categorization (digital nudge or dark pattern) is affected by a person's individual factors, background information, contextual factors, and pattern attributes.

7.2 Discussing factors influencing the perception of social influence-based patterns in E-Commerce

An online survey was conducted to answer the second research question, that is, which traits in the respondents are linked to how they categorize patterns into digital nudges and dark patterns. Four images were artificially created for the use of this survey to represent the often-used social influence-based patterns in E-Commerce: ratings and reviews, product recommendations, product badges, and activity messages. These patterns were shown to the respondents followed by a set of attribute pairs measuring the usability of the pattern, and Likert-scale questions to measure the feelings triggered by the pattern. The survey also included open-ended questions in which respondents could explain their answers in more detail if they so wished.

Of the four patterns studied, ratings and reviews (pattern 1), and product recommendation systems (pattern 2) were considered digital nudges, and product badges (pattern 3) and activity messages (pattern 4) were considered dark patterns by most of the respondents. Ratings and reviews were considered the least dark of all the patterns, while activity messages were considered the darkest. This is in line with Messer et al. (2017) theorization of two distinct routes of non-interactive form of social presence. Patterns in E-Commerce can work either through the social proof route, like patterns 1 and 2, persuading the consumer to make certain actions online; or through the social pressure route, like patterns 3 and 4, manipulating the consumer behavior.

The varying perceptions of different UEQ characteristics also influenced whether a pattern was considered a dark pattern. For ratings and reviews, respondents who considered this type of pattern impractical perceived this pattern as a dark pattern, and respondents who considered it practical perceived it as a digital nudge. For product recommendations, people who perceived the pattern unlikable rated it as a dark pattern, while those who found it likable categorized it as a digital nudge. For product badges and activity messages the differentiating characteristic was the pattern's perceived annoyingness. If the respondent perceived these patterns as annoying, they rated them as dark patterns, whereas people who found them enjoyable considered them as digital nudges.

According to the research model developed in Chapter 4.3, multiple factors influence consumers' subjective online customer experience (OCE), and thus their assessment of a pattern. In this thesis, only antecedents to OCE (background information and individual factors) and mediating factors were considered. The factors relevant to this study are presented in Figure 16 below. The effect of antecedents to and mediators of OCE on the perception of patterns are now considered.

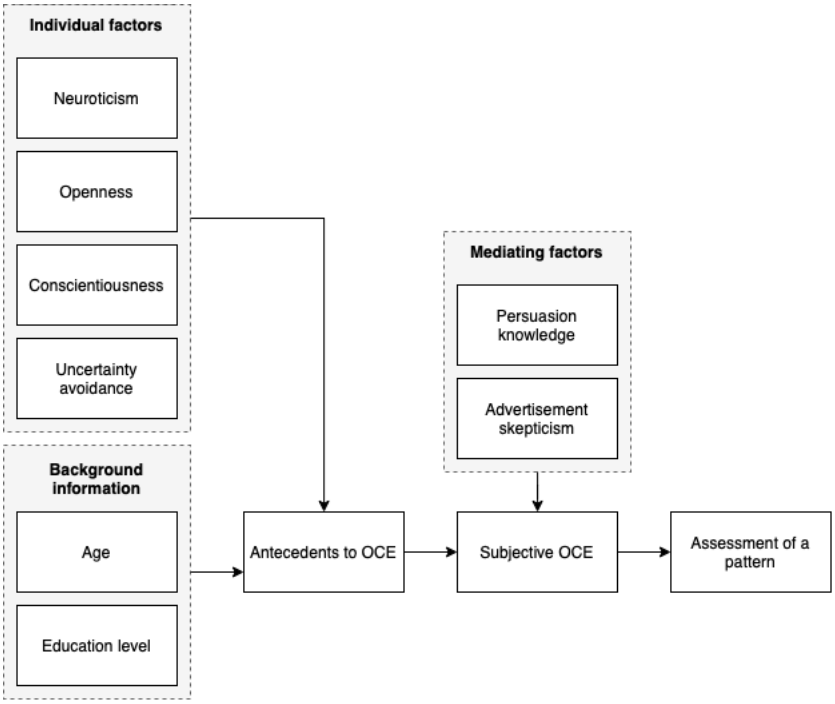

Figure 16: Research model

7.2.1 Background factors

Age and education can be seen as background factors to create an antecedent to the formation of subjective OCE. According to previous research, younger and more highly educated people are more likely to recognize dark patterns when they encounter them (Bongard-Blanchy, 2021), and thus it was hypothesized that younger, more educated respondents would be more likely to categorize the patterns studied in the survey as dark patterns.

In the survey, older respondents were more likely to categorize ratings and reviews as a dark pattern and felt more negatively toward ratings and reviews and product recommendation systems. The effect of age on the perception of patterns can be seen in Figure 17 below. A uniform line describes a statistically significant relationship between pattern categorization and age, and a dotted line describes a statistically significant relationship between triggered feelings and age.

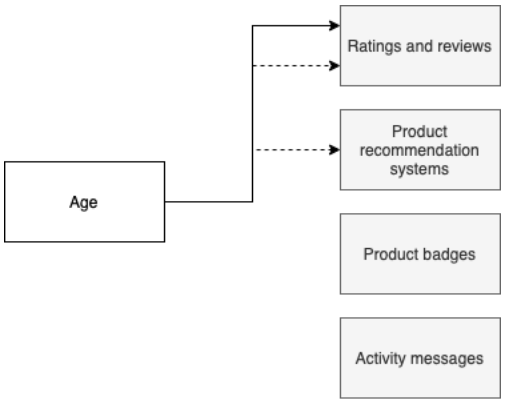

Figure 17: Effect of age on pattern perception

More highly educated respondents felt more negatively toward ratings and reviews, product recommendations, and activity messages. The effect of education level on the perception of patterns can be seen in Figure 18 below.

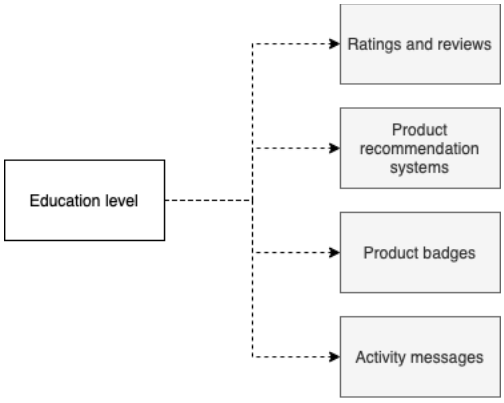

Figure 18: Effect of education level on pattern perception

Thus, the results of the survey are not fully in line with previous research. Even though more educated respondents did show more negative feelings toward pattern 1, 2, and 3, as per the hypothesis, younger people were less likely to categorize the patterns studied as dark patterns. One explanation as to why older respondents were more eager to categorize ratings and reviews as dark patterns than younger respondents might be the development of persuasion knowledge (Friestad, 1994). Through their previous interactions in E-Commerce, older respondents might thus be more aware that many of the ratings and reviews displayed online are fabricated or hand-picked only to show positive experiences about the product to increase sales.

The difference in the results compared to previous studies might also be attributed to the age distribution of the study, which skews toward younger respondents. The oldest respondent in the study was 67 years old, and only 2.8% of the participants were 50 or older. To gain a better understanding of how age affects the categorization of patterns, one should try to gain sample in which the distribution of respondents' age is more balanced.

7.2.2 Individual factors

Literature regarding influencing consumers suggests that people with high neuroticism, low openness, low conscientiousness (Oyibo, 2019), and high uncertainty avoidance (Fenko, 2017) are more susceptible to persuasion and manipulation, and it was thus hypothesized that they would also be less likely to categorize patterns as dark patterns.

Respondents who scored high in neuroticism were less likely to categorize activity messages as a dark pattern. Neurotic people are more prone to doubting their decisions (Delgado, 2022), and might consider the information provided by such a pattern as helpful for their decision-making, rating their usability higher

than respondents low in neuroticism. Patterns studied in the survey also triggered more negative feelings, especially anxiety, for respondents who scored high in neuroticism. Neuroticism is linked to more negative appraisal styles, and people with higher neuroticism are more vulnerable to negative emotions (Tong, 2010), which can be seen represented in neurotic respondents perceiving all the patterns in the study causing more negative feelings when compared to respondents low in neuroticism. The effect of neuroticism on the perception of patterns can be seen in Figure 19 below.

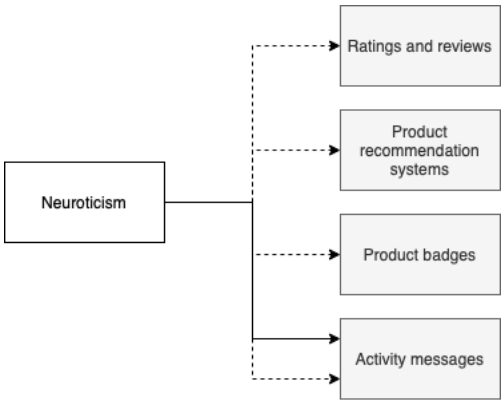

Figure 19: Effect of neuroticism on pattern perception

Low openness was found to decrease respondents' tendency to categorize product badges and activity messages as dark patterns. Less open people are more prone to the influence of social proof (Oyibo, 2019), and might have thus considered product badges and activity messages - patterns that make use of social proof, useful and thus rate their usability higher than people who are more open and less susceptible to social proof. People with low openness had more negative feelings toward product recommendation systems than those with high openness. High openness is related to being open-minded and open to new ideas, including new products (Roccas, 2002). People who score high on openness might thus feel more positively about product recommendations that recommend them novel products, whereas people with low openness show resistance toward new, recommended products. The effect of openness on the perception of patterns can be seen in Figure 20 below.

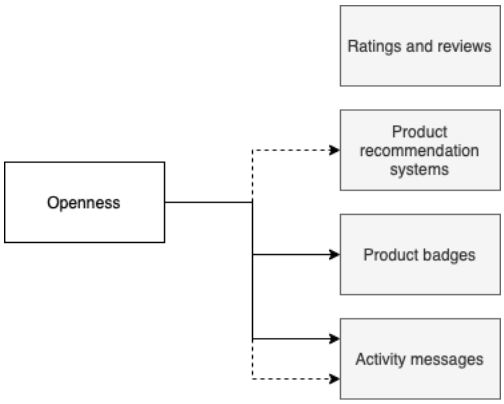

Figure 20: Effect of openness on pattern perception

Even though previous research has linked low conscientiousness to being more susceptible to persuasion and manipulation (Oyibo, 2019), no such relationship was found for any of the patterns. Instead, less conscientious respondents reported more negative feelings toward all patterns. This might be due to the differences in decision-making for people with low versus high conscientiousness. People with high conscientiousness are deliberate decision-makers, wanting to consider all available information to make their decision (Roccas, 2002). They might feel more positive about all the patterns studied in this thesis because they provide extra information (truthful or not) to aid their decision-making. The effect of conscientiousness on the perception of patterns can be seen in Figure 21 below.

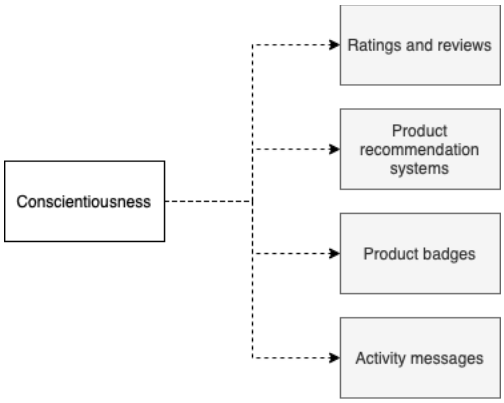

Figure 21: Effect of conscientiousness on pattern perception

High uncertainty avoidance correlated with respondents' perceptions of patterns – respondents scoring high in uncertainty avoidance were less likely to categorize patterns studied in this thesis as dark patterns. Highly uncertainly avoidant respondents rated the usability of patterns 1, 3, and 4 higher than respondents with low uncertainty avoidance. This might be due to highly uncertain people's tendency to rely on heuristics to avoid uncertainty (Fenko, 2017), and thus to make use of even manipulative patterns in their decision-making. Surprisingly, even though respondents with high uncertainty avoidance rated the usability of patterns 1, 3, and 4 higher than those with low uncertainty avoidance, they felt more negatively about all the patterns. This might be caused by the E-Commerce environment of the patterns. Uncertain situations, which often are present in E-Commerce due to information asymmetry, create more anxiety in people with high uncertainty avoidance (Matsumoto, 2008). The effect of uncertainty avoidance on the perception of patterns can be seen in Figure 22 below.

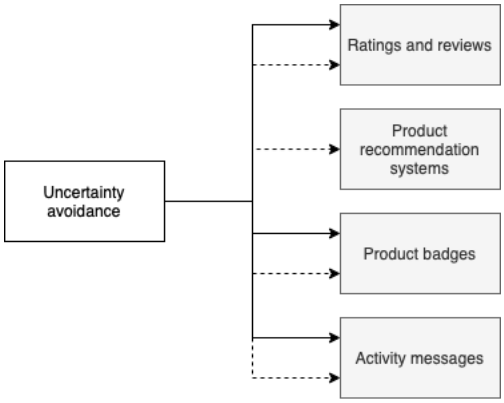

Figure 22: Effect of uncertainty avoidance on pattern perception

7.2.3 Mediating factors

According to previous research, it was suspected that respondents with high persuasion knowledge would more likely categorize the patterns present in the study as dark patterns. Respondents scoring high in persuasion knowledge did rate the usability of patterns 3 and 4 more negatively. People with higher persuasion knowledge are better at recognizing when they are being influenced (Fenko, 2017), and thus might have rated the usability of patterns 3 and 4 worse than people with lower persuasion knowledge. According to the answers to the open-ended questions, many respondents are aware that these patterns are often implemented to boost sales, not to inform customers. On the other hand, respondents with higher persuasion knowledge had fewer negative feelings toward patterns 1 and 2. They might be better at recognizing the value of patterns 1 and 2 and have developed strategies on how to recognize when a pattern provides them with truthful, useful information to aid their decision-making, and when they should be ignored. The effect of persuasion knowledge on the perception of patterns can be seen in Figure 23 below.

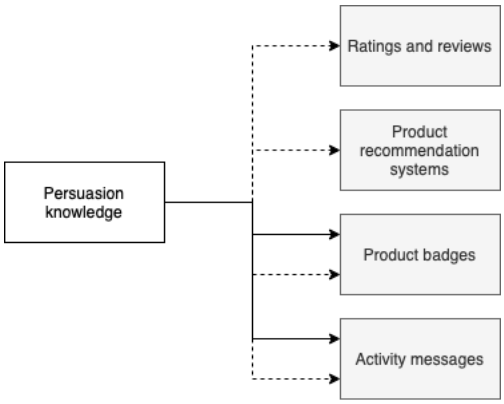

Figure 23: Effect of persuasion knowledge on pattern perception

Like high persuasion knowledge, ad skepticism is linked to being more likely to spot attempts at persuasion and manipulation (Obermiller, 1998). Respondents with high ad skepticism did categorize patterns more often as dark patterns than

respondents with low ad skepticism. Ad skepticism helped respondents regulate their feelings toward the patterns – they reported fewer negative feelings toward all the patterns. The effect of advertisement skepticism on the perception of patterns can be seen in Figure 24 below.

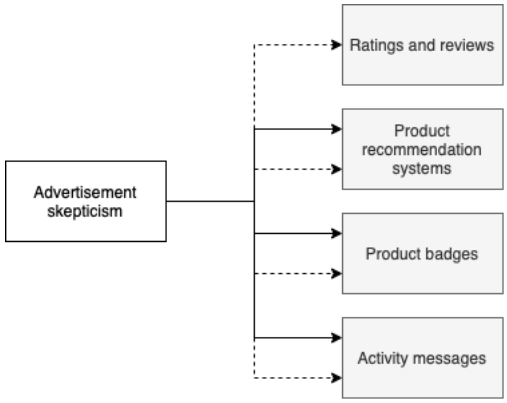

Figure 24: Effect of advertisement skepticism on pattern perception

7.2.4 Summary

Respondents' age, education level, neuroticism, openness, conscientiousness, uncertainty avoidance, persuasion knowledge, and advertisement skepticism all effect the way how respondents perceive patterns and what kind of feelings they trigger.

Respondents' age, neuroticism, openness, uncertainty avoidance, persuasion knowledge, and advertisement skepticism affected their categorization of the patterns studied. Age, education level, neuroticism, openness, conscientiousness, uncertainty avoidance, persuasion knowledge, and advertisement affected the feelings triggered by the patterns.

The statistically significant findings of the study are displayed in Table 22 below.

Table 22: Findings of the study

	Ratings and reviews	**Product recommendation systems**	**Product badges**	**Activity messages**
Age	Older resp. categorized as a dark pattern; felt more frustration, anger, anxiety	More alertness in older resp.	-	-
Education level	More frustration, anger, anxiety in more educated resp.	More anger, anxiety, alertness in more educated resp.	-	More anxiety in more educated resp.
Neuroticism	More anxiety in more neurotic resp.	More frustration, anxiety in more neurotic resp.	More frustration, anxiety, alertness in more neurotic resp.	More neurotic resp. categorized as a digital nudge; felt more anxiety, alertness
Openness	-	More anger, anxiety, alertness in less open resp.	Less open resp. categorized as a digital nudge	Less open resp. categorized as a digital nudge; felt less frustration
Conscientiousness	More anger, anxiety in less conscientious resp.	More anger, anxiety, alertness in less conscientious resp.	More frustration, anger, anxiety, alertness in less conscientious resp.	More anxiety, alertness in less conscientious resp.
Uncertainty avoidance (UA)	High UA resp. categorized as a digital nudge; felt more anxiety, alertness	More frustration, anger, anxiety in resp. with high UA	High UA resp. categorized as a digital nudge; felt more anxiety, alertness	High UA resp. categorized as a digital nudge; felt more anxiety, alertness
Persuasion knowledge (PK)	Less frustration, anger, anxiety in high PK resp.	Less frustration, anger, anxiety, alertness in high PK resp.	High PK resp. categorized as a dark pattern; felt less anger, anxiety	High PK: resp. categorized as a dark pattern; felt more frustration, anger, less anxiety
Advertisement skepticism (AS)	Less frustration, anger, anxiety in high AS resp.	High AS. resp. categorized as a dark pattern; felt less frustration, anxiety, alertness	High AS. resp. categorized as a dark pattern; felt less anxiety	High AS. resp. categorized as a dark pattern; felt more frustration, anger, less anxiety, alertness

7.3 Limitations of the study and considerations for future

This study has some limitations. First of all, the gender and age distribution of participants was not normally distributed but skews more toward younger and male respondents. Over 59% of the participants were 30 or younger, and 62% of the respondents identified as male. This uneven distribution might result from the way the study was shared. The study was shared on the author's social media channels, on the email list of the Faculty of Information Technology, and on SurveyCircle. This attracted a lot of student respondents, many of whom were male. To gain a better understanding of the general population, the survey should be repeated in the sample that has a more even distribution of respondents' age and gender.

Second, the respondents were more active online shoppers than the general population. According to Posti's online shopping survey, 60% of Finns have ordered something within the last month (Posti, 2021). In this survey, 85.8% of the respondents had ordered something online within the last month. This difference might be attributed to the survey being shared online. This might have attracted participants who are in general more active Internet users and thus online shoppers than the general population.

Third, not all sum variables used in the study achieved an acceptable level of internal consistency when measured with Cronbach's alpha. TIPI sum variables were all low in their internal consistency (neuroticism: 0.589, conscientiousness: 0.498, openness: 0.224), and no alterations to the sum variables could be made to improve their internal consistency as each TIPI personality trait variable only consisted of two questions in the survey.

However, this was to be expected as the TIPI scale was originally developed to broadly measure each Big 5 personality trait, instead of obtaining a detailed personality profile of each respondent. Historically, calculated alphas for TIPIs have been low, but their test-retest reliability reaches adequate levels, and respondents' self-evaluations match those of observers' and peers' (Gosling, 2003). Thus, the low alphas of TIPI sum variables can be tolerated in this study. It was more important to try to prevent abandonment rates of the survey by introducing a short measurement of respondents' personalities than to gain a detailed report on their Big 5 traits.

Still, if the study was to be replicated in the future, one might want to define the scope of the study further and focus only on for example personality traits and their effect on the perception of digital nudges and dark patterns. That way a more deliberate measurement of the respondents' personality could be conducted.

Fourth, the language of the survey might have affected its results. The survey was only available in English, which was not the first language for many of the respondents. Multiple people noted in the answers to the open-ended questions that they did not understand some of the questions or had a hard time

choosing an option that fits them best. If the study was to be replicated, it could be translated and localized to multiple languages to ensure that all participants understand the questions fully.

Many answers to the open-ended questions indicated that the respondents questioned the truthful nature of the patterns. Especially reviews and activity messages faced doubts about the possibility of them being automatically generated by a bot. Hence, future studies could elaborate on the role of contextual factors (social cues, cues about certainty, amount of information available) on the formation of subjective OCE.

7.4 Practical implications

Information gained from this thesis can be used by E-Commerce providers to better design E-Commerce environments in the future. Even if a UI pattern had potential to create profit in short-term, the use of often negatively perceived patterns could have a dissatisfactory effect on the company in long-term. Companies must therefore carefully consider why they want to influence consumers' behavior, and how they can do it in a sustainable manner to both sustain their reputation to attract new customers and ensure the loyalty of their existing customers.

The results of this study can also be used to better protect consumers. This study found that younger, less educated people with high neuroticism, low openness, and high uncertainty avoidance are especially vulnerable to persuasion and manipulation. Regulation can be used to help create online environments that help consumers make wise decisions online and help them recognize manipulation attempts they might face.

8 SUMMARY

Digital nudges and dark patterns are becoming ever more prevalent in the E-Commerce landscape due to heightened competition and economic pressure. These patterns work by making use of known psychological vulnerabilities to influence human behavior. We as humans are especially vulnerable to social proof – the tendency to model our own behavior according to that of others around us. In the E-Commerce environment, this social influence can be used to get consumers to donate money to a charity at the checkout (digital nudge) or make them spend more money impulsively (dark pattern).

Some patterns can unanimously be considered digital nudges or unethical dark patterns, but many reside in a gray area between the two. The perception of those patterns is dependent on the highly subjective online customer experience (OCE) a consumer forms when shopping online. OCE is affected by factors like the consumers' background information, personal traits, contextual factors, previous experience online, and previous interactions with that company. Due to the highly subjective nature of OCE, consumers do not always perceive digital nudges and dark patterns similarly. Others might be more skeptical toward all patterns, whereas some consumers might find value even in deceitful or manipulative patterns.

The differing perceptions of often used social influence-based patterns were considered in the empirical part of this thesis. The patterns that were selected to be studied were ratings and reviews, product recommendation systems, product badges, and activity messages. Of those patterns, ratings and reviews and product recommendation systems were considered as digital nudges by most of the respondents. Product badges and activity messages faced a more negative reception, most of the respondents categorizing them as dark patterns.

To find out which traits in respondents affected the way how the patterns were perceived, different factors that were deemed to influence susceptibility to persuasion and manipulation were chosen based on the literature analysis. Different factors that were considered in this thesis were the respondents' age, education level, personality (neuroticism, conscientiousness, openness, uncertainty avoidance), persuasion knowledge and advertisement skepticism.

This study found that older consumers are more wary of social-influence based patterns online and are more likely to categorize them as dark patterns than their counterparts. Similar relationship was not found between education level and pattern categorization, but more highly educated respondents felt more negatively about the patterns. When it comes to personality, consumers with high neuroticism and low openness are less likely to categorize the patterns studied in this thesis as dark patterns. High uncertainty avoidance was also linked to lesser tendency to categorize the patterns as dark patterns. Persuasion knowledge and ad skepticism were linked to more negative ratings of the patterns' usability.

Categorizations of patterns and triggered feelings did not always go together. Even though respondents high in neuroticism and uncertainty avoidance were more susceptible to dark patterns, they also felt more negatively about the patterns studied in this thesis. It must be thus kept in mind that even if a company's customers would not necessarily consider the patterns used by the company as dark patterns, they might still feel negatively of such patterns, negatively affecting their online customer experience.

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APPENDIX 1

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	**df**	**Sig.**	**Statistic**	**df**	**Sig.**
Age	0.124	478	0.000	0.937	478	0.000
Nationality	0.484	478	0.000	0.946	478	0.000
Education level	0.231	478	0.000	0.868	478	0.000
Last purchase	0.254	478	0.000	0.800	478	0.000
Neuroticism	0.095	607	0.000	0.976	607	0.000
Openness	0.127	607	0.000	0.974	607	0.000
Conscientiousness	0.099	607	0.000	0.977	607	0.000
Uncertainty avoidance	0.077	607	0.000	0.983	607	0.000
Persuasion knowledge	0.090	607	0.000	0.965	607	0.000
Advertisement skepticism	0.091	607	0.000	0.950	607	0.000
Pattern 1 UEQ score	0.074	478	0.000			
Pattern 2 UEQ score						
Pattern 3 UEQ score						
Pattern 4 UEQ score						

a. Lilliefors Significance Correction

APPENDIX 2

Full survey

Social Influence Based Features in E-Commerce

Thank you for choosing to take part in this survey!

The goal of this survey is to gain insight into perceptions of social influence based features that are used in E-Commerce. The results of the survey will be used as a part of my Masters Thesis in the University of Jyväskylä.

Answering the survey will take under 10 minutes. All answers to the survey will be collected and stored anonymously.

You will first answer background questions.Then you will be shown four types of features often used in E-Commerce, and are asked to rate them. Finally, you can give your feedback regarding the features and their use in E-Commerce.

Participants of this survey may enter a give away where they have a chance of winning a 20€ Amazon gift card. Amazon is not affiliated with this survey. Three gift cards are given away. If you wish to enter, fill in your email address in the giveaway form linked on the last page of this survey to ensure the anonymity of the questionnaire. Your email address cannot be linked to your answers in this survey. Read the privacy notice of the giveaway here: http://users.jyu.fi/~emjoneva/gradu/privacy-notice.pdf

Thank you in advance!

If you have any questions regarding the survey, feel free to contact me.
Emma Nevala
emjoneva@student.jyu.fi

Gender *

- ◯ Female
- ◯ Male
- ◯ Other

Age *

Nationality *

Education level *

- ◯ High school/vocational school
- ◯ Bachelor's degree
- ◯ Master's degree
- ◯ Doctorate
- ◯ Other, please specify

When was the last time you purchased something online? *

- ◯ During the last week
- ◯ During the last month
- ◯ During the last year
- ◯ Over a year ago
- ◯ I have never purchased anything online

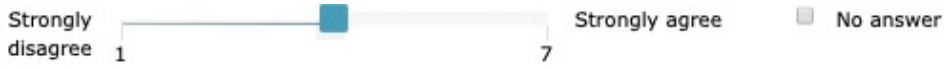
Consider the following statements

I prefer structured situations to unstructured situations *

I prefer specific instructions to broad guidelines *

I tend to get anxious easily when I don't know an outcome *

I feel stressful when I cannot predict consequences *



I would not take risks when an outcome cannot be predicted *

I believe that rules should not be broken for mere pragmatic reasons *

I don't like ambiguous situations *

Consider the following personality traits. I see myself as...

... extraverted, enthusiastic *

... critical, quarrelsome *

... dependable, self-disciplined *

... anxious, easily upset *

... open to new experiences, complex *

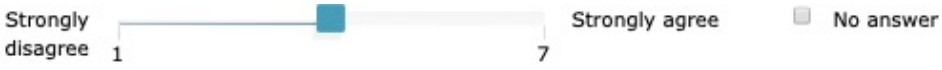
... reserved, quiet *

... sympathetic, warm *

... disorganized, careless *

... calm, emotionally stable *

... conventional, uncreative *



Consider the following statements

I know when an offer is too good to be true *

I can tell when an offer has strings attached *

I have no trouble understanding the bargaining tactics used by advertisers *

I know when a advertiser is pressuring me to buy *

I can see through sales gimmicks used to get consumers to buy *

I can separate fact from fantasy in advertising *

Consider the following statements

We can depend on getting the truth in most advertising *

Advertising's aim is to inform the consumer *

I believe advertising is informative *

Advertising is generally truthful *

Advertising is a reliable source of information about the quality and performance of products *

Advertising is truth well told *

In general, advertising presents a true picture of the product being advertised *

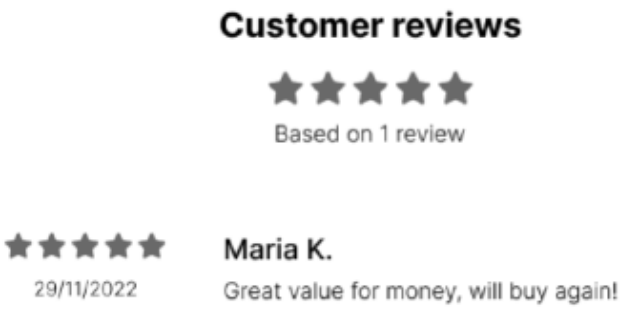
I feel I've been accurately informed after viewing most advertisements *

Most advertising provides consumers with essential information *

Feature 1: Ratings and reviews

Ratings and reviews are a common type of feature used in online stores. Ratings and reviews of other customers are displayed to help the consumer in their decision-making process.

An example of this feature is given below.



I found this feature...

1 2 3 4 5

	1	2	3	4	5	
... annoying	○	○	○	○	○	... enjoyable
... unlikable	○	○	○	○	○	... pleasing
... impractical	○	○	○	○	○	... practical
... clear	○	○	○	○	○	... confusing
... supportive	○	○	○	○	○	... obstructive

This feature makes me feel...

...frustrated *

... angry *

... anxious *

... alert *

Here you can explain your answer in more detail

Feature 2: Product recommendation systems

Product recommendation systems are used to help consumers to find other products that are relevant to them, and to avoid choice overload. The products in the recommendation system are often based in the behavior of other (similar) customers that visit the online store.

An example of this feature is given below.

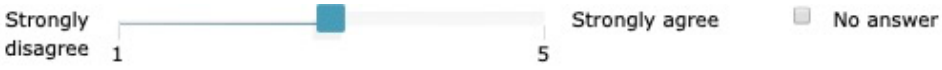
I found this feature...

	1	2	3	4	5	
... annoying	○	○	○	○	○	... enjoyable
... unlikable	○	○	○	○	○	... pleasing
... impractical	○	○	○	○	○	... practical
... clear	○	○	○	○	○	... confusing
... supportive	○	○	○	○	○	... obstructive

This feature makes me feel...

... frustrated *

3



... angry *

... anxious *

... alert *

Here you can explain your answer in more detail

Feature 3: Product badges

Product badges can be used on the home page or on category pages to notify the consumer about products that are very popular or low in stock.This can aid their decision-making process, or help them avoid missing out on a product they want.

An example of this feature is given below.

Shampoos

ONLY 1 LEFT
Lavender Shampoo
9.99 €

Honey Shampoo
9.99 €

Raspberry Shampoo
9.99 €

I found this feature...

	1	2	3	4	5	
... annoying	○	○	○	○	○	... enjoyable
... unlikable	○	○	○	○	○	... pleasing
... impractical	○	○	○	○	○	... practical
... clear	○	○	○	○	○	... confusing
... supportive	○	○	○	○	○	... obstructive

This feature makes me feel...

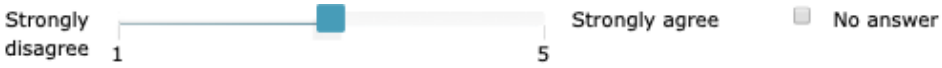
... frustrated *

Strongly disagree 3 1 5 Strongly agree ☐ No answer

... angry *

Strongly disagree 3 1 5 Strongly agree ☐ No answer

... anxious *



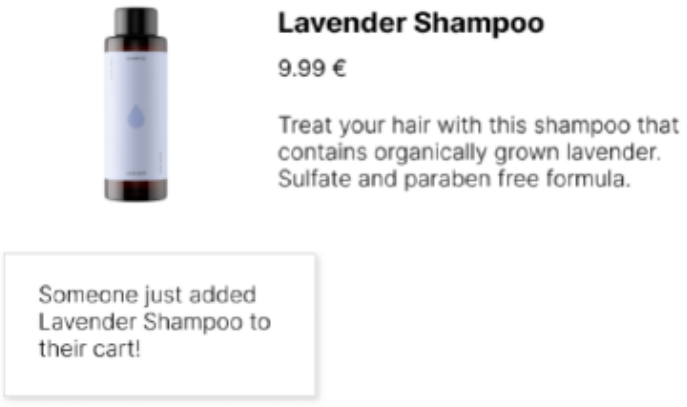
... alert *

Here you can explain your answer in more detail

Feature 4: Activity messages

Activity messages notify customers about the actions of others on the site. It can help consumers to not miss out on a product, if it is low in stock.

An example of this feature is given below.

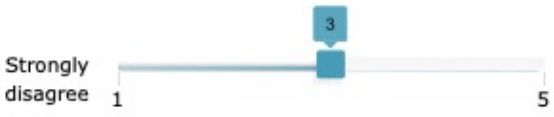


I found this feature...

	1	2	3	4	5	
... annoying	○	○	○	○	○	... enjoyable
... unlikable	○	○	○	○	○	... pleasing
... impractical	○	○	○	○	○	... practical
... clear	○	○	○	○	○	... confusing
... supportive	○	○	○	○	○	... obstructive

This feature makes me feel...

... frustrated *

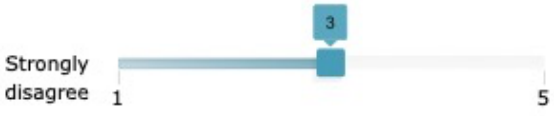


☐ No answer

... angry *

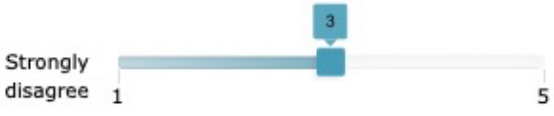
☐ No answer

... anxious *



☐ No answer

... alert *



☐ No answer

Here you can explain your answer in more detail

Do you want to add something? Here you may explain your answers in more detail, or give more general feedback regarding these features in E-Commerce.