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Guided Choices in the Digital Age: Hypernudge and Recommender Systems

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Introduction

Many of us have experienced receiving personalized recommendations for digital content or products and services to purchase, often feeling surprised by how closely some suggestions align with our preferences while others seem off. Consequently, many have wondered how digital platforms manage to grasp our interest in one topic over another or why specific topics are suggested. These questions are addressed by delving into the realm of digital nudge and hypernudge in their various forms. Furthermore, an insinuation arises in our minds: did we make choices autonomously or were we influenced by various recommender systems? Was this conditioning a genuine facilitation in decision-making or a form of manipulation?

The idea behind developing this work stems from a deep interest in consumer psychology. I have always believed that thoroughly understanding the motivations and dynamics behind human decisions is crucial in the field of marketing. This approach was also central to my undergraduate thesis, where I explored neuromarketing and its application within social media. I have always been fascinated by behavioral economics and believe that now, in the digital age, it is more relevant than ever. Technology and artificial intelligence have revolutionized marketing strategies and how companies interact with consumers. However, even in this digital landscape, behavioral economics provides valuable insights into how cognitive biases and heuristics play a crucial role in the decision-making process. With the widespread use of social media and algorithms, we are exposed to subtle influences that seek to guide our choices. Understanding how traditional nudges have transformed into hypernudges in the digital world to give rise to recommender systems commonly used by major online platforms is crucial.

In the first chapter, I will introduce behavioral economics, a field that merges psychology and economics, revolutionizing our understanding of human decisions. I will begin by analyzing concepts such as bounded rationality, heuristics, and cognitive biases, which challenge the traditional idea of the rational *homo economicus*. From the pioneering studies of Herbert Simon to the groundbreaking contributions of Tversky and Kahneman, I will then illustrate the nudge and the theory of "libertarian paternalism" proposed by Thaler and Sunstein, suggesting how small changes in the decision-making environment can positively influence people's choices without limiting their freedom. But what happens when these theories are translated into the digital world, where Artificial Intelligence and Big Data dominate the landscape? This is where the digital nudge and hypernudge come into play. Of particular relevance in this context are recommender systems, true digital navigators in the vast ocean of online options, which steer our choices through the personalization of presented options.

In the second chapter, I will examine the implications of recommender systems and hypernudge, addressing both the advantages and concerns associated with the use of these technologies. I will particularly address ethical and social objections, such as freedom of choice and transparency, as well as economic and epistemic concerns. This will be followed by a brief description of the European regulatory landscape, within which the discussed themes fall: the GDPR and new legislative initiatives, such as the Digital Markets Act and the Digital Services Act, alongside the Artificial Intelligence Act of 2024.

Finally, the third chapter will focus on the empirical quantitative study conducted through a questionnaire. The primary data collected will be analyzed to test the developed hypotheses and draw conclusions on the research subject.

The ultimate goal of this work is not only to contribute to the existing literature but also to provide food for thought for business practices in order to balance the level of persuasion inherent in these technologies, ensuring both added value for companies and greater overall satisfaction for users.

1. Digital nudge, hypernudge and recommender systems

This chapter aims to explore the relationship between the classical theory of nudging in behavioral economics and its adaptations in the digital realm: digital nudge and hypernudge. It begins with a concise introduction to the interdisciplinary field of behavioral economics, which emerged from the intersection of economics and psychology. Subsequently, it delves into foundational concepts such as individuals' bounded rationality, heuristics, and cognitive biases. The chapter then proceeds to elucidate the theory of nudge as formalized by Thaler and Sunstein (2008), along with the concept of "libertarian paternalism" commonly associated with it. Following this, attention is directed towards the themes of Artificial Intelligence and Big data, which underpin the contemporary digital landscape. It is through the integration of these techniques with the classical theory of nudge that two variants emerge: digital nudge and hypernudge. Specifically, hypernudge encompasses all nudge techniques implemented by algorithm-based platforms. Within this context, recommender systems are classified as a subset of both hypernudge and digital nudge.

1.1 The nudge theory as a branch of behavioral economics

1.1.1 Definition and birth of behavioral economics

Behavioral economics is an interdisciplinary field that merges psychology and economics to investigate and model human behavior, considering cognitive limitations (Mirsch et al., 2017). Within this domain, it is argued to provide more realistic psychological foundations to economics, thus enhancing its explanatory power (Colin et al., 2004). Richard Thaler was the first to introduce the concept of "behavioral economics" in 1992. This field, emerging in the 1980s as a sub-discipline of financial economics, built upon behavioral investigations conducted by Daniel Kahneman and Amos Tversky in 1979 (Kahneman & Tversky). A crucial aspect of Kahneman, Tversky, and Thaler's work was the distinction between the "normative" rules of decision-making, based on logic, statistics, and expected utility theory, and the "descriptive" theory of how people actually make decisions (Thaler, 1987). Throughout the 1990s and 2000s, Thaler and other behavioral economists significantly expanded the scope of behavioral economics, moving from a small research program focused on deviations from neoclassical theory in financial economics to a predominant research program drawing from various scientific disciplines and behavioral research methods (Loewenstein & Thaler, 1989). This expansion led behavioral economists to distinguish themselves distinctly from psychology and experimental economics (Thaler, 1993), redefining their scope of study and emphasizing the significant contribution not only of Kahneman and Tversky but also of Herbert Simon. This process led to the creation of a vast and solid economic research program, characterized by a clear separation from experimental economics and psychology (Tversky Kahneman &, 1974). In particular, behavioral economics began as an attempt to understand consumer decisions, challenging the idea of the rational consumer within classical economics (Camerer, Loewenstein, & Rabin, 2004). According to traditional thought, proposed by John Stuart Mill (Persky, 1995), individuals follow the model of homo economicus, acting based on complete awareness of the costs and benefits associated with each action (Persky, 1995). It is therefore assumed that they seek to maximize their long-term profits. However, it is evident that this does not always occur, and behavioral economics has aimed to address this discrepancy (Persky, 1995).

For much of the 20th century, the predominant approach to decision-making was represented by neoclassical economics, a microeconomic perspective outlined by Marshall (1890) and passed down by subsequent economists such as Samuelson and Nordhaus (2009). This model is based on the idea of rationality and optimization within the context of markets. It is presumed that rational decisions involve consistent preferences, logical thinking, and complete information about all aspects of the situation, enabling decision-makers to effectively maximize resource usage to achieve maximum profit in both the consumption and production of goods and services. The idea of maximizing utility in markets has its origins in the theories of Adam Smith (1776) and was formalized in the expected utility theory of Von Neumann and Morgenstern (1944). According to this theory, decision-makers seek to maximize the expected values of their choices, following rigorous conditions of mathematical logic. Numerous criticisms have been leveled against the maximization of expected utility as an effective descriptive theory of decision-making (Arrow, 1950; Allais, 1953; Ellsberg, 1961; Savage, 1954; Akerlof, 1970; Shiller, 1978; Galbraith, 1952). Despite these criticisms, the maximization of expected utility remained the dominant economic theory until the advent and acceptance of behavioral economics.

1.1.2 Bounded rationality, heuristics and cognitive biases

Herbert Simon, the Nobel Prize in Economics in 2002, laid the groundwork for Behavioral Economics (BE) in his pioneering articles: "A Behavioral Model of Rational Choice" in the Quarterly Journal of Economics (Simon, 1955) and "Theories of Decision-Making in Economics and Behavioral Science" in the American Economic Review (Simon, 1959). Simon criticized the traditional idea of the rationality of economic decisions, based on his studies of administrative managers in the 1940s. He argued that decision-makers cannot have a perfect understanding of a decision situation and are limited in their cognitive abilities and information processing, as well as often being subject to time constraints that limit their ability to calculate utility perfectly. Behavioral research reinforced Simon's assertion that rationality is limited and that when faced with complex or incomplete information, people tend to find satisfactory rather than optimal solutions.

A detailed explanation of how bounded rationality, proposed by Simon, influences the human decision-making process was provided by Kahneman (1973; 2003), who introduced the "two-system theory" (also known as dual-process theory). This theory suggests that individuals use different cognitive approaches during the decision-making process. In particular, based on the original formulation by Stanovich and West (2000), it distinguishes between a fast-thinking system (System 1) and a slow-thinking one (System 2). These two systems, also known as automatic and reflective, operate simultaneously and interact during the decision-making process. Specifically, System 1 is characterized by speed, automaticity, and emotionality, and is driven by innate and instinctive behaviors. When facing a decision, it is System 1 that immediately springs into action, producing intuitions based on past experiences and automatic associations. In contrast, System 2 is slower, controlled, and flexible, governed by precise rules. Both systems produce impressions about the objects to be evaluated, but while System 1 operates automatically and associatively, System 2 is based on rationality and characterized by slow and controlled information processing. Although they operate as distinct systems, System 1 and System 2 can interact and influence each other. As described by Kahneman and Frederick (2002), System 2 supervises the intuitive responses generated by System 1, evaluating them and correcting them if necessary. Empirical studies in the field of social psychology have established that daily activities are predominantly influenced by System 1, making the decision-making process susceptible to heuristics and biases (Kahneman, 2011).

Heuristics, also defined as cognitive simplification strategies, are systematically used to address complex decision problems by reducing them to more manageable situations (Sanjari et al., 2017; Ross, 2014). These strategies tend to operate automatically and intuitively, enabling rapid information processing, especially when cognitive resources are limited. Although they can facilitate immediate and efficient decisions, depending on the context, heuristics can also lead to incorrect assessments and distortions in perception, thereby shaping cognitive biases (Haselton et al., 2005; Tversky & Kahneman, 1974).

Cognitive biases, which are systematic deviations from accurate or desirable evaluation, often stem from the use of heuristics (Sanjari et al., 2017; Ross, 2014). These biases represent predictable and regular errors in information processing, resulting from external influences or misguided interpretations based on previous experiences (Tagliabue et al., 2019). In this way, biases can be seen as a consequence of human limited rationality in the decision-making process.

1.1.3 *Overview of the main cognitive biases and heuristics*

Tversky and Kahneman (1974) identified three fundamental heuristics, based on Simon's work, that influence human decisions: availability, representativeness, and anchoring and adjustment bias.

Availability refers to people's tendency to assess the likelihood of events based on the ease with which relevant examples can be recalled from memory (Tversky & Kahneman, 1974). For example, if individuals are frequently exposed to news about plane crashes through the media, they might overestimate the probability of such an event, even though statistically it is unlikely. This heuristic is influenced by the salience of events, meaning their ability to capture attention and remain memorable.

Representativeness, according to Kahneman and Frederick (2002), Lim and Benbasat (1997), and Nisbett and Ross (1980), concerns how people assess the probability of an event based on its similarity to a stereotype or a set of events. For instance, one might infer someone's occupation based on stereotypes, even though such attributes are not necessarily indicative of reality. Additionally, when applying this heuristic, people tend to give more weight to current information than their overall knowledge (Liu & Du, 2016).

Lastly, *anchoring and adjustment* bias, as described by Tversky and Kahneman (1974), occurs when people make initial estimates based on an "anchor" provided by previous information or a first impression. This can lead to an excessive reliance on initial information, influencing subsequent assessments. For example, if an arbitrary number is presented before making an estimate, individuals tend to anchor their evaluation on that number, even if it is unrelated to the actual situation. This phenomenon is also known as the "first impression bias."

In addition to the three general heuristics identified by Tversky and Kahneman (1974), research has identified a wide range of cognitive and behavioral obstacles in the rational decision-making process. Among these, there are some particularly well-known and significant cognitive biases for our study.

The first is the *status quo* bias, also known as "inertia," which refers to people's tendency to stick with the current situation because the costs associated with leaving the status quo are perceived as higher than the benefits of change (Mirsch et al., 2017). Another important bias is loss aversion, a concept introduced by Kahneman (1991), which highlights people's tendency to give more weight to losses than gains. In other words, people are more inclined to take risks to avoid a loss rather than to achieve a gain (Lockton, 2012). Kahneman and Tversky's prospect theory (1979) sought to explain how people evaluate choices in terms of loss or gain. For example, studying preferences behind choices like A: 'an 80% chance of £4,000, a 20% chance of nothing' or B: 'a 100% chance of £3,000,' it was found that many people tend to prefer option B, despite option A having a higher expected value.

Social norms, as described by Cialdini et al. (1998), are rules and standards that influence social behavior without resorting to the force of laws. People often orient themselves toward others' behavior when unsure about what is appropriate behavior in a given situation. For example, campaigns leveraging social norms, such as promoting seatbelt use in the United States, can influence people's behavior through social proof.

The *framing effect,* according to Waldman (2020), refers to how opportunities are presented to consumers, either positively or negatively. People are influenced by how information is framed and may make different decisions based on how options are presented to them. For example, presenting information emphasizing benefits rather than losses can influence people's decisions.

Hyperbolic discounting, as discussed by Thaler and Benartzi (2004), describes individuals' tendency to value the present and near future more than the distant future. This can lead people to prefer options with immediate benefits, even if long-term effects might be better. For example, rewards like direct cash payments or price subsidies are used to incentivize long-term healthy behaviors.

Choice overload, as highlighted by Scheibehenne et al. (2010), occurs when people are exposed to an excessive amount of options, which can overwhelm and paralyze consumers. This phenomenon can lead to decision fatigue, procrastination, and choosing default options. Although society often values variety and freedom of choice, studies show that excessive variety can have negative effects on psychological well-being and performance.

Finally, *confirmation bias*, according to Nickerson (1998), occurs “when people seek, interpret, and remember information that confirms their pre-existing beliefs”. Evidence supporting a viewpoint is often more readily accepted, while evidence that may challenge existing beliefs is often ignored or critically evaluated. This can lead to a distorted interpretation of evidence and a lack of objectivity in the decision-making process.

1.1.4 Nudge theory: the concept of “libertarian paternalism"

The concept of "nudge," first introduced by Wilk (1999) and later popularized in the book "Nudge: Improving Decisions about Health, Wealth, and Happiness" by Thaler and Sunstein (2008), has sparked growing interest in the field of behavioral influence. Recently, there has been increasing attention to understanding how to intervene on cognitive biases and improve decision-making for the benefit of individuals (Battaglio et al., 2019). Thaler, awarded the Nobel Prize in 2017, has contributed to shaping the concept of libertarian paternalism, which is based on the idea that small variations in decision contexts can have a significant impact on final decisions (Sunstein and Thaler, 2003). "Choice architects," who design the decision environment, have the power to influence people's decisions. "Choice architecture" refers to the environment in which people make decisions, and choice architects can use stimuli that influence people's behaviors to improve their well-being, according to their own judgments (Thaler et al., 2012). Often, people make decisions they might avoid if they had greater attention, complete information, unlimited cognitive capacity, and full self-control (Thaler, 2017; Thaler and Sunstein, 2008). Consequently, "nudges" have been proposed as tools to help people make better decisions. Defined by Sunstein and Thaler (2009), "nudges" are elements of the decision environment that predictably alter people's behavior without limiting available options or significantly changing their economic incentives. Hausman and Welch (2010) suggest broadening the concept of "nudge" to include all other types of incentives that influence choices without limiting available options or making them significantly more costly in terms of time, inconvenience, or social sanctions. According to Thaler and Sunstein, libertarian paternalism justifies the use of "nudges" as it preserves freedom of choice while guiding people toward decisions that improve their well-being (Thaler & Sunstein, 2003). The goal of "nudges" is to make decision-makers "better" according to their own judgment, aligning their actual choices with those that would be generated by their rational preferences (Sunstein & Thaler, 2003).

"Nudges" influence decisions through various mechanisms, as highlighted by Lin et al. (2017):

(a) Providing relevant information to alter the perception of options (e.g., leaflets on the benefits of taking stairs over using the elevator).

(b) Correcting misconceptions about social norm behaviors (e.g., providing individuals with data on alcohol consumption habits among their peers).

(c) Altering the profiles of different choices to make some options more appealing (e.g., increasing the visibility and accessibility of healthy food in school cafeterias).

(d) Implementing default options to guide decisions in a desired direction. In particular, a "default" is considered the option automatically selected when a decision-maker fails to actively choose (Thaler et al., 2013). Specifically, the implementation of default options, such as switching from an opt-in to opt-out[1] organ donation system, has been shown to be effective in guiding people's decision-making behavior (Bonell et al., 2011; Johnson & Goldstein, 2003). Default rules simplify people's choices and are widely used to promote desired behaviors in various sectors.

[1] Johnson and Goldstein (2003) studied how defaults and framing influence organ donation by examining opt-in and opt-out options. In countries with presumed consent, such as Austria and France, the default is donation unless one opts out. In countries like the United Kingdom and Denmark, explicit consent is required, with a default of non-donation. The study compared participants' choices under opt-in, opt-out, and neutral conditions. Donation rates were significantly higher under opt-out conditions compared to opt-in, highlighting the importance of the default in the decision to donate organs.

1.2 Artificial Intelligence and Big Data

The roots of Artificial Intelligence (AI) date back to the 1950s, as indicated by Duan et al. (2019). The concept of AI, defined as "the ability of a machine to learn from experience and perform human-like tasks", is closely linked to the evolution of Big Data (Duan et al., 2019). Thanks to the progress in Big Data technologies, AI has experienced significant growth, fueling the rapid development of AI and offering unprecedented opportunities to analyze vast amounts of information (Duan et al., 2019). Digital technologies based on algorithms, as emphasized by Harasimiuk & Braun (2021), have permeated every aspect of modern life, with AI playing an increasingly central role (Harasimiuk & Braun, 2021; McCarthy et al., 2006). In particular, AI is emerging as a fundamental resource in the business context, as highlighted by Hickman & Petrin (2021), with applications that improve operational efficiency and customer interaction. At the same time, key AI technologies such as machine learning (ML), deep learning (DL), and natural language processing (NLP) instruct computers to process large amounts of data to generate market-relevant insights, as indicated by Paul and Rakshit (2021). In the field of marketing, AI has assumed an increasingly important role in decision-making, overcoming traditional challenges, according to Krishnamoorthy et al. (2022). Thanks to its advanced analytical capabilities, AI enables companies to proactively predict customer needs and preferences, transforming marketing strategies. A tangible example of AI usage in marketing is predicting the times when users are most likely to check their email inbox, as indicated by Krishnamoorthy et al. (2021) and Anbuchezhian et al. (2020). This allows email service providers to send more targeted and effective messages, enhancing customer engagement. Additionally, AI provides valuable insights into consumer interaction and identifying their characteristics, as highlighted by Krishna et al. (2023). Through data analysis, companies can better understand customer needs and personalize their offerings more accurately. Predictive analysis, facilitated by AI, allows companies to anticipate customer needs and adopt optimal pricing strategies, as illustrated by Rane (2023). This contributes to improving customer satisfaction and optimizing business operations. Furthermore, data-driven technologies are revolutionizing customer service by introducing chatbots and virtual assistants that provide immediate responses to customer inquiries (Rane, 2023).

Closely related to AI, the concept of Big Data refers to the management and analysis of large amounts of data, including the collection, processing, and visualization of vast sets of information (Emmanuel & Stanier, 2016). This definition was introduced in 2008 by the Gartner Group and led to a comparison with traditional data systems, highlighting the differences and opportunities offered by the new technology (Gartner Research, n.d.). Definitions of Big Data commonly rely on the original three "Vs" proposed by Laney (2001): Volume, Velocity, and Variety, reflecting the quantity, speed, and diversity of data. Over time, other dimensions have been added, such as Value and Veracity, emphasizing the importance of fully understanding the potential of data and its reliability. The process of creating virtual value associated with the concept of Big Data involves various stages, including data collection, organization, selection, synthesis, and distribution (Rayport & Sviokla, 1995). This process aims to extract value from available information, enabling the formulation of informed decisions and the optimization of business operations. The potential of Big Data extends across a wide range of sectors, from human language analysis to financial management, and even urban energy planning (Mayer-Schönberger & Cukier, 2013). In the medical field, Big Data could revolutionize pharmacological therapy, enabling personalized treatments for patients, improving their effectiveness, and reducing side effects. Applications of Big Data are rapidly spreading, facilitating the customization of offers, services, and products (Mayer-Schönberger & Cukier, 2013). For example, automatic language recognition and processing are highlighted by systems like Apple's Siri and Google Maps (Mayer-Schönberger & Cukier, 2013). In the financial sector, most market transactions are now managed by automated trading algorithms (Mayer-Schönberger & Cukier, 2013). However, Big Data also poses new challenges, such as managing the volume, velocity, variety, and veracity of data, requiring the development of new algorithmic and computational strategies (Mayer-Schönberger & Cukier, 2013). Additionally, with the annual production of data surpassing all of human history, the need to address ethical and security issues related to data management is emerging (Mayer-Schönberger & Cukier, 2013).

In conclusion, while Big Data and AI offer unprecedented opportunities to optimize processes and support decisions, they also require rigorous data management and careful attention to their ethical and security implications (Mayer-Schönberger & Cukier, 2013).

1.3 Digital nudge in decision-making

Digital nudging is a concept that has gained increasing importance in the digital environment, where more and more decisions are made on screens such as websites or mobile apps (Mirsch et al., 2017). This approach relies on the use of user interface design elements to influence users' behavior in digital choice environments (Weinmann et al., 2016). Digital interfaces serve as environments where individuals make decisions, being choice architectures that present the decision context (Dalecke & Karlsen, 2020). The concept of digital nudging incorporates insights from behavioral economics and nudge theory into Information Systems (IS) research. Initially, nudges were studied in offline decision contexts, mainly focusing on decisions related to health or financial well-being (Jesse & Jannach, 2021b). Subsequently, with the increasing popularity of the concept, several authors introduced the term "digital nudging" when applying the concept to the online context (Mirsch et al., 2017; Schneider et al., 2018; Weinmann et al., 2016). According to a shared definition, digital nudging refers to elements of software application user interfaces (UI) that influence users' decisions (Weinmann et al., 2016). The main goal is to help them make decisions that are better for them, guiding them towards predefined and desired options without limiting their freedom of choice (Jesse & Jannach, 2021b). Weinmann et al. (2016) define digital nudging as "the use of user interface design elements to influence people's behavior in digital choice environments" (Schneider et al., 2018). Furthermore, they propose a five-phase process for developing nudges in online decision environments (as illustrated in Figure 1).

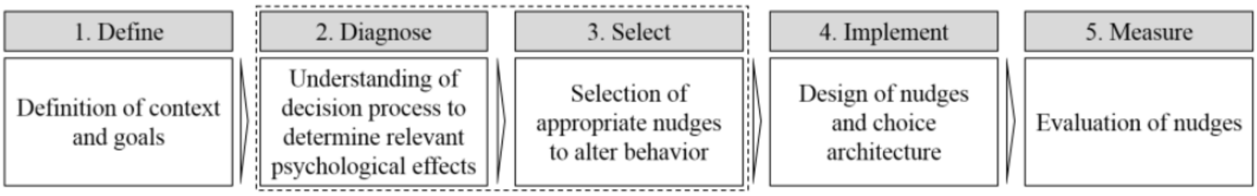

Figure 1: Digital Nudge Process (Weinmann et al., 2015)

Meske and Potthoff (2017) build on this definition, extending it to also include the aspect of free choice. Additionally, they broaden the concept of nudging beyond changes in the user interface, considering choices regarding the form and content of information as possible nudges. They define digital nudging as a "subtle form of using design, information, and interaction elements to influence user behavior in digital environments, without limiting the individual's freedom of choice." Compared to analog nudging, digital nudging offers several unique advantages. Developers have greater freedom to modify digital interfaces at minimal cost, thanks to digital prototyping and other techniques (Simon, 1981). This makes the implementation and testing of digital nudges simpler and faster compared to analog counterparts (Lembcke et al., 2019). Additionally, online environments offer a wide range of opportunities to personalize user choices, thanks to data collection and analysis (Fan & Poole, 2006; Sætra, 2019). Personalizing information and nudges based on users' specific contexts occurs across a broad online spectrum, with greater depth leading to more effective outcomes (Mills, 2022a). In the digital environment, people's tendency to make hasty decisions is fueled by the abundance of information on the internet, making it difficult to process all relevant details for optimal choice (Benartzi et al., 2015). This context underscores the importance of nudging as a tool to influence users' decision-making process, leveraging specific internet functionalities such as user tracking (Weinmann et al., 2016).

Empirical evidence suggests that digital environments favor a more automatic and intuitive approach, known as "System 1" (see dual-process theory, section 1.1.2), due to their high visibility and the vast amount of information available (Benartzi & Lehrer, 2015). This richness of information can lead to decision overload and reduced ability to maintain attention on digital screens, especially in young individuals who often tend to engage in superficial information processing behaviors, marked by quick shifts in attention and diminished reflection (Liu, 2005; Loh & Kanai, 2016). Under conditions of limited attention, people become more susceptible to judgment errors during digital information processing, influenced by both "traditional biases" and digital-specific phenomena, such as "visualization bias"[2] (Benartzi & Lehrer, 2015). The layout and visual salience of options can influence decision-making, for example through the "center bias" that makes options or information placed in the center of the screen more likely to be noticed, amplified in the digital space by screen visibility (Christenfeld, 1995; Milosavljevic et al., 2012; Reutskaja et al., 2011; Simons et al., 2017). In addition to these challenges, digital applications offer a wide range of innovative tools and features with the potential to enhance the effectiveness of nudges. Among these are filtering options, recommendation systems, advanced tracking and targeting methods, as well as feedback tools and a variety of techniques for individualization and personalization (Mirsch et al., 2017).

In digital contexts, a classic example of universal digital nudge is represented by the presence of a pre-selected privacy checkbox during online service registration, used to obtain user consent to the processing of their personal data (so-called "default option", see section 1.1.4, letter (d)) (Mirsch et al., 2017). Elsewhere, companies adopt strategies based on the status

[2] The "visualization bias" in digital environments refers to the distortion or manipulation of data or their presentation to support a specific agenda, perspective, or impression. This can compromise the accuracy and effectiveness of visualizations, leading to misleading conclusions (Dougherty & Ilyankou, 2024).

quo bias (see section 1.1.3) by setting default values on their websites, such as insurance options on travel sites or delivery modes on e-commerce sites. For instance, online car configurators like the one found on Tesla.com are another practical manifestation of digital nudging. Here, default settings are proposed during the configuration of a model, influencing user choices (Mirsch et al., 2017). A similar approach is taken for software products, where pre-selected installation options are offered. On e-commerce sites like Amazon, the principle of social norms (see section 1.1.3) is evident in product recommendation systems, where items are suggested based on other customers' purchases ("Customers who bought this item also bought"). This approach uses others' buying behavior as a social norm, influencing user choices (Mirsch et al., 2017). Another example of nudging related to loss aversion bias (see section 1.1.3) can be found on Booking.com, where statements like "Booked 36 times today," "-45% TODAY!", "8 people are looking right now," or "Very popular!" are shown on the hotel search results page to urge users not to miss out on opportunities. This information about popularity or scarcity of supply can influence users' purchasing decisions (Mirsch et al., 2017). Europcar employs an approach based on hyperbolic discounting bias (see section 1.1.3) on its website, offering immediate rewards to customers. On the search results page for car rentals, two prices are displayed for each option. The "One Price" option allows users to save 9% on the booking if they decide to pay online along with the car reservation. This incentivization mechanism aims to push users toward immediate purchase by offering them a financial advantage (Mirsch et al., 2017).

In particular, research and development on digital nudges have sparked great interest and attention in two specific sectors: health and sustainability (Mirsch et al., 2017). In health-related contexts, nudges aim to promote behaviors such as balanced diet, increased physical activity, smoking cessation, and proper medication adherence. These technologies, akin to personalized consultations provided by healthcare professionals like nutritionists or personal trainers, seek to offer tailored advice adapted to the needs, desires, and trends of each individual. Automated interventions focus on personalizing nudges based on specific health conditions and modifiable factors, such as level of social support, stress, and health literacy (Seixas et al., 2020). Research on the effectiveness of such approaches is extensive and utilizes various metrics to assess success. Some researchers rely on end-user opinion, measured through survey tools, as an effectiveness indicator. More sophisticated studies, such as randomized controlled trials, evaluate the effects of personalized interventions on physical activity and dietary habits. Preliminary evidence suggests that personalized interventions can increase physical activity and improve outcomes in terms of weight loss and maintenance

(Rabbi et al., 2015; Asbjørnsen et al., 2015; Van Velsen et al., 2019; Latimer et al., 2010). Attention toward environment-focused digital nudges has also garnered interest. Researchers have investigated the effectiveness of such nudges in promoting eco-friendly behaviors, such as more moderate driving to reduce fuel consumption (Boriboonsomsin, n.d.; Froehlich et al., 2009; Siero et al., 1989; Tulusan et al., 2012), adherence to deviation instructions to improve fuel efficiency (Xu et al., 2020), and adoption of more environmentally friendly transportation alternatives (Bothos et al., 2014). In many cases, such nudges have been shown to significantly influence individuals' behaviors.

In summary, digital nudging represents an evolution of the traditional nudging approach, leveraging the peculiarities of online environments to guide users' decisions more effectively and efficiently.

1.4 Hypernudge: Definitions, current applications and differences from traditional nudge

As mentioned earlier, the field of digital economy is increasingly user-centric, with processes of datafication and monetization of daily activities (Couldry & Mejias, 2019). The central focus of this transformation is the individual, upon whom online entrepreneurial strategies concentrate, aiming to influence user behavior by exploiting their peculiarities and situations (Kosinski et al., 2013). Among the most advanced forms of this influence are hypernudging processes. The concept of "hypernudge" was coined by legal scholar Karen Yeung (2017) to describe the merger of behavioral science and computer science for algorithmic regulation. This term encapsulates this synergy, with "hyper" referring to the vast availability of computational resources and data in the computing domain, while "nudge" (as highlighted in section 1.1.4) refers to a subtle action of behavioral modification.

In particular, Yeung (2017, p. 122) describes hypernudges as: "[N]imble, unobtrusive, and highly potent, providing the data subject with a highly personalized choice environment … Hypernudging relies on highlighting algorithmically determined correlations … dynamically configuring the user's informational choice context in ways intentionally designed to influence decisions". According to Yeung, two crucial aspects of hypernudge are instant algorithmic personalization and the redefinition of decision structures based on large (personalized) datasets. Through a continuous process of personalization and redefinition of the user's decision context, typically by algorithmically analyzing data streams from various sources, these interventions subtly but extremely effectively influence user choices (Yeung

2017: 119). These processes rely on the analysis of real-time data and the user's personal data history. Other scholars have offered similar definitions. Morozovaite (2021, p. 117) writes, “Hypernudging is one of the most sophisticated forms of digital nudging that allows for dynamically personalized user steering, where the aim is to reach the right user, with the right message, by the right means, at the right time, as many times as needed”.

Based on the so-called "algorithmic governance," which is increasingly prevalent in the digital context, hypernudge focuses on massive data acquisition to identify robust correlations. This information can then be processed and transformed into algorithmically delineated directives, changes in the everyday digital environment, or nudge strategies (Kalpokas, I., & Kalpokas, I., 2019). According to McAfee and Brynjolfsson (2017), the shift towards algorithmic governance has been driven by five major recent developments: "data, algorithms, networks, cloud, and exponential improvement in hardware." The abundance of data has allowed unprecedented detailed access to the world and its inhabitants. Algorithms have enabled the analysis and recognition of patterns within this vast flow of information. Networks have facilitated economic, instantaneous, and near-universal transmission of both data and the results of their analysis. The cloud has provided extended and flexible storage and processing space, useful for both data-related operations and the development of new and more powerful algorithms. Finally, improvements in hardware have added pure power to data acquisition and analysis. All these advancements have profoundly disrupted, and indeed transformed, not only private life and the economy but also decision-making processes related to governance (Kalpokas, I., & Kalpokas, I., 2019).

Hypernudges distinguish themselves from Thaler and Sunstein's nudges due to their greater complexity, invasiveness, and potency. Thaler's criteria for defining a good nudge are difficult to meet due to two characteristics that differentiate hypernudges from traditional nudges: dynamism and predictive capability (Lanzing, 2019). Dynamism is a key characteristic of hypernudging, which relies on personalized real-time feedback. Using instantly updated data, it can adapt choice options for millions of users with a simple click of the mouse, providing each of them with a tailored range of options (Lanzing, 2019). In contrast, a traditional nudge addresses a general audience and offers uniform options for everyone (Lanzing, 2019). Regarding predictive capacity, the main difference between a traditional nudge and a hypernudge lies in the instantaneous change in response to feedback (Mill, 2022). Predictive capacity involves the use of intelligent algorithms that learn from data and make predictions about behavior, thus leading to constant redefinition of individual choices (Lanzing, 2019). While nudges can be adapted, they require time to be modified. Hypernudges, on the other hand, receive immediate feedback on the effectiveness of their actions (Lanzing, 2019). It is also possible to differentiate between intra-platform hypernudging, which takes place within a single platform ecosystem, and inter-platform hypernudging, where a choice architect not tied to any specific platform creates hypernudges that extend across multiple platforms (Morozovaite, 2023)..

Concrete examples of hypernudges include:

- Targeted advertising (Morozovaite, 2021): Targeted advertising is a form of hypernudge that provides personalized ads based on users' characteristics and online behavior. In particular, intra-platform hypernudge focuses ads within a single platform such as Google or Facebook, while inter-platform hypernudge delivers ads across multiple platforms, targeting users wherever they are online. For instance, while an ad on Facebook might be an example of intra-platform hypernudge, a advertising campaign using targeted ads on various websites and social media platforms exemplifies inter-platform hypernudge.

- Self-tracking technologies (Lanzing, 2018), thanks to which users' behavior is recorded while wearing digital devices or oversee their behaviors using apps installed on their mobile devices, offering personalized feedback. In particular, there are fitness apps and devices such as Strava, FitBit and Runkeeper that provide reports to athletes; Other examples of self-tracking technologies include SleepCycle (improve your sleeping patterns), Lose it (aimed at weight loss) and What to Expect (pregnancy), as well as medical apps for diagnosing symptoms (23andMe) and apps for monitoring specific parameters, such as blood glucose levels for diabetic patients (MySugr).

- Virtual assistants: Virtual assistants based on artificial intelligence, such as Amazon's Alexa, Apple's Siri, and Google Assistant, represent concrete examples of hypernudges. These virtual agents dynamically personalize responses and suggestions based on user interactions, creating a highly profiled digital environment. For instance, Alexa can suggest Amazon products based on past searches, while Siri can provide driving directions based on the user's location.

- Recommender systems (see next section)

1.5 Recommender systems

When an individual suggests a restaurant, a movie, or a novel, they are usually rewarded for such recommendation. Over time, the recipient evaluates whether to follow the suggestion, based on their own knowledge and circumstances. However, with the advent of AI-based recommendation systems, recommendations for restaurants, movies, books, and other relevant items are often generated by algorithms rather than by people (Bartmann, M., 2023).

1.5.1 Recommender systemse: definition

In the online world, the vast array of options available can turn the decision-making process into a complex maze, often leaving users searching for a compass to guide them towards the most appropriate choices (Jannach et al., 2010; Ricci et al., 2011). This is where recommendation systems (RS) come into play, serving as true digital advisors that act as personalized guides to help users navigate through the jungle of online choices and identify what best suits their tastes and needs (Ricci et al., 2021). RS tap into our natural inclination to trust others' opinions to make informed decisions in everyday life, whether it's choosing a book to read, a movie to watch, or even hiring a new employee (Paul Resnick and Hal R. Varian, 1997). Leveraging sophisticated algorithms, these systems analyze user behavior to anticipate their preferences, enabling them to make more informed and targeted choices (Paul Resnick and Hal R. Varian, 1997).

RS are powered by data mining[3] and machine learning[4], processes that allow them to generate personalized predictions considering users' preferences, interests, and past interactions (Gössl, SL, 2023; Vargas & Castells, 2011). The main goal of these systems is to simplify the decision-making process by providing clear and targeted recommendations that reduce the time needed to make a decision and minimize regrets associated with unmade choices (Ricci et al., 2015). Recommendations are presented in an orderly and structured manner, offering users easy access to available options and allowing them to explore more complex choices with greater ease (Jesse & Jannach, 2021b). Besides streamlining the selection process, RS have a significant impact on digital platforms and the businesses that use them. They represent a fundamental element of digital architecture, enhancing user experience on platforms like Amazon, Airbnb, Netflix, and Tinder (Bartmann, M., 2023). Additionally, recommendation systems play a crucial role in companies' profits, with enterprises like Amazon attributing a significant percentage of their sales to recommendation systems (Jannach and Jugovac, 2019), and platforms like Netflix and YouTube basing much of the content viewed by users on personalized recommendations (Amatriain and Basilico, 2012; Davidson et al., 2010). Examples of recommendation systems are provided in Figures 2 and 3.

[3] Data mining, also known as knowledge discovery in data (KDD), is "the process of uncovering patterns and other valuable information from large data sets" (What is data mining? | IBM. (n.d.).

[4] Machine learning (ML) is a process in which computing systems learn from data and use algorithms to execute tasks without being explicitly programmed (Wazid et al., 2022).

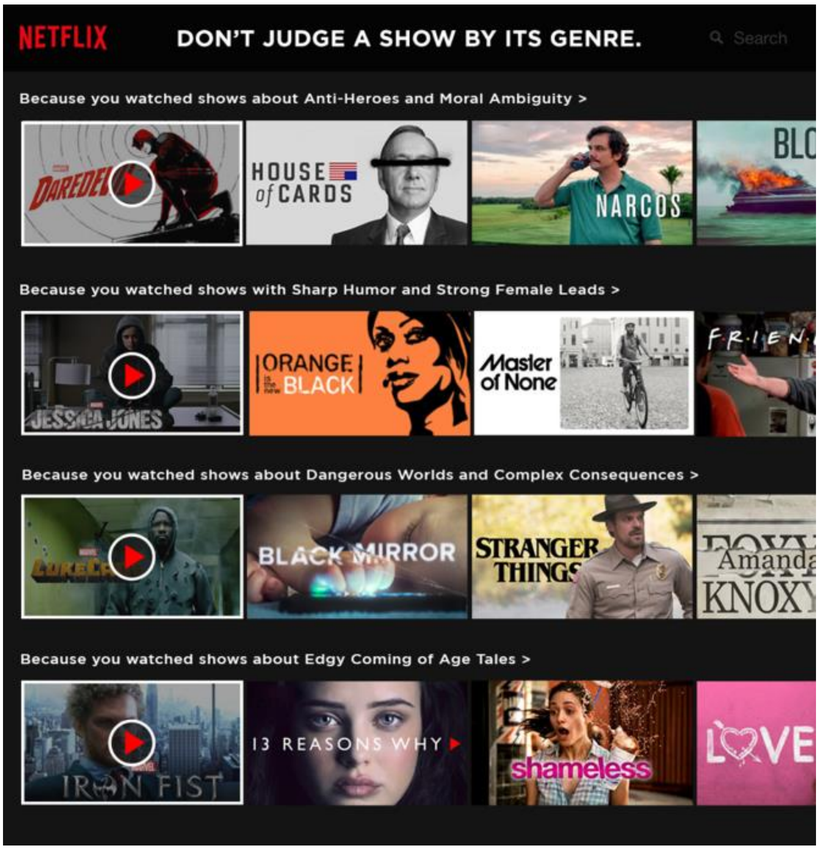

Figure 2: Recommender systems on Netflix

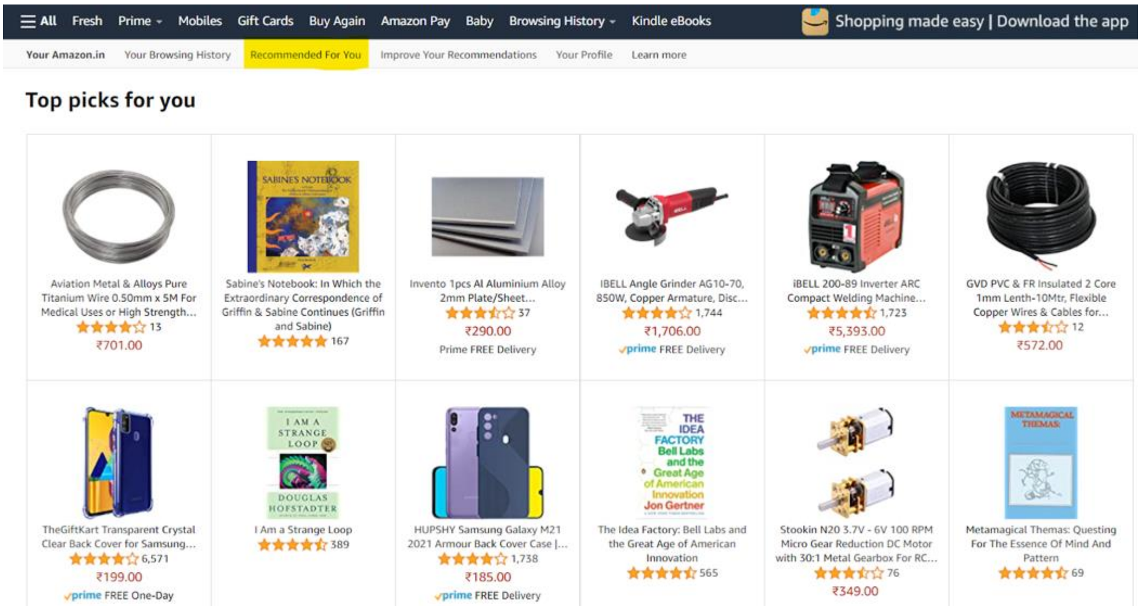

Figure 3: Recommender systems on Amazon

The Digital Services Act (DSA) (see section 2.3.4) contains a legal definition of recommendation systems. According to art. 3 letter. S, a recommendation system is defined as "a fully or partially automated system used by an online platform to suggest in its online interface specific information to recipients of the service or prioritize that information, including as a result of a search initiated by the recipient of the service or otherwise determining the relative order or prominence of information displayed" (DSA, art. 3 (s)). This definition highlights the method ("fully or partially automated"), the objective ("to suggest"), the content ("specific information"), the recipient ("recipients of the service"), the input ("as a result of a search initiated by the recipient"), and the output ("determining the relative order or prominence of information displayed") of a recommendation process (Fabbri M., 2023).

To assess the effectiveness of a recommendation system, Silveira et al. (2019) propose evaluating six key aspects: usefulness, novelty, diversity, surprise, serendipity, and coverage. Usefulness, also known as relevance or recommendation value, represents the benefit that users gain from recommendations (Silveira et al., 2019). Essentially, it is the value that users attribute to the recommendations received. This concept is crucial to ensure that recommendations are actually helpful and satisfactory for users (Ricci et al., 2011). Novelty, on the other hand, refers to the introduction of new elements in recommendations (Silveira, T. et al., 2019). Essentially, it indicates the presence of elements that are little or completely unknown to users, thus offering a variety of consumption options. This concept is important because it adds freshness and interest to recommendations, avoiding monotony and predictability (Herlocker et al., 2004; Vargas S. et al., 2011). Diversity is related to the variety of elements in recommendations and contrasts with similarity (Silveira, T. et al., 2019; Ricci et al., 2011). In practice, it means ensuring that recommendations are balanced and cover a wide range of user interests, avoiding repetition and excessive focus on certain types of items (Ziegler C. et al., 2005). Surprise and serendipity are connected concepts, both related to surprise and variety in recommendations (Silveira, T. et al., 2019). In short, they refer to the system's ability to offer unexpected and interesting recommendations to users, adding an element of surprise and satisfaction to the recommendation experience (McNee et al., 2006; Kaminskas and Bridge, 2014; Murakami et al., 2008; Adamopoulos P. et al., 2014; Iaquinta et al., 2008; Ge M. et al., 2010; Farris PW. et al., 2010). Finally, coverage is crucial in recommendation systems and refers to the system's ability to provide recommendations for the entire space of available items (Silveira, T. et al., 2019; Ricci et al., 2011; Vargas et al., 2014). This includes coverage of recommended items, coverage of users receiving effective recommendations, and coverage of genres of items recommended to users. Good coverage ensures that the system is able to meet the needs of a wide audience, offering diverse and relevant recommendations.

1.5.2 *Types of recommender systems*

Recommender systems are commonly divided into three main categories: content-based recommender systems, collaborative recommender systems, and hybrid recommender systems (Roy and Dutta, 2022).

Content-based recommender systems

In content-based recommender systems, all information is categorized into various data profiles based on their descriptions or features (Roy and Dutta, 2022). For example, for a book, features may include the author, the publisher, etc., while for a movie, they may concern the director and the actors. When a user expresses a positive judgment on an item, other items within that profile are grouped to create a user profile. This user profile combines the features of all items positively rated by the user and suggests other corresponding items (Roy and Dutta, 2022). This practice, illustrated in Figure 4, implies a recommendation of items similar to those liked by the user.

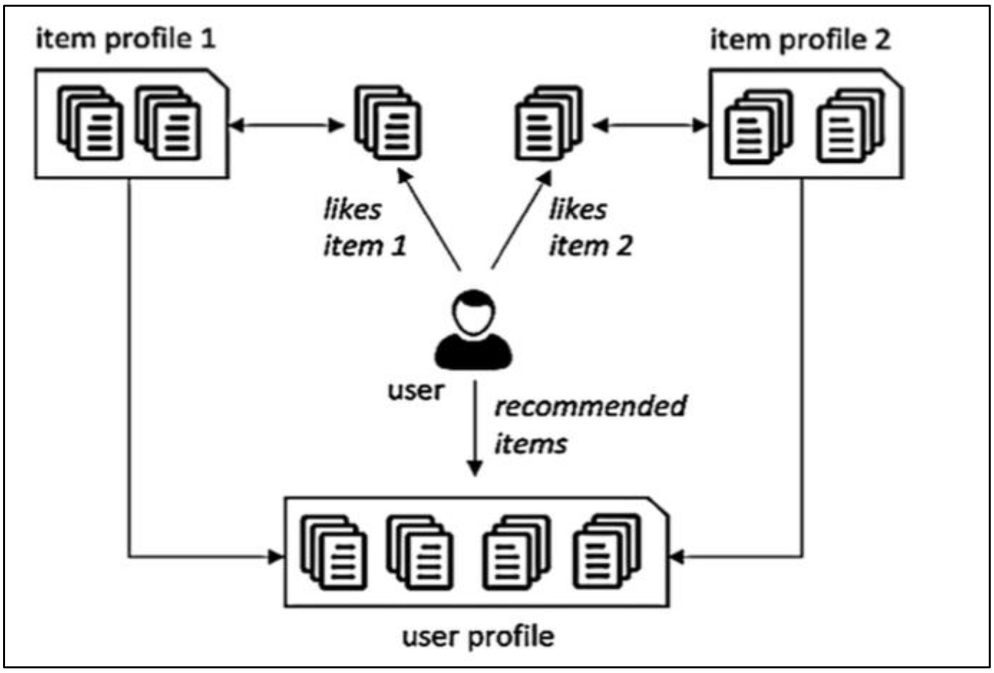

Figure 4: Content-based recommender systems (Roy and Dutta, 2022)

Although these approaches require a detailed knowledge of item features, they have advantages such as adaptability to changing preferences and protection of user privacy (Roy and Dutta, 2022). Additionally, if new items are adequately described, they can overcome the cold-start problem, also suggesting items without previous ratings. Often employed in contexts such as personalized news recommendations and web pages, content-based systems are not exempt from criticism, such as limited content analysis and lack of serendipity for new users (see definition of serendipity in section 1.5.1) (Lops et al., 2011).

Collaborative filtering recommender systems

Collaborative filtering recommender systems suggest items similar to those liked by users with similar tastes. Using the measure of similarity between users, they identify a group of users X, known as the "neighborhood" of a user A, whose tastes are similar to those of A (Roy and Dutta, 2022). Items preferred by the majority of users in X are then recommended to A (see Figure 5).

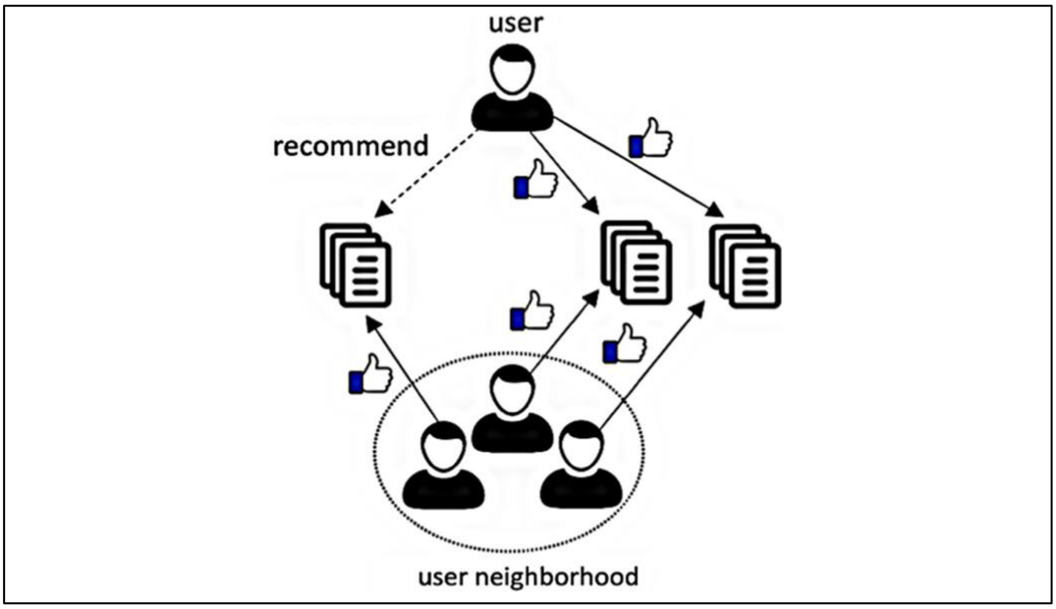

Figure 5: Collaborative filtering recommender systems (Roy and Dutta, 2022)

The effectiveness of this approach depends on the accuracy in identifying the neighborhood of the target user. Although subject to issues such as cold start and privacy concerns related to user data sharing (Roy and Dutta, 2022), collaborative filtering systems do not require detailed knowledge of item characteristics to generate recommendations. Additionally, they can broaden user interests by presenting new items. Among the limitations of these systems are data scarcity and the presence of "gray sheep" (users with unique preferences whose opinion does not coincide with the majority) (Su and Khoshgoftaar, 2009).

Hybrid recommender systems

A hybrid approach merges two or more recommendation methods to surpass the constraints of individual techniques. This could involve integrating content-based and collaborative filtering. Such a combination of approaches tends to improve the performance and accuracy of recommendations. This synergy between different techniques produces more robust and precise solutions, adaptable to a wide range of recommendation contexts. (Roy and Dutta, 2022).

Other types of recommender systems

In addition to the three categories mentioned earlier, Burke (2002) proposed three other types of RSs. These include demographic RSs, which recommend items positively rated by groups with which the user is associated based on their demographic characteristics such as age or gender; knowledge-based RSs, which suggest items based on explicit knowledge about the items; and utility-based RSs, which recommend items with the highest utility calculated using a utility function.

1.5.3 Sequential Recommender Systems (SRS) VS Traditional RSs

The evolution of recommendation systems has been closely linked to the development of the web, becoming increasingly crucial as the amount of online information grew exponentially (Bobadilla et al., 2013). However, the notion that such systems are guided by an objective conception of relevance is rapidly changing. Initially, the effectiveness of recommendation systems was primarily assessed through metrics like Root Mean Squared Error (RMSE)[5], measuring how accurately they could predict user preferences (Seaver, 2018). But with the evolution of the digital landscape and the increasing complexity of algorithms, there has been a shift towards engagement metrics, where successful recommendation is defined not only by its predictive accuracy but also by its ability to maintain user attention on the platform (Seaver, 2018). In this context, Sequential Recommender Systems (SRS) emerge, going beyond

[5] Root mean squared error (RMSE) is the square root of the mean of the squared differences between predicted and actual values. It is widely used as an error metric for numerical predictions (Georga et al., 2018).

traditional static approaches to model user preferences. SRS focus on user-item interactions in sequence, recognizing that user preferences can change over time and based on previous interactions (Wang et al., 2019). This dynamic approach allows SRS to offer more precise and personalized recommendations, taking into account the context and evolution of user preferences (Xu Chen et al., 2018).

In Figure 5, two examples of Sequential Recommendation Systems (SRS) are presented.

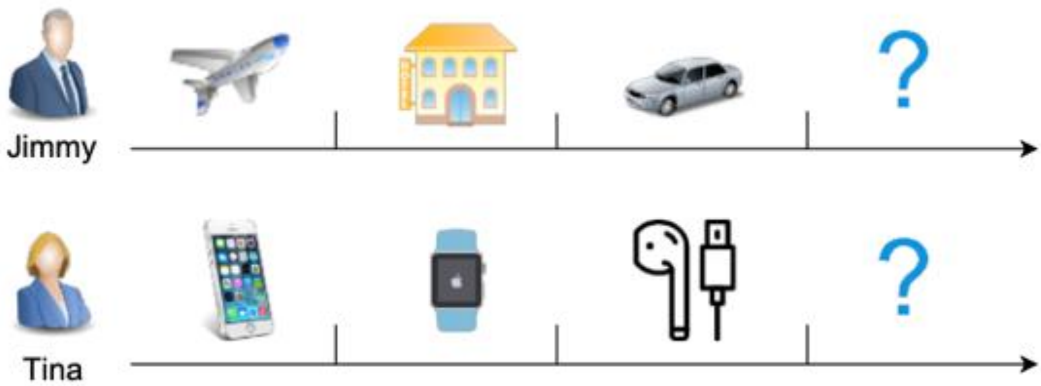

Figure 6: Two examples of Sequential recommender systems (SRS) (Wang, S. et al., 2019)

In the first example, after Jimmy booked a flight, a hotel, and rented a car, his next action is hypothesized. In the second example, after Tina purchased an iPhone, an iWatch, and a pair of AirPods, her next purchase is predicted. These scenarios highlight how user actions are often interconnected and dependent on the sequential context of their activities (Wang, S. et al., 2019). The transition from conventional recommendation systems to SRS has been motivated by several factors. Firstly, user-item interactions are generally sequential, as user actions tend to occur chronologically and influence each other. For example, Jimmy's choices in booking a flight, a hotel, and a car rental influence his next tourism-related activity. These sequential dependencies are not always well captured by traditional systems (Wang-Cheng Kang et al., 2018). Secondly, both user preferences and item popularity tend to change over time. For instance, the success of certain products may gradually decline while others gain popularity. This dynamism requires a more flexible and adaptable approach, such as SRS, to maintain accurate recommendations in the long term (Wang, S. et al., 2019).

Finally, user-item interactions often occur within a specific sequential context, which can influence user decisions. For example, the timing of a user booking a flight can influence the choice of hotel or subsequent tourist activities. Different contexts often influence user interactions with items, but this variation is often overlooked by traditional recommendation systems like collaborative filtering. In contrast, an SRS considers past interactions as context to predict which items will be chosen in the future. This simplifies the diversification of recommendations, avoiding continuously suggesting items similar to those already selected.

These advanced recommendation systems are supported by reinforcement learning (RL) techniques, an area of machine learning that focuses on how agents can learn to make decisions through interaction with the surrounding environment to maximize a numerical reward (Sutton and Barto, 2018). In recommendation systems, RL is used to make an algorithm learn to suggest items to users by interacting with them and receiving implicit or explicit feedback, aiming to maximize specific objectives such as profit or user satisfaction (Ricci et al., 2011). The fundamental features of RL make it particularly suitable for the context of recommendation systems. Firstly, RL manages the dynamics of sequential interaction between users and the system, adapting actions based on the continuous feedback received from the environment (Sutton and Barto, 2018). Secondly, it considers the long-term engagement of users with the system, allowing for more accurate customization of recommendations over time (Sutton and Barto, 2018). Finally, RL optimizes its decision-making policy through sequential interaction with the environment, without the need for explicit user evaluations (Sutton and Barto, 2018). On the other hand, deep reinforcement learning (DRL) represents an advanced evolution of traditional RL, where deep learning techniques are integrated with reinforcement learning methods to further improve the performance of recommendation systems (Zhang et al., 2021). DRL addresses both immediate and long-term rewards, using deep neural networks to learn complex data representations and improve the accuracy of recommendations (Zhang et al., 2021). This level of advanced complexity enables DRL to handle various user situations and preferences more sophisticatedly and effectively than traditional RL, leading to more accurate and personalized recommendations over time (Zhang et al., 2021). In summary, while both RL and DRL are employed in recommendation systems to tailor recommendations to users, DRL represents a more advanced version that harnesses the capabilities of deep neural networks to further enhance the performance of sequential recommendation systems.

1.5.4 *Recommender systems as a type of digital nudge and hypernudge*

Research in decision psychology confirms that people are influenced by environmental and cognitive constraints when making decisions (Simon, 1955; Kahneman, 2011; Tversky & Kahneman, 1974). The design of digital interfaces, including recommender systems, significantly impacts user behavior and choices (Morozovaite, 2023). Recommender systems, ubiquitous in online stores, music streaming platforms like Spotify, and social media news feeds, are designed to guide users towards relevant choices and avoid option overload (Jesse & Jannach, 2021b). By offering personalized suggestions, these systems influence user decisions, acting as digital nudges and hypernudges. The automatic recommendation of online platforms can be considered a digital nudge, as it influences user behavior without coercing them (Leonard et al., 2008). Smart nudges, introduced by Karlsen & Anderson (2019), aim to modify user behavior for the common good, adapting to the user's current situation and goals. These personalized nudges are designed to increase the likelihood of a positive response from the user (Karlsen & Anderson, 2019). Recommendation systems thus act as hidden nudges, presenting users with only a subset of available options and prominently positioning certain choices (Caraban et al., 2019). This increased visibility and accessibility of certain options can be interpreted as an attempt to influence user behavior, making it more likely for them to choose certain items or content (Sunstein, 2014; Johnson et al., 2012). Additionally, recommender systems can dynamically adapt to user behavior, using information collected from various sources to personalize suggestions and optimize user responses over time (Karlsen & Anderson, 2019). This ability to adapt and personalize reflects the essence of hypernudging, where complex algorithms and personal data are used to subtly but effectively influence user choices (Yeung, 2017; Morozovaite, 2021).

In summary, recommender systems represent a tangible example of how digital design can act as nudges and hypernudges, shaping user decisions through customization and optimization of presented choices.

2. Lights and shadows of hypernudge and recommender systems

The increasingly widespread use of AI-based technologies is revolutionizing multiple aspects of our daily lives. These innovations promise a wide range of benefits, from improved diagnosis and treatment of diseases to the reduction of environmental impact through energy savings. Additionally, they offer us the opportunity to optimize resources, anticipate disasters, and enhance road safety (Harasimiuk & Braun, 2021). However, we cannot ignore that some of these technologies pose significant ethical and moral challenges. Dark patterns (see section 2.2.1), for example, raise profound doubts about their compatibility with fundamental ethical principles. Similarly, targeted advertising and recommendation systems, while offering undeniable benefits such as simplifying information search and personalizing online experiences, raise questions about privacy and behavioral manipulation (Susser and Grimaldi, 2021). Moreover, there is a risk of creating disparities in access to knowledge due to the complexity of technological solutions and the concentration of power in the hands of a few large companies like Google, Facebook, and Amazon. Thus, while we are immersed in an era of unprecedented technological progress, we must carefully balance the benefits offered by innovations with the challenges they present.

In this chapter, we will closely examine both the positive and negative implications of hypernudge and recommender systems for our society and identify possible paths for the ethical and responsible use of these emerging technologies.

2.1 Positive aspects of implementing hypernudge and recommender systems

Commercial strategies based on hypernudge, such as recommender systems, have the potential not only to increase company profits but also to improve user well-being. These systems can generate significant value for businesses (Adomavicius et al., 2018; Jannach & Jugovac, 2019; Lee & Hosanagar, 2019). For example, a company could leverage an evidence effect to increase sales of a smartphone with the best quality-to-price ratio, thus creating a beneficial transaction where both parties are satisfied (Congiu et al., 2022). Furthermore, a retailer could encourage customers to purchase an expensive and energy-efficient refrigerator, benefiting both consumers and society (Blasch et al., 2019). As the retailer increases profits, consumers experience lower energy bills, and society benefits from reduced energy consumption and pollution. Finally, even in a context such as a cafeteria, the manager might want to make healthy food more visible and accessible to customers since the profit margin obtained from such food, like organic vegetables, is higher than that obtained from chips, candies, and other unhealthy foods (Congiu et al., 2022).

Jannach and Zanker (2012) identified four key actors involved in recommender systems (see Table 1):

- Customers (also known as users)
- Suppliers
- System owners

- Society at large

Stakeholder	Description
Consumers	Consumers are the end users of recommendation systems, and their behavior is potentially influenced by the system's recommendations.
Recommendation service providers	These are organizations that provide the recommendations as part of their services. They invest in recommendation technology and are the ones in control of the system.
Suppliers	These are organizations that provide (some of) the products or services that are recommended to consumers. The recommendation of their offerings can, for instance, influence the overall demand on the market.
Society	Depending on the size of the population of end users, recommender systems like on news or social media platforms, can have effects on parts of society as a whole. Note that the impact on society may be more than the aggregate impact on individuals, e.g., when the directly affected consumers act as multipliers of opinions in a society.

Table 1: Stakeholders of Recommender Systems (Jannach et Bauer., 2020)

Customers are the end users who receive recommendations on various items. Suppliers are those who provide the recommended items (such as a book publisher on Amazon). The organization itself, which has created the platform and its related recommendation system to connect customers to items, represents a significant actor. For example, a travel recommendation system is usually provided by a travel intermediary, such as Booking.com or AirBnB, or by a tourism promotion agency, such as Visitfinland.com. The first group of actors primarily focuses on selling services (such as hotel rooms and other travel services), while the second aims to increase tourist flow to different regions of a destination (Borràs et al., 2014; Ricci, 2002). Finally, the entire society can represent another actor that may undergo at least an indirect impact from the recommendations. Currently, there are various widely used online services, such as social media platforms like Facebook or Twitter, news aggregation sites like Google News, or multimedia platforms like YouTube. The content selection presented on such platforms can significantly influence users' perception of the world, especially in political contexts.

2.1.1 Benefits for businesses

In this context, Ricci et al. (2021) present some of the main reasons why both distributors and recommendation system managers may want to use RSs:

• *Increase the quantity of products sold*. This is probably the primary purpose for an RS in a commercial context, namely to promote the sale of an additional set of products compared to those usually purchased without recommendation. This goal is achieved because it is likely that the recommended products correspond to the needs and desires of the user. Non-commercial systems also pursue similar objectives, although there is often no associated cost for the user in selecting a product. For example, a public content platform like the BBC (UK) or RAI (IT) aims to increase the number of news articles read on its website. In general, we can say that from the service provider's point of view, the main objective in introducing an RS is to increase the conversion rate, i.e., the number of users who accept the recommendation and purchase a product, compared to the number of simple visitors who consult the information.

• *Offer a wider range of products*. Another important function of an RS is to allow users to discover items that may be difficult to find without targeted recommendations, i.e., not just proposing the most popular items. For example, in an RS dedicated to the tourism sector, the service provider aims to promote all attractions in an area, not just the most well-known tourist destinations. This is a key objective for a tourism RS managed by a public tourism promotion organization. Similar challenges arise for managers of public content platforms. However, achieving this goal could be complex without the assistance of an RS, as the content provider cannot risk promoting places (or media) that may not be appreciated by a particular user.

• *Enhancing user experience*. A well-developed RS can also contribute to optimizing the user experience on the website or application. The recommendations provided will be deemed interesting and relevant by the user, who, thanks to well-designed human-computer interaction, will find the system's usage enjoyable. The effectiveness and accuracy of the recommendations, coupled with an intuitive interface, will increase user satisfaction with the system. This, in turn, will boost the system's usage and the likelihood that the recommendations will be accepted.

• *Fostering user loyalty.* A website that recognizes and values a regular customer helps establish a loyal relationship with the user. This feature is common in RSs, which use information collected during previous interactions, such as item ratings or visited pages, to calculate personalized recommendations. Over time, the user's preference model becomes more accurate, allowing the system to adapt recommendations more effectively to the individual needs of the user.

• *Better understanding of user preferences*. Another crucial function of an RS, which can also be leveraged by other applications of the system owner, is the ability to describe user preferences, acquired both explicitly and implicitly by the system. This knowledge can be reused to optimize inventory management or production itself. For example, in the travel industry, destination management organizations can use data collected by the RS to create targeted promotional campaigns for new customer segments or specific promotional messages.

2.1.2 Benefits for end-users

Regarding end-users, Ricci et al. (2021), based on the research by Herlocker et al. (2004), have identified several popular tasks that recommender systems can help perform. In particular, these systems allow users to discover new relevant items and receive personalized recommendations based on their preferences, thus simplifying the decision-making process and enhancing the browsing experience. The ability to find items of interest, both through personalized recommendations and contextualization, enables users to explore a wide range of options with ease. Additionally, the possibility of receiving recommendations on sequences of items or product bundles enables users to plan trips and activities efficiently and conveniently. At the same time, recommender systems allow users to express their perspectives and judgments, thus contributing to forming a more engaged and collaborative community. The ability to enhance one's profile and influence other users through their feedback promotes a sense of active participation and involvement. Additionally, recommender systems provide users with tools to evaluate the reliability of the recommendations received and the performance of the systems themselves, thereby increasing trust and satisfaction in using such platforms.

In conclusion, the use of recommender systems offers numerous significant benefits for all stakeholders involved. For item distributors, RSs enable increased sales by promoting additional products and diversifying the offerings, thereby improving the conversion rate and increasing customer loyalty. Managers of the recommendation system benefit from optimizing the user experience, leading to increased platform usage and acceptance of recommendations. For end-users, RSs simplify the decision-making process, allowing them to discover new relevant items and plan trips and activities efficiently. Furthermore, they contribute to creating a more interactive and collaborative community, allowing users to express their opinions and evaluations.

2.2 Possible concerns regarding the use of hypernudge and recommender systems

Experts, politicians, and activists have sounded the alarm about the harms caused by automated influence, highlighting how targeted advertising, digital recommendations, and recommender systems can wield influence that is both tailored and widespread (Susser et al., 2019). These technologies, initially presented as tools to offer personalized digital experiences based on the preferences and desires of individual users, can lead to unfair discrimination (Noble, 2018), deception, and social polarization (Nadler et al., 2018), interfering with both individual and collective decision-making (Zuboff, 2019). On the other hand, legitimate concerns arise regarding the potential harms caused by these technologies. The massive collection of data fueling these systems raises significant privacy issues (Susser and Grimaldi, 2021). There is fear that automated influence could undermine individual autonomy and lead to economic and epistemic harm for those targeted. Therefore, deciding whether and when the use of such technologies is morally acceptable requires careful consideration of these ethical issues and assessing the impacts on privacy, autonomy, and other fundamental ethical values.

2.2.1 Ethical and social concerns

2.2.1 Ethical and Social Concerns

Thaler and Sunstein (2008) outlined some ethical principles for the use of nudges. According to these principles, for an intervention to be considered a nudge, it must adhere to certain criteria:

a) Preserve freedom of choice: The concept of freedom of choice implies the absence of obstacles or constraints that limit individual options (Thaler and Sunstein, 2008, 2003). This means that a nudge intervention must be easily avoidable, for example, with a simple mouse click. Furthermore, according to the concept of "opportunity" proposed by Carter (2004), true freedom of choice is manifested when individuals can make "reasonable" decisions without being limited by third parties. However, there are other aspects of freedom, such as autonomy, which concern the control an individual has over their own evaluations and choices (Veetil, 2011). Therefore, to ensure freedom of choice, it is not sufficient to consider only the value of procedural freedom; it is also essential that the choice architecture does not significantly limit the ability to discern and consider options and to act according to one's preferences, otherwise the autonomy of the individual could be compromised (Blumenthal-Barby, 2013).

b) It must be transparent: The need for transparency has been emphasized by Sunstein (2015c). Some critics have highlighted the risk that nudges may obscure access to available options at the time of decision-making, thus jeopardizing informed and free choice (Clavien, 2018). Therefore, it is essential to ensure that individuals exposed to nudges can easily recognize when and where they are being influenced (type transparency), as well as understand the goals and functioning of the nudges (token transparency) (Bovens, 2009; Barton and Grüne-Yanoff, 2015). By respecting the principle of transparency, nudges must be clearly identifiable to the subjects exposed to them (Sunstein, 2015c).

c) "Influence choices in a way that will make people better off, as judged by themselves" (Thaler and Sunstein, 2008).

However, some scholars argue that libertarian paternalism, including the use of nudges and hypernudges, may not be as libertarian as suggested by Thaler and Sunstein (Congiu et al., 2022). A first criticism concerns the very definition of "preservation of freedom" proposed by Thaler and Sunstein, according to which a policy is considered libertarian to the extent that it preserves freedom of choice. Thaler and Sunstein (2003, 2009) seem to define the preservation of freedom as the ability to freely select any of the available options, without restrictions or constraints. If this perspective of freedom is adopted, nudges can be justified by libertarian paternalism since they do not limit the set of available choices or impose significant costs on the decision-maker. However, algorithmic systems capable of ordering and classifying the available choice options to individuals, and thus continuously learning from their immediate reactions and ongoing behavior to alter the choice landscape, become particularly powerful governance mechanisms. These mechanisms do not explicitly coerce people into choosing a particular option, but they shape the choice environment (such as available information, understanding of the world, and accessible solutions) in such a way that only the pre-set option (as in purchasing or voting choices) is still likely to be chosen (Kalpokas, I., & Kalpokas, I., 2019). Algorithmic governance can manifest in multiple forms. Some of these involve the direct closing and opening of spaces and opportunities, the creation and elimination of choice options. However, a more subtle and pleasing aspect of algorithmic governance involves pushing individuals in the preferred directions of those who control the code (Kalpokas, I., & Kalpokas, I., 2019).

Furthermore, nudges should always be in the best interest of the nudgee. However, there is a risk that the preselection of choices offered by the algorithm to the self-tracker is more aligned with the interest of the actor controlling the technology rather than with that of the user. This could steer the user in a specific commercial or political direction (Owens & Cribb, 2017: 12–14). An hypernudge may dictate what to choose, as it would require several actions to negotiate and correct the default options or to discover options not displayed (Brey, 2006). This significantly limits the user's control in mitigating interference with their decisions based on their information, and it could even be argued that this constitutes a case of coercion (Raz, 1986: 377–378). Legna (2014) defines coercion as the act of limiting the range of acceptable choices of a target to a single option. Although both coercion and manipulation seek to guide the target's behavior, they fundamentally differ. Unlike manipulation, coercion does not compromise the decision-making capacity of the victim. Instead, it exploits the fact that the victim rationally selects the only option presented by the coercer (Susser et al., 2019).

Through a multidisciplinary meta-analysis, Milano et al. (2020) identified six main areas of ethical concern regarding recommendation systems: *inappropriate content, privacy, autonomy and personal identity, opacity, fairness, and social effects.* In this study, we will focus on four of the six ethical concerns: privacy, autonomy and personal identity, opacity, and social effects.

1) *Privacy*: The issue of user privacy represents one of the primary challenges for recommendation systems (Friedman et al., 2015; Koene et al., 2015). This problem is inevitable, as most successful commercial recommendation systems rely on hybrid or collaborative filtering techniques, which involve building user models to generate personalized recommendations (Milano et al., 2020). The dangers to privacy protection manifest in at least four distinct stages. Initially, they may arise when data is collected or disclosed without the explicit consent of the user. Subsequently, once the data is stored, there is the additional risk that it may be exposed to third parties or subject to de-anonymization attempts (Narayanan, 2008). Additionally, regardless of the robustness of the security measures adopted for data collection and storage, privacy-related issues arise in the inference phase where the system can draw conclusions from such data. Users may not be fully aware of the inferences the system makes and may object to such use of their data if they were more informed. Privacy risks are not limited to the data acquisition stage, as, for example, an external observer

could deduce sensitive information about the user by observing the recommendations generated by the system (Friedman et al., 2015). Finally, an additional significant systemic issue arises in the context of collaborative filtering: the system could create a user profile based on data collected from other users' interactions. In other words, provided a sufficient number of users interact and share their data with the system, it could manage to build a fairly accurate profile even for users it has less information about. This suggests that individual users may not be able to fully protect themselves from the conclusions the system draws about them. While this may be a positive feature in some domains, such as medical research, it can prove problematic in other sectors, such as recruitment or finance.

Informational and decisional privacy

Informational and decisional privacy emerge as central concepts in the use of hypernudges and Big Data-based recommendation systems. Specifically, *informational privacy* entails control over the access and extent of one's personal information, highlighting the importance of managing the disclosure of such data. However, the use of these technologies raises concerns regarding the collection and processing of data without the informed consent of users, jeopardizing the fundamental right to informational privacy (Yeung, 2017; Solove, 2013). Current laws, based on the concept of "privacy self-management," give individuals control over their personal data, but the paradigm of "informed consent" is subject to criticism as people often do not understand online privacy policies and provided notices are ineffective (Acquisti et al., 2015; McDonald and Cranor, 2008; Cranor et al., 2013-2014). Furthermore, challenges related to bounded rationality and managing relationships with various digital service providers make it difficult to assess the risk of privacy harm, which can accumulate over time (Solove, 2013). On the other hand, *decisional privacy* is historically and conceptually linked to informational privacy and should be considered as a complementary concept. It concerns not only the right against unwanted intrusions but also the ability to make autonomous decisions free from external interference. This implies that unknown actors or entities have access to our behavior and decisions, influencing them without it falling within the reasonable expectations of the user or individual (Allen, 1988; Roessler, 2005). Hypernudges undermine decisional privacy because users may not be aware or expect from whom their decisions will be interfered with based on the collected information (Lanzing, 2019). This interferes with the user's ability to control interference in their decisions based on their own information.

2) *Autonomy and personal identity*: Personal identity and autonomy are crucial aspects for consumers, who perceive themselves as autonomous agents capable of making independent decisions (Wegner, 2004; Bloom, 2009; Zheng et al., 2016). This perception is rooted in the concept of free will and trust in one's ability to deliberate and act intentionally (Wegner & Wheatley, 1999; Nisbett & Wilson, 1977; Clark et al., 2014). However, this self-perception risks being undermined by recommendation systems, which can subtly condition users' choices and restrict their options (Burr et al., 2018). Recommendation systems act as true "sticky traps," sticking users to certain solutions and limiting their freedom of choice (Burr et al., 2018). This is reflected in user retention metrics used to assess the effectiveness of such systems, as in the case of YouTube's recommendation algorithm (Seaver; Chaslot, 2018). Such persistent user engagement indicates a potential threat to individual autonomy, as users' decisions may be influenced without their full consent or awareness. Similarly, digital influence, including that exerted by nudges, raises questions about the transparency and integrity of individual autonomy (Sunstein, 2016). Although nudges may sometimes be justified as promoters of the recipient's interests (Sunstein, 2016), it is difficult to ascertain such interests definitively, especially in the context of digital nudges (Hausman et Welch, 2010; Meske et Amojo, 2020).

3) *Opacity*: Personalized recommendations can be likened to "word-of-mouth" recommendations among users, but with a significant difference: while offline word-of-mouth relies on trust and shared personal experience, in recommendation systems, users do not have access to the identities of other users or the models used by the system to generate recommendations (Herlocker et al., 2000). This lack of transparency can compromise user autonomy, as they are not fully aware of the decision-making processes influencing the recommendations they receive.

4) *Social Effects*: A widely discussed effect of some recommendation systems is their transformative impact on society. As previously mentioned in section 1.5.2, many recommendation systems and hypernudge techniques are based on the so-called "collaborative filtering." This means that the suggestions offered are not simply the result of our preferences, but also of those of other users who share demographic characteristics, hobbies, or similar content consumption patterns with us. As a hidden

consequence of this practice, users run the daily risk of being influenced by groups of other users whose interactions with the system can generate intense feedback, increasing the rate of recommendations for specific items (Chakraborty et al., 2019). This issue will be addressed more specifically in section 2.2.3 "Epistemic Concerns."

Among the various manipulative practices used online, *dark patterns* emerge as a particularly insidious type (Brignull, 2010). These deceptive schemes are designed to confuse users and manipulate their decision-making environment to the benefit of those who implement them (Sunstein, 2015a). For example, intrusive default settings, such as automatic opt-out from privacy options, coerce users into sharing more information than they desire (Lavi, 2018). Other examples include signals of scarcity and urgency, such as "Only 1 left!" (see Figures 7 and 8), which prompt users to act impulsively (Brignull, 2010). Dark patterns can also involve user interface designs that hide options to cancel or undo an action, making it difficult for users to express their true preferences (Sunstein, 2015a).

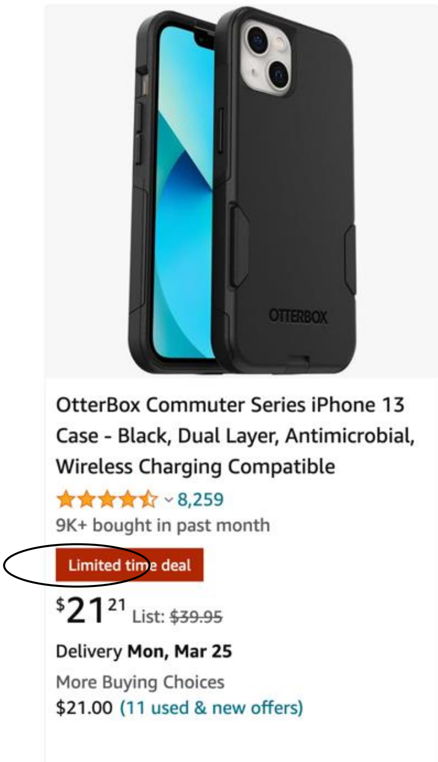

Figure 7: Urgency effect on Amazon.com

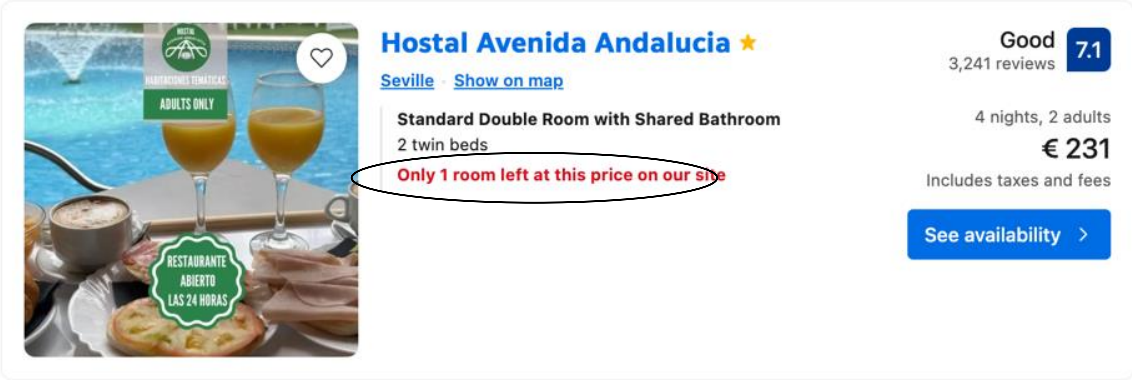

Figure 8: Scarcity effect on Booking.com

In conclusion, hypernudging practices and recommendation systems raise serious ethical and social concerns. Hypernudging, with its ability to subtly influence user behavior without their explicit consent, raises questions about transparency and manipulation of the decision-making environment. Similarly, recommendation systems can erode user autonomy by guiding them towards predetermined choices based on collected personal data (Morozovaite, 2023). Finally, dark patterns and similar deceptive practices add further risks, confusing users and leading them to take actions against their own interests (Brignull, 2010; Sunstein, 2015a; Lavi, 2018).

2.2.2 *Economic concerns*

The manipulative influences that raise concerns about autonomy have also raised doubts about economic harm. Targeted advertising strategies, recommendation algorithms, and dark practices that exploit both the "common human biases" identified by behavioral economists and the specific "peculiar" decisional vulnerabilities of individuals, not only jeopardize individual independence but also financial stability. From an economic perspective, two possible issues emerge. Firstly, dark practices, product recommendation systems, and manipulative targeted advertisements could push consumers to purchase goods they would not - upon reflection - choose to buy, generating inefficiencies in resource allocation (i.e., distributing products to people who would not derive the maximum benefit from them) (Zarsky, 2019). Secondly, manipulative influences could allow sellers to set higher prices for products than buyers would be willing to pay. While sellers have always engaged in what economists term "first-degree price discrimination" and tech companies call "price personalization," i.e., adjusting prices based on individual buyer characteristics, many fear that monitoring and dynamic experimentation in digital environments could amplify such tactics (Mohammed, 2017). Moreover, as emphasized by Zarsky, these technologies do not have to "work" - in the sense of successfully influencing people to buy items they don't actually want or pay more than they otherwise would - to introduce market inefficiencies. Even completely ineffective targeted advertising can annoy or stress consumers, leading them to waste time and energy seeking ad-blocking tools and fostering a general distrust of sellers (Zarsky, 2019). Similar concerns have been raised regarding product recommendation systems. Many have complained, for example, that product recommendations on Amazon are based on fake reviews, resulting in a waste of time for buyers and fueling a general distrust of the site's recommendations (Nguyen, 2019).

2.2.3 Epistemic concerns: polarization, filter bubbles and echo chambers

In addition to concerns about privacy, autonomy, and economic well-being, academics have been warning for several years about the serious epistemic harms caused by automated influence: harms that affect people's knowledge. About ten years ago, Eli Pariser warned that personalized digital environments seemed to isolate people in echo chambers, offering only news, media, and other content that confirmed their existing beliefs and aligned with their tastes, preferences, and values (Pariser, 2011). As Pariser highlighted at the time, this can be harmful both for individuals and for society. Individually, people's perspectives narrow, their intellectual horizons shrink, and their beliefs become polarized. Collectively, people lose the sense of living in a shared world, prioritizing personal interests over the common good. Not everyone is convinced that filter bubbles are so completely sealed, at least not yet (Bruns, 2019; Fletcher et al., 2020; Borgesius et al., 2016). And some argue that traditional media, especially cable news, are a more significant factor in political polarization than digital technologies. However, the spread of political misinformation online, conspiracy theories, and health misinformation remains a persistent concern for many. A report from the Data & Society Research Institute warns that digital technologies enable a combination of surveillance, targeting, and automation - what they call a "digital influence machine" - that can be "weaponized" by malicious actors (Nadler et Donovan, 2018), damaging both individual and autonomous experience and collective and democratic experience. In particular, it is highlighted that online news distributors, especially online media, social media, search engines, and news aggregators, use what can be termed as "interest-matching recommendation systems" to personalize individual news feeds (Kaye, 2018, 6–7). As a result, online interfaces show users articles that match the characteristics of their profile. For example, if a user has previously chosen to watch thrillers on Netflix, the system might recommend other thrillers in the future, thus creating a kind of "filter bubble" as described by Pariser (2011). Pariser argued that the human capacity to adapt and learn from new information is hindered by recommendation systems, which trap users in an immutable environment, limiting user creativity and learning, reinforcing their beliefs (Pariser, 2011). Sunstein (2002) expanded on this view, suggesting that absorbing personalized experiences reduces common experiences among users, thus undermining social cohesion and the ability to address common problems. He warned that without shared experiences, heterogeneous societies might struggle to confront social challenges, with the risk that people do not understand each other (Sunstein, 2002).

Automated recommendations not only shape the content displayed on platforms but also influence users' potential interest in new categories of content. This power of influence can be seen as a manifestation of the "new emerging gray force" of tech companies, which control what questions can be asked, when and where, by whom, and what answers can be received (Floridi, 2015). An eloquent example of this dynamic is represented by platforms like TikTok, which primarily rely on recommendation systems. Here, the endless stream of recommended content determines what the user views, with content related to the videos the user watches the longest (Floridi, 2015). However, this practice can have harmful consequences, as highlighted by Edwards (2022). For example, if a vulnerable individual casually interacts with a video about a dangerous activity, they might end up seeing similar content more and more often, risking negative influence over time. In this way, platforms influence not only what users see but also the questions they pose about their interests and the answers they receive, significantly shaping users' online and sometimes offline experiences (Floridi, 2015).

To ensure a functioning democracy, it is crucial that users are exposed to opinions, debates, and ideas with which they may disagree or even dislike. This goes beyond optimizing news recommendation systems based on user preferences, as often happens currently. The public value of diversity, both in terms of a variety of topics and opinions, is fundamental (Helberger, 2015, 2019). Depending on the adopted conception of democracy, different interpretations of news diversity as an important element can emerge. For instance, the deliberative approach to democracy (Habermas, 2006) underscores the necessity of reasoned debate in society regarding a variety of viewpoints and concepts. Likewise, the agonistic model (Mouffe, 2005) highlights the significance of fostering civil disagreements among a spectrum of political convictions, ideologies, and sentiments (Bozdag and van den Hoven, 2015;

Dahlberg, 2011; Helberger, 2019; Strömbäck, 2005). Regardless of the democratic theory advocated in the context of news diversity, it is widely recognized that promoting diversity of viewpoints is crucial. Both deliberative and agonistic democracy models agree on the importance of encouraging encounters between contrasting ideas (Karppinen, 2013). This implies that citizens in a democracy must be exposed to a wide range of viewpoints through a diversified news diet. Such diversity can foster understanding and sometimes even empathy towards others' viewpoints. Moreover, exposure to diverse viewpoints provides information that can help citizens critically reflect and deliberate on issues of personal or social interest. Additionally, serving citizens a diversified set of viewpoints can contribute to stimulating productive debates on politics or ideology (Helbing, 2015). However, in the era of personalized information, this entails a decrease in exposure to information that does not align with our beliefs and tastes. While this may give the impression of living in a world tailored to us, we may lose awareness of others' needs and viewpoints. This could hinder our ability to communicate and interact constructively when confronted with diverse opinions (Helbing, 2015). In the past, information scarcity provided us with the necessary time to evaluate its value, although often we did not have enough to decide optimally. With the advent of technologies like web search, Wikipedia, and digital maps, orientation has become more accessible. However, we are now inundated with an abundance of data, making us incapable of processing and evaluating them fully. This information overload makes us vulnerable to manipulation, as we are constantly exposed to information filters that may have particular interests, such as maximizing ad clicks or influencing opinions in favor of certain ideologies (Helbing, 2015). This phenomenon can lead to the formation of *echo chamber* opinions and the accentuation of local trends through repetition, creating social polarization known as the "*echo chamber effect*" (Helbing, 2015).

In conclusion, the resulting social polarization from the use of technologies like hypernudge and recommendation systems makes it difficult to reach political compromises and threatens social cohesion. This phenomenon of societal fragmentation can lead to its progressive disintegration, as separated groups become increasingly distant and conflictual with each other.

2.3 Notes on the regulatory framework on hypernudge and recommender systems

Until recently, there were no specific regulations for the regulation of algorithmic rankings and recommendations at the EU level. Regarding the issue of content diversity (discussed in section 2.2.3 of the previous chapter), Article 10 of the European Convention on Human Rights deals with the "freedom to receive information and ideas." According to this provision, every individual "has the right to freedom of expression, including the right to hold opinions and to receive and impart information and ideas without interference by public authority and regardless of frontiers" (ECHR, Article 10). The European Court of Human Rights has continuously acknowledged that this provision encompasses the right to be adequately informed and to receive information and ideas on matters of public interest. These are issues that concern the public to such an extent as to attract its attention or significantly influence the well-being of citizens or the life of the community (Couderc and Hachette Filipacchi Associés v. France [GC] 2015, para. 103). According to the Court, political and social news are the most relevant information protected by Article 10 of the ECHR. States, as parties to the European Court of Human Rights, have a responsibility to ensure that individuals receive a diversity of viewpoints on matters of public interest. The Court has established the obligation for States to ensure, through their legislation and practice, that the public can access a wide range of opinions and comments, representing the diverse political viewpoints present in the nation, especially through audiovisual media (Voorhoof D., 2012). However, there are no legal rulings to date imposing a similar obligation in the online media sector (Vermeulen, J., 2022). In a judgment from 2013, the Court held that "there is no evidence of a sufficiently serious shift in the respective influences of new media and broadcast media," despite the significant development of the former in recent years. However, today it is evident that the Internet, as a vehicle for transmitting information, and particularly news, is at least as important as television and radio, if not more so (Council of Europe/European Court of Human Rights 2015, para. 40). Media usage reports indicate that digital channels have become equally, if not more, relevant than traditional media (television, radio, print) for accessing news (Newman et al. 2020; Commissariaat voor de Media 2020). Therefore, it is justified to argue that States should now take positive action to ensure online access to a variety of viewpoints on matters of public interest (Vermeulen 2022).

Moving swiftly to the present day, the European Union is emerging as a leading global force in regulating digital markets (Commissione Europea, 2015, 2020a, 2021a; Van Dijck, 2021b). The review of existing regulatory frameworks has been initiated in response to a series of concerns and signals regarding the dynamics of digital markets, which lead to concentrations of private power and violations of fundamental rights (Van Dijck, 2021b). In response to these concerns, the EU has embarked on a process of revising existing regulations identified as European digital constitutionalism - "a reaction against the power exercised by online platforms, which are increasingly involved in determining the scope of rights and freedoms in the information society" (De Gregorio, 2021, p. 53). Aligned with the European Union's goal of promoting a social market economy (Article 3 TUE[6]; Gerbrandy et al., 2019), the emerging digital constitutionalism is committed to preserving society from full digital commercialization and the establishment of a digital surveillance state (Gohl et al., 2021). However, despite concrete efforts to integrate digital policy into European values, policymakers are struggling to balance the economic and public interests involved (Mansell, 2021). The European response to digital nudging (data-driven) in the policy areas of consumer protection and data protection is instructive in describing the tensions in finding a balance between different constitutional values and progressing towards architectural solutions. These technologies can indeed conceal dark patterns that lead users to make choices compromising privacy (Soe et al., 2022).

Furthermore, it is not uncommon for tracking to occur without user consent, especially in the settings of mobile applications (Bilge et al., 2019; Helberger et al., 2022). These concerns are compounded by the lack of adequate tools and resources by data protection authorities to detect violations (Helberger et al., 2022). In this scenario, European digital policy is progressing to address structurally entrenched concerns that influence competition, fairness, and reliability in digital markets, including the ongoing and opaque processes of hypernudging.

The EU's foray into data governance was marked by the landmark GDPR, which introduced new standards for personal data protection. However, the GDPR was just the beginning of a broader journey. Subsequent regulations such as the Digital Markets Act (DMA) and the Digital Services Act (DSA) have been integrated into the EU regulatory landscape to address the challenges of data governance, while the AI Act further expands it (Pathak M., 2024). In particular, the Artificial Intelligence Act (AIA) aims to create an environment of excellence and trust in the field of artificial intelligence. The Digital Markets Act (DMA) aims to uphold fairness and competition in digital markets, ensuring they remain contestable to innovators, businesses, and newcomers. Finally, the Digital Services Act (DSA) represents an additional legal instrument aimed at increasing and harmonizing the responsibilities of online platforms and information service providers towards end-users. Together, the DSA and DMA constitute the so-called "Digital Services Package."

[6] OPOCE. (nd). EUR-LEx - 12008M003 - IT . https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX%3A12008M003

Although none of the proposals directly address hypernudging, they include important provisions to guide future policy developments in digital markets.

2.3.1 General Data Protection Regulation (GDPR)

The General Data Protection Regulation (GDPR) is European Union (EU) legislation aimed at protecting the privacy and rights of individuals regarding the processing of their personal data. This regulation defines rules for the collection, processing, and storage of personal data and applies to all organizations operating in the EU or processing data of EU citizens. Current recommendation systems (RecSys) often rely on the collection of online and potentially offline behavioral data, such as clickstream[7] behavior, browsing patterns, purchase models, location, traffic data, as well as data obtained through Quick Response (QR) codes. It is important to note that this collected data is considered personal data if the related person can be identified "reasonably." Given the ability to link much of this behavioral data to others, this frequently occurs, making the GDPR applicable. Once the GDPR is applied, those determining the purpose and means of processing become responsible for GDPR compliance, primarily the user of the system (e.g., an online store or provider of a social network or search engine), known as the "controller.[8]" This entity is required to ensure they have a legal basis for processing, which can be represented by the user's consent or legitimate interest[9] (Hildebrandt, 2022). The transparency requirements imposed by the GDPR reconfigure the decision-making architecture of data controllers, which, to be lawful, should be clear and specific regarding its purpose (Hildebrandt, 2022). In this sense, Articles 12-14 impose transparency obligations on data controllers. In particular, Article 13(1)(c) and Article 14(1)(c) state that: "The controller shall provide the data subject with all of the following information: [...] the purposes of the processing for which the personal data are intended as well as the legal basis for the processing." This implies that they should acknowledge that their recommendations are specifically aimed at increasing their own revenues, enabling end-users to anticipate potential distortions intrinsic to the recommendation. This brings us to the principle of purpose limitation. In this regard, Article 5(1)(b) of the GDPR states that:

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[7] *Clickstream* is defined as "a record of a person's activities on the internet, such as the websites they visit, and how long they spend on each one" (Cambridge Dictionary)

[8] Art. 4(7) GDPR defines "controller" as "the natural or legal person, public authority, agency or other body which, alone or jointly with others, determines the purposes and means of the processing of personal data."

[9] In reality, there are six potential legal bases available in Art. 6 of the GDPR: consent, contract, vital interests of the data subject or another person, a legal obligation, performance of a task carried out in the public interest or in the exercise of official authority, and legitimate interests pursued by the controller (Hildebrandt, 2022).

"Personal data shall be collected for specified, explicit and legitimate purposes and not further processed in a manner that is incompatible with those purposes [...]."

Therefore, the following article limits all processing to what is necessary for the specified purpose, noting that data controllers are obligated to define one or more legitimate purposes and make them explicit (Hildebrandt, 2022). In accordance with this, consent is valid only if given for a specific purpose and if the processing for which it is given is necessary for that particular purpose. According to Article 6(1)(a) of the GDPR, "The data subject has given consent to the processing of his or her personal data for one or more specific purposes." This concept is linked to the principles of data minimization and storage limitation, which similarly dictate the choices of the data controller: they must select processing operations that are not only appropriate but also necessary for the intended purposes (Hildebrandt, 2022). This implies particular attention to selecting the necessary data to provide relevant recommendations. Additionally, those implementing a recommendation system should be clear and specific about additional purposes that determine which data is processed. The GDPR includes several elements that contribute to defining the choice architecture for recommendation systems within the EU, influencing the design decisions of backend systems that end-users cannot access or control. For example, the prohibition of solely automated decisions that produce significant legal effects on the end-user is a relevant aspect. According to Article 22(1) of the GDPR, "The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her." However, there are three exceptions to this provision, which "shall not apply if the decision:

(a) is necessary for entering into, or performance of, a contract between the data subject and a data controller;

(b) is authorised by Union or Member State law to which the controller is subject and which also lays down suitable measures to safeguard the data subject's rights and freedoms and legitimate interests; or

(c) is based on the data subject's explicit consent" (Article 22(2)).

When exceptions (a) and (c) apply, "the data controller shall implement suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision" (Article 22(3)). Additionally, according to the fourth paragraph of Article 22 of the GDPR, it is prohibited to collect sensitive data for profiling purposes. However, it is common for sensitive data to be inferred from non-sensitive data acting as proxies: for example, income may be inferred from the residential address. Exception (a) might be invoked in situations where users are required to accept the terms of service of a platform, which establish the contract between the user and the data controller. Exception (c) applies when the user is prompted to give consent online, for example, regarding cookies. Consequently, it could be argued that automatic recommendations are compliant with GDPR requirements, as by accepting the terms of service, users often consent to profiling and inferences. Regarding exception (c), an issue arises as research indicates that the majority of internet users are inclined to grant consent to access a website without actually paying attention to the content of the agreement (Carolan, 2016, pp. 462–473; for further details, see also Machuletz and Böhme, 2020, pp. 481–498). If consent is readily given, without genuine informed choice, Article 22 of the GDPR does not offer sufficiently robust protection. Moreover, Article 22 does not provide details on how users can identify whether a decision has been fully automated. However, a direction in this regard is indicated in Articles 13 and 14, which deal with the right to information, and in Article 15, which concerns the right of access. According to these articles, the data controller must inform users about the existence of automated decisions, including profiling as defined in Article 22, and, at least in such cases, provide significant details about the logic used and the envisaged implications of such processing for the data subject (Giovanni Sartor et al., 2018).

Article 15(1)(h) of the GDPR establishes that the individual has the right to obtain confirmation from the data controller about the existence of automated processing of their personal data, including profiling as defined in Article 22, paragraphs 1 and 4. If such processing exists, they have the right to access their personal data and receive meaningful information about the logic used, as well as the envisaged consequences of such processing for the data subject. This implies that providers of RecSys must adapt their practices to ensure that the decisions made by the system are understandable to users, thus reflecting a shift in the choice architecture dictated by these obligations (Hildebrandt, 2022).

In conclusion, the GDPR represents a crucial pillar in protecting the privacy and rights of individuals in the context of recommendation systems and hypernudge practices. This regulation imposes strict rules on transparency, purpose limitation, and informed consent, reconfiguring the decision-making architecture of data controllers and promoting responsible management of users' personal data. However, despite its efforts, the GDPR still faces significant challenges, such as superficial user consent and the need to ensure the comprehensibility of automated decisions.

2.3.2 *Digital Markets Act (DMA)*

The Digital Markets Act (DMA), definitively adopted by the Council of Europe on July 18, 2022, represents a crucial step in the EU's governance of digital data. This regulation differs from the General Data Protection Regulation (GDPR) as it addresses not only the protection of personal data but also the broader challenges posed by digital markets, with an emphasis on preventing unfair practices and promoting healthy competition. Specifically, the DMA is intended as a complement to the EU's and Member States' competition rules. The legal basis for the legislative proposal is Article 114 of the TFEU[10], which facilitates the harmonization of rules at the EU level to avoid fragmentation that could otherwise undermine the functioning of the internal market (Akman, 2021). In particular, the DMA targets so-called "gatekeepers," i.e., large online platforms that hold a dominant position in the digital market, exerting significant control over access and dynamics in this market (Pathank M., 2024; Chiarella, 2023). The innovative character of the DMA lies in the fact that while the enforcement of antitrust rules focuses on resolving restrictive or abusive practices once they have occurred, involving time-consuming investigative procedures that specifically intervene in specific markets, the DMA, on the contrary, aims to prevent the harmful effects of unfair practices before they occur. In other words, while antitrust rules primarily operate reactively and retrospectively, the DMA seeks to act proactively and preventively, anticipating potential problems and establishing rules that can prevent such unfair practices before they can have a negative impact on digital markets. This proactive approach aims to minimize the need for ex-post interventions, although leaving open the possibility of further interventions if necessary (Akman, 2021).

This new European regulation aims to create a fair and competitive digital environment, ensuring that gatekeepers do not abuse their dominant position to limit competition and innovation, but rather promoting a more equitable distribution of digital opportunities for businesses and consumers. As highlighted in Article 1, paragraph 1, the purpose of the DMA is to "contribute to the proper functioning of the internal market by establishing harmonized rules that ensure for all businesses, contestable and fair markets in the digital sector throughout

[10] The TFEU is one of 2 primary treaties of the EU, alongside the Treaty on European Union (TEU). It forms the detailed basis of EU law by defining the principles and objectives of the EU and the scope for action within its policy areas. It also sets out organisational and functional details of the EU institutions (*EUR-LEX.*, n.d.).

the Union, where gatekeepers are present, for the benefit of commercial users and end-users." It applies "to the core platform services provided or offered by gatekeepers to commercial users established in the Union or to end-users established or situated in the Union, irrespective of the place of establishment or residence of the gatekeepers and irrespective of the law otherwise applicable to the provision of the service" (paragraph 2). Therefore, it emerges that the DMA is binding only for those providers who meet clearly defined criteria to be considered "gatekeepers". Before the adoption of the DMA, the identification of "gatekeepers" and related issues were not (or not effectively) addressed by existing EU legislation or national laws of the Member States. The gatekeeper status is described in Chapter II of the DMA. It can be determined both with reference to quantitative metrics, which can serve as rebuttable presumptions, to determine the status of specific providers as gatekeepers, and based on a qualitative case-by-case assessment through a market investigation (Chiarella, 2023). According to these qualitative criteria and the related quantitative thresholds, a company qualifies as a gatekeeper if:

(a) it has a significant impact on the internal market: this is the case where it has achieved an annual turnover in the EU exceeding €7.5 billion in each of the last three financial years, or where its average market capitalization amounted to at least €75 billion in the last financial year and it provides the same CPS in at least three Member States;

(b) the CPS it provides is a significant gateway[11] for commercial users to reach end-users: this is the case where in the last financial year, the CPS had at least 45 million monthly active end-users established or situated in the EU and at least 10,000 active commercial users annually established in the EU;

(c) it enjoys a consolidated and durable position: this is the case where the thresholds of (b) have been met in each of the last three financial years (Bostoen, 2023).

The gatekeeper test appears to have been developed through reverse induction: the EC had an idea of which companies should be involved - particularly the GAFAM (Google, Apple, Facebook, Amazon, and Microsoft) - and then formulated the thresholds accordingly (Mariniello & Martins, 2021). On the other hand, a study assessing the impact of the DMA on nineteen companies showed that, regardless of the metric used, two clusters emerge: one with the GAFAM and one with other platforms (Sunderland et al., 2020). Specifically, in Article 2(2), the EC states that the DMA applies to ten core platform services: online intermediation

[11] A *gateway* is a computer that sits between different networks or applications (Gartner Information Technlogy Glossary).

services (e.g., Amazon Marketplace, Appstore), online search engines (e.g., Google), online social networking services (e.g., Facebook/Meta), video sharing services (e.g., YouTube), number-independent interpersonal communication services (e.g., WhatsApp), operating systems (e.g., Android, iOS), web browsers (e.g., Chrome), virtual assistants (e.g., Amazon Alexa, Siri, Google Assistant), cloud computing services (e.g., Amazon Web Services), and online advertising services (e.g., Google Ads) (Gröf, 2023). Bostoen (2023), relying on limited information and preferring exclusion over over-inclusion, formulated a list of CPS meeting the market capitalization/revenue thresholds and user thresholds outlined in Table 2, and thus considered possible gatekeepers[12].

Potential Gatekeeper	Core Platform Services			
	Intermediation	Search	Social	Video-sharing
Google (Alphabet)	Play Store	Google Search	—	YouTube
Apple	App Store	—	—	—
Microsoft	Microsoft Store	—	LinkedIn	—
Amazon	Amazon Marketplace	—	—	—
Facebook (Meta)	Facebook Marketplace	—	Facebook Blue, Instagram	Facebook Watch, IGTV/ Reels
	NIICS[120]	OS	Browser	Advertising[121]
Google (Alphabet)	Gmail, Messages, Google Meet	Android (Auto)	Chrome	Related to CPS (search), intermediation
Apple	Mail/iCloud, iMessage	iOS (CarPlay), macOS	Safari	Related to CPS (intermediation)
Microsoft	Outlook, Teams	Windows	Edge	Related to CPS (social)
Amazon	—	—	—	Related to CPS (intermediation)
Facebook (Meta)	Messenger, WhatsApp, Instagram	—	—	Related to CPS (social), intermediation

Table 2: List of possible gatekeepers (Bostoen, 2023)

Once a provider of a core platform service is identified as a "gatekeeper," it becomes subject to "directly applicable" obligations set out in Articles 5 and 6 for each of its core services. Generally, there are three types of obligations in the DMA aimed at different objectives: some obligations between Articles 5 and 6 seek to ensure a fair relationship between the gatekeeper and its commercial users or competitors. Other obligations address specific conflicts of interest that may arise when the gatekeeper is involved both in facilitating transactions for commercial users and competing with them, especially if it is

[12] In formulating the proposed list, Bostoen (2023) states that other platforms potentially classified as gatekeepers in the future include SAP, Oracle, and Salesforce as cloud computing services (the definition of which appears to include software-as-a-service [SaaS] providers), Alibaba, Airbnb, Booking.com, and Uber as intermediation services, and TikTok as a social network.

vertically integrated. Finally, some obligations in the DMA are directly aimed at maintaining competition in the relevant markets, encouraging platform usage diversification, reducing entry barriers, and increasing transparency (Akman, 2021). The obligations under Article 5 range from prohibiting the combining of personal data across the gatekeeper's services to the obligation to allow commercial users to offer their products/services at prices and conditions different from those set on the gatekeeper's platform. A crucial obligation is to allow commercial users to promote offers and conclude contracts directly with end-users outside the gatekeeper's platform. These obligations aim to ensure a fair competitive environment and address contestability issues in relevant markets (Akman, 2021).

The obligations set forth in Article 6 include prohibiting the gatekeeper from favoring its own services and products over those of third parties in placement, a practice known as "self-preferencing," which has been central to numerous disputes in the enforcement of competition laws in digital markets[13]. The DMA prohibits this practice and requires the gatekeeper to apply fair placement conditions. Other significant obligations concern the access of third-party search engine providers to placement data and the possibility of interoperating with the gatekeeper's operating system[14]. Additionally, obligations related to the installation and use of third-party apps are included, with the possibility of accessing them through means other than the gatekeeper's main platform.

Article 10 of the DMA allows the Commission to update gatekeepers' obligations following a market investigation to identify new rules against practices that limit competition or are unfair. If a practice gives gatekeepers a disproportionate advantage over commercial users or weakens competition, it is deemed unfair or harmful. Although the DMA establishes these general rules, it does not specifically mention consumers or competition. Additionally, the DMA requires gatekeepers to notify the Commission of concentrations in the digital sector and to subject their consumer profiling techniques to independent audits[15]. This is important because it enhances transparency and puts pressure on gatekeepers to maintain fairer standards and prevent abuses of power. These new rules may change the way large tech companies operate and could lead to further discussions on privacy and competition in digital markets.

[13] DMA (n 2) Article 6(d)
[14] DMA (n 2) Article 6(j)
[15] DMA (n 2) Articles 12 and 13.

The DMA also provides the Commission with investigative and enforcement powers similar to those in competition rules to ensure compliance[16]. The Commission may request information, conduct inspections, and impose fines for violations. If a gatekeeper fails to meet its obligations, the Commission can issue a "non-compliance decision" and require the gatekeeper to comply with it[17]. The DMA also introduces a "market investigation" mechanism to designate gatekeepers, establish systematic non-compliance, and examine new services for inclusion. Member States may request market investigations if they suspect that a core platform service provider should be designated as a gatekeeper[18].

2.3.3 *Digital Services Act (DSA)*

The Digital Services Act (DSA) was approved by the European Parliament on July 5, 2022, representing a significant initiative to regulate intermediary services in the European Union (Chiarella, 2023). This law, proposed by the Commission in December 2020, replaces and updates the previous liability regime for online service providers, as established by the 2000 E-Commerce Directive. The main goal of the DSA is to harmonize the rules on the provision of intermediary services in the EU, avoiding legal fragmentation and facilitating the offering of innovative digital services cross-border (Chiarella, 2023). Additionally, the DSA aims to ensure a consistent legal environment, preventing obstacles arising from differences in national laws. This helps to adequately supervise digital services and promote trust, innovation, and economic growth in the European internal market. Unlike the Digital Markets Act (DMA), which focuses on economic imbalances and unfair business practices of platform "gatekeepers," the DSA primarily deals with the liability of online intermediaries for third-party content, as well as online user safety and due diligence obligations for different online service providers, depending on the social risks represented (Chiarella, 2023).

The DSA completes existing sectoral legislation by introducing a comprehensive regulatory framework for all categories of online content, products, services, and activities. Its legal basis is Article 114 of the Treaty on the Functioning of the European Union. The DSA is divided into five chapters and one hundred seven considerations. Chapter I provides general provisions and key definitions, while Chapter II deals with the liability of intermediary service providers. Chapter III outlines the obligations of digital service providers to ensure a safe and

[16] DMA (n 2) Recital 68.
[17] DMA (n 2) Article 25.
[18] DMA (n 2) Article 33

transparent online environment. These obligations cover various aspects, such as the designation of contact points, transparency of operations, handling of reports and complaints, out-of-court dispute resolution, publication of reports, and protection of minors. Chapter IV focuses on implementation, cooperation, and sanctions related to digital services law. Here, the competences of competent authorities and national coordinators are detailed, along with cooperation mechanisms and the role of the European Council for Digital Services. Supervision, investigations, sanctions, and monitoring, especially for large online platform providers and search engines, are also discussed. Chapter V contains final provisions, including amendments to existing directives, review procedures, and provisions on entry into force.

The DSA introduces a novelty by defining and regulating Very Large Online Platforms (VLOPs) and Very Large Online Search Engines (VLOSEs). VLOPs are defined as online platforms that reach an average monthly number of active recipients of the service in the Union equal to or exceeding 45 million, while VLOSEs are online search engines that reach the same number of monthly active recipients in the Union. These large platforms are subject to special obligations to address societal risks, such as the need to conduct systematic risk assessments and adopt measures to mitigate them. They must also allow access to data to supervisory authorities and publish regular reports on content moderation (Chiarella, 2023). The DSA recognizes that recommender systems can pose risks such as the spread of harmful content and discriminatory treatment of consumers and citizens (European Commission, 2020c). To address these issues, the proposal requires online platforms that display advertising on their interfaces to ensure that recipients receive personalized information to understand the context of the displayed ads (European Commission, 2020c; Recital 52). In relation to this, Article 27(1) of the DSA states that "Providers of online platforms that use recommender systems shall set out in their terms and conditions, in plain and intelligible language, the main parameters used in their recommender systems, as well as any options for the recipients of the service to modify or influence those main parameters" (DSA, art. 27(1)). The purpose of this provision is to "explain why certain information is suggested to the recipient of the service": therefore, the parameters must include, at least, "the criteria which are most significant in determining the information suggested to the recipient of the service" (i.e., content) and the reasons for its "relative importance" (i.e., ranking) (DSA, art. 27(2)). Additionally, when options to modify or influence the main parameters are indicated in the terms and conditions, "providers of online platforms shall also make available a functionality that allows the recipient of the service to select and to modify at any time their preferred option" (DSA, art. 27(3)).

After the implementation of the DSA, there could be a reversal of the traditional passive role of the recipient, as it is now possible for them to directly influence the method used by the recommendation system (RS) by selecting the parameters and, indirectly, also the data that the system uses to generate its results. This opportunity to increase user clarity and control has not been positively received by prominent companies in the digital sector such as Meta, which have raised concerns about the potential interference of the stringent audit rules envisaged by the DSA with the development of the industry. However, online platforms that do not fall into the VLOP or VLOSE category and adopt profiling-based recommendation systems will not be required to offer parameter modification options to users unless explicitly stated in their terms and conditions. It is unlikely that these platforms will voluntarily provide such an option, as it may not be in their interest. Consequently, while Article 27 formally recognizes users' right to influence the recommendation process, this possibility may be limited in rare cases, as also indicated by Helberger et al. (2021). Furthermore, the practical effectiveness of such provisions will primarily depend on users' ability to understand the workings and logic behind the provided recommendations.

Article 30 of the DSA imposes further responsibilities on large online platforms (VLOPs), requiring them to allow public access to archives of the advertisements displayed on their platforms for a period of twelve months. This provision aims to facilitate monitoring and research on emerging risks associated with the spread of online advertising (European Commission, 2020c; Leerssen, 2021). Additionally, the DSA imposes transparency obligations on VLOPs that use recommender systems. These systems not only significantly influence users' ability to access and interact with online content but are also considered tools for amplifying messages, spreading viral content, and promoting online behaviors (European Commission, 2020c; Jesse & Jannach, 2021). Article 29 of the DSA states that VLOPs are required to clearly describe, in an accessible and understandable manner in their terms and conditions, the main parameters used in their recommendation systems, offering recipients of the service the ability to modify these parameters, including at least one alternative option not based on profiling. Regarding VLOPs, Article 38 of the DSA states that "providers of very large online platforms [VLOPs] and of very large online search engines [VLOSEs] that use recommender systems shall provide at least one option for each of their recommender systems which is not based on profiling" (DSA, art. 38). It is essential to emphasize that while the rules established in Article 27 apply to all online platforms, the scope of Article 38 is limited to very large online platforms (VLOPs) and very large online search engines (VLOSEs). Consequently, only in these contexts users will always have the option to choose between at least two types of recommendations (Fabbri M., 2023).

In detail, the DSA aims to counteract potential systemic risks and harms arising from the adoption of recommendation systems in very large online platforms (VLOPs) and very large online search engines (VLOSEs), with the goal of preventing the violation of fundamental rights and protecting vulnerable individuals such as minors. According to Article 34, “Providers of very large online platforms and of very large online search engines shall diligently identify, analyse and assess any systemic risks in the Union stemming from the design or functioning of their service and its related systems, including algorithmic systems, or from the use made of their services”, including: “(a) the dissemination of illegal content through their services”; “(b) any actual or foreseeable negative effects for the exercise of the fundamental rights [. . .] to human dignity”, “to respect for private and family life”, “to the protection of personal data”, “to freedom of expression and information”, “to non-discrimination”, “to respect for the rights of the child” and “to a high level of consumer protection”; (c) “any actual or foreseeable negative effects on civic discourse and electoral processes, and public security”; (d) “any actual or foreseeable negative effects in relation to gender-based violence, the protection of public health and minors and serious negative consequences to the person’s physical and mental well-being”. The risks assessments operated by very large online platforms should take into account, among other aspects, “the design of their recommender systems and any other relevant algorithmic system” (DSA, art. 34(2)), which will need to be adapted following risk mitigation measures (DSA, art. 35(1)).

After the extensive regulatory framework outlined by the DSA, in April 2023, the European Commission established the European Centre for Algorithmic Transparency (ECAT). This center is tasked with contributing scientific and technical expertise to the Commission's exclusive role in supervising and enforcing systemic obligations concerning Very Large Online Platforms (VLOPs) and Very Large Online Search Engines (VLOSEs) as envisaged by the DSA. ECAT engages in a series of fundamental activities to ensure transparency and accountability in the use of algorithmic systems. These actions include in-depth assessments and investigations of online platforms, inspections of algorithmic systems to ensure compliance with the DSA, and technical testing for a better understanding of such systems' operations. Additionally, it provides consultancy on procedures to ensure access to data for regulators and researchers. Through scientific research, ECAT examines the social impact of algorithmic systems in the short, medium, and long term, identifying and assessing systemic risks associated with online platforms and developing methodologies for fair, transparent, and responsible algorithmic approaches. It also promotes networking and community building, sharing knowledge, and facilitating discussions on algorithmic transparency with international stakeholders, serving as a reference point for data-driven research provided by the DSA (European Centre for Algorithmic Transparency, n.d.).

2.3.4 *Artificial Intelligence Act (AIA)*

Considering the widespread use of artificial intelligence systems as pervasive facilitators of hypernudging, it is crucial to focus on the Artificial Intelligence Act. The latter, officially approved on March 13, 2024, adopts a risk-based approach to regulate the various uses of artificial intelligence, aiming to guide market innovation and mitigate risks, particularly those related to negative impacts on fundamental rights (European Commission, 2021b; Veale & Zuiderveen). The Artificial Intelligence Act (AIA) aims to provide clear guidelines and well-defined responsibilities for developers, distributors, and users of AI technologies in specific domains. At the same time, it aims to alleviate bureaucratic and financial burdens for businesses, especially small and medium-sized enterprises (SMEs). The AI Act is part of a broader regulatory package on artificial intelligence, which also includes a coordinated updated plan for the development and implementation of these technologies. Together, these regulatory and programmatic tools will ensure the protection of fundamental rights of individuals and businesses in the field of AI while promoting diffusion, investments, and innovation in the sector throughout the European Union (AI Act, 2024b). The AIA will constitute the first comprehensive set of global regulations concerning AI. The primary goal of these new regulations is to promote the adoption of reliable AI technologies both in Europe and internationally, ensuring that such systems respect fundamental rights, safety, and ethical principles. The proposed regulations specifically address the risks arising from artificial intelligence applications, proposing a list of applications considered high-risk. Additionally, they establish clear requirements for artificial intelligence systems intended for such high-risk applications and define specific obligations for both users and providers of such systems. A conformity assessment is expected before the deployment or introduction to the market of such systems, followed by the enforcement of rules once the system is on the market. Finally, a governance structure at both European and national levels is proposed to ensure effective implementation of the rules and monitoring of compliance.

A system of AI is defined in Article 3(1) of the AIA as "software that is developed with one or more of the techniques and approaches listed in Annex I and can, for a given set of human-defined objectives, generate outputs such as content, predictions, recommendations, or decisions influencing the environments they interact with." Annex I lists various methods and approaches used in the field of artificial intelligence, including:

(a) Machine learning techniques, including supervised, unsupervised, and reinforcement learning, with a wide range of methods, including deep learning;

(b) Logic-based and knowledge-based methods, including knowledge representation, inductive programming (logic), knowledge bases, inference and deductive engines, reasoning (symbolic), and expert systems;

(c) Statistical approaches, such as Bayesian estimation[19], search and optimization methods.

The definition focuses on systems, outlining them through four criteria: (1) they must be comprised of software; (2) the software must be developed using one or more of the techniques listed in the annex; (3) the system must be developed based on human-defined objectives, which is inevitable but relevant; and (4) the AI system must produce outputs that influence the environments it interacts with.

The Regulatory Framework defines 4 levels of risk in AI (as highlighted in Figure 8):

[19] Bayesian estimation is a Bayesian statistical technique that uses prior knowledge about a particular event or variable as an estimate. In other words, it utilizes conditional probability; the probability that X is true depends on previous observations or knowledge of X or some related variable (www.study.com).

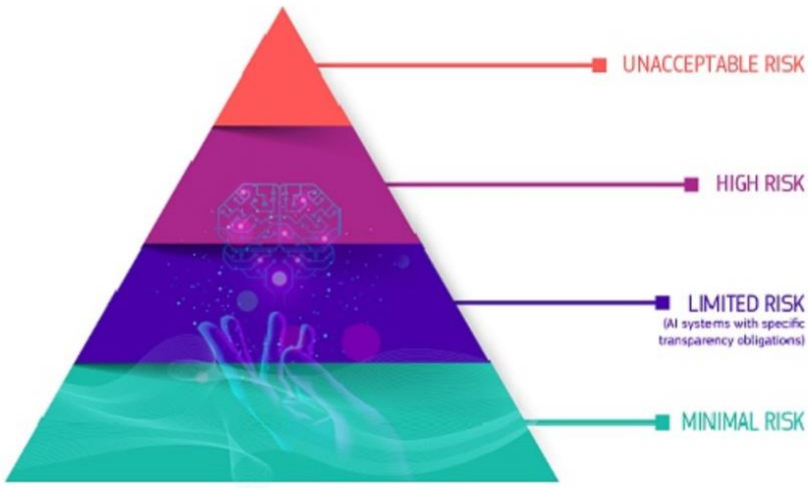


Figure 9: four levels of AI risk (AI Act., 2024b)

The concept of "limited risk" applies to artificial intelligence systems that require specific transparency obligations. For example, when using chatbots or other types of interactive AI systems, it is crucial for users to be aware that they are interacting with a machine so they can make informed decisions on how to proceed or whether to withdraw from the interaction. An important question concerns whether a recommender system can be considered high-risk and under what circumstances it might fall into this category. This depends on the impact such systems can have on individuals. Annex III of the Regulatory Framework lists various contexts and uses that present significant risks, such as those influencing access to education, employment, social benefits, or credit assessment. These risks can also emerge in public domains, such as border control or the criminal justice system. In the field of marketing and advertising, the AIA prohibits the use of artificial intelligence systems for subliminal manipulation and exploitation of vulnerable groups if such use "causes or is likely to cause […] physical or psychological harm" to an individual. However, proving this connection could be complicated (Hildebrandt, 2022). If a RecSys is classified as high-risk, there are several legal obligations that must be followed, primarily by the providers of such systems. These providers must implement a risk management system that assesses potential consequences on health, safety, and fundamental rights, both when the RecSys is used for its intended purpose and for other reasonably foreseeable uses. The law emphasizes the importance of data selection and care, as well as various types of testing, and highlights the need for accurate performance measurement, ensuring robustness and cybersecurity, and maintaining detailed documentation and accurate records, in addition to implementing automated logging and post-sale monitoring procedures. Furthermore, providers must establish a quality management system and ensure, through design and instructions, that human supervision is meaningful, effective, and practical (Hildebrandt, 2022). In essence, the AIA narrows the options available to providers of artificial intelligence systems in guiding their development. This impacts providers' decision-making architecture, promoting the adoption of AI systems that are resilient, robust, reliable, and accountable (Hildebrandt, 2022).

The European AI Office, founded in February 2024 under the Commission's purview, supervises the enforcement and execution of AI legislation alongside Member States, with the goal of fostering an atmosphere where AI advancements uphold human dignity, rights, and trust. Furthermore, it fosters cooperation, innovation, and AI exploration across diverse stakeholders while participating in discussions and global partnerships concerning AI concerns, aiming for universal conformity on AI regulation. Through these efforts, its objective is to establish Europe as a front-runner in the moral and sustainable progression of AI technologies.

The Coordinated AI Plan of 2024, based on previous plans from 2018 and 2021, reflects a policy shift towards Generative AI in response to recent technological developments. Its goal is to accelerate investments in AI, fully implement AI strategies and programs, and ensure policy alignment to prevent fragmentation in the EU. The 2024 communication aims to empower startups and innovation in reliable AI through a strategic investment framework, collaboration among industrial actors, support for companies to become global leaders in reliable AI, and a package of measures to support startups in adhering to EU values and regulations. Implemented actions include initiatives to develop critical computing capacity, such as the Chips Act[20] and the EuroHPC JU[21], creating a synergistic ecosystem to advance microelectronics and computing capacity in Europe.

2.4 Research gap, conceptual framework and hypothesis development

Research on the implications of recommender systems (RS) is still in its early stages, with fragmented debate among different scientific communities focusing on specific aspects

[20] The Chips Act is a European law aimed at strengthening the semiconductor ecosystem in the EU, ensuring supply chain resilience, and reducing external dependencies. It focuses on five strategic objectives, including strengthening research, developing production capacity, addressing skills shortages, and developing an understanding of global supply chains (European Chips Act, 2024).

[21] EuroHPC JU is “a joint initiative between the EU, European countries and private partners to develop a World Class Supercomputing Ecosystem in Europe” (EuroHPC JU, 2024)

and applications of the systems in various contexts. This fragmentation can be mainly attributed to the novelty of the technology and issues related to data ownership and privacy. Currently, the operational details of recommender systems are considered trade secrets, making it difficult for researchers to access detailed information to assess their impact. At the same time, for privacy reasons, RS providers may be reluctant to share information that could compromise users' personal data. From a legal and ethical perspective, there are no court rulings yet imposing an obligation to ensure diversity of online content resulting from the use of RSs and hypernudges. Although organizations across sectors are increasingly adopting artificial intelligence, knowledge about the overall impact of AI on the economy and society is limited. This is particularly concerning as AI is making an already complex world even more intricate, underscoring the urgency of more in-depth economic research on the topic. Nudge, including hypernudge, has been integrated into recommender systems, but research directly connecting these themes is scarce. There are few studies examining nudges and hypernudges within recommender systems, and this gap is also reflected at the regulatory level. While there are legal instruments like the GDPR focusing on privacy, specific provisions addressing the intersection between AI, digital nudging, and hypernudging in recommender systems are lacking. The Artificial Intelligence Act, while representing a step forward in addressing AI challenges, does not yet provide clear guidelines on how to comprehensively and effectively address these issues.

Therefore, the aim of the study is to explore more deeply the correlation between hypernudge and recommender systems. In particular, the study focuses on exploring users' recognition of the inherent persuasive nature of recommendation systems and its potential impact on their intention to use these systems and the perceived value they attribute to them.The research question will be:

How do users' intentions to use recommender systems differ based on their persuasion knowledge and perceived value?

The research is divided into two parts: the first will investigate the direct relationship between users' *persuasion knowledge* and their *intention to use* recommender systems.

The second part of the research aims to identify a possible positive moderating effect of *perceived value* (of recommendation systems) on the relationship between *persuasion knowledge* and *intention to use* (recommender systems).

Based on these premises and relevant findings in the existing literature, the moderation model will be structured as follows:

1. **Independent Variable (X):** Persuasion knowledge
2. **Dependent Variable (Y):** Intention to use (recommender systems)
3. **Moderating Variable (W):** Perceived value

Based on the above, Figure 10 summarizes the research model followed by the corresponding hypotheses.

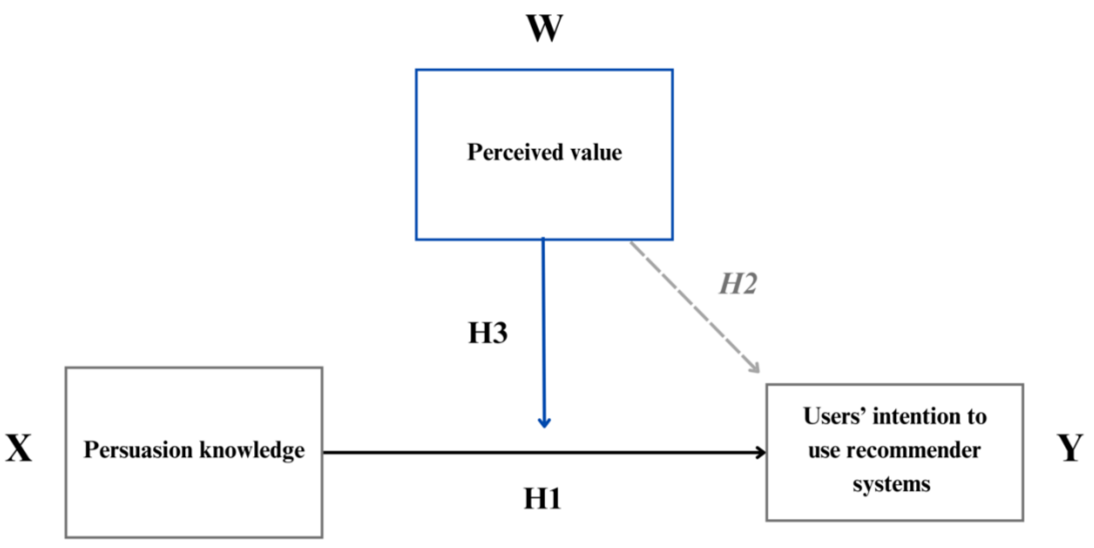


Figure 10: Research model

H1: *A greater level of persuasion knowledge among users is associated with a lower intentionto use recommender systems.*

H2: *A greater level of perceived value is correlated with a greater intention to use recommender systems.*

H3: *Perceived value positively moderates the relationship between persuasion knowledge and users' intention to use recommender systems.*

3. Empirical analysis

3.1 Research methodology

Quantitative data collection was conducted through the administration of a closed-ended questionnaire via the web platform Qualtrics. Survey respondents were reached by sharing a unique link across various social media platforms: Whatsapp, Facebook, Instagram, and Linkedin. The questionnaire was set up to ensure complete anonymity so that respondents felt free to express honest and truthful opinions. The estimated average completion time for the entire questionnaire was approximately 4 minutes, a timeframe aligned with the platform's suggestion to ensure all participants completed the study without abandoning it due to excessive length. Given that the questionnaire was administered to a heterogeneous sample in terms of demographic variables, a brief definition of hypernudge was provided in the introductory section to enable all respondents to understand and answer the questions. Respondents were asked the same questions, divided in order according to the variables under study, as outlined in the conceptual framework (see section 2.4). The full structure of the questionnaire can be found in Appendix A.

Familiarity: Before delving into the main investigation, it was deemed appropriate to assess the existence and degree of familiarity with the topic of recommender systems. Respondents were thus asked to indicate, on a bipolar scale (Yes or No), whether they had ever heard the term "recommender system". For respondents who indicated unfamiliarity with the term, a brief definition was provided. The familiarity scale used was pre-validated by Mrazek, A. J et al. (2020), utilizing only one item.

Intention to use: The second section aims to analyze the dependent variable of the research model, namely users' intention to use recommender systems. To this end, the scale pre-validated by Kleijnen, M. et al. (2007) was chosen, utilizing all five items. Specifically, participants were asked to indicate on a scale from 1 (negative) to 7 (positive) their level of agreement or disagreement with the provided statements. Referring to the scale described above, different terms from the extremes 1 and 7 of the Likert scale were associated with each question, for example: Uncertain/Certain; Definitely would not use/Definitely would use etc.
It was decided to examine this variable first – rather than the independent variable *Persuasion Knowledge* - to prevent the implicit idea of a persuasive nature of recommender systems from

influencing the sincerity of participants' opinions on their actual intention to use such technologies.

Persuasion knowledge: The third section is dedicated to investigating the independent variable of the model, namely users' level of knowledge about the persuasive nature inherent in recommender systems. For this purpose, the Persuasion Knowledge model by Ham, C. D. et al (2015) was utilized. This model comprises several items and various pre-validated scales. For our study, it was decided to incorporate 5 items belonging to various scales, specifically: 1 item from the "Persuasive intent" scale by Van Noort et al (2012), 2 items from the "Inference of Manipulative intent (IMI)" scale by Campbell (1995), 1 item from the "Persuasion Knowledge (PK)" scale by Bearden et al. (2001), and 1 item from the "Persuasion Knowledge" scale by Tutaji and Van Reijmersdal (2012). Before displaying the questions, respondents were shown an image representing a plausible login scenario on the Amazon.com platform. On the website's home screen, personalized product recommendations based on past purchases and user preferences were displayed. After observing the image, respondents were asked to express their level of agreement or disagreement with the proposed statements on a 7-point Likert scale (where 1 indicates *strongly disagree* and 7 *strongly agree*).

Perceived value: The next section aims to analyze the value that each user associates with recommender systems, whether it be positive or negative. This is in order to subsequently evaluate how the subjectively associated value of recommender systems may somehow influence both the knowledge of their persuasive nature and the intention to use such technologies. To this end, all respondents were asked the following question: "How do you rate recommender systems?" Response options were based on a scale pre-validated by Kleijnen et al (2007), from which all five items were selected. Specifically, the scale provided different response extremes: "Practical/Impractical", "Useless/Useful", "Inefficient/Efficient", "Unproductive/Productive", and "Bad/Good". Participants were asked to express their opinion about recommender systems on a 7-point Likert scale (where 1 indicates the negative extreme and 7 the positive extreme), in order to allow for a more detailed assessment of responses.

Demographic questions: The last section includes five demographic questions aimed at obtaining a precise overview of the sample reached for the study's evaluations. Specifically, the questions pertained to gender, age range (divided by generations), occupation, and origin.

Since the questionnaire was exclusively administered to individuals of Italian nationality, the origin aimed to investigate whether respondents hailed from the North, Central, or Southern Italy. The demographic questions were intentionally placed last to allow respondents to maintain a higher level of attention and concentration when answering the more specific questions.

In summary, references to all pre-validated scales used for constructing the items in the questionnaire can be found in Appendix B.

3.2 Sample Characteristics

This paragraph will provide a more detailed presentation of the survey's reference sample. As anticipated, the survey was constructed using the Qualtrics platform and shared online via various platforms: Whatsapp, Instagram, Linkedin, and Facebook. In total, 275 respondents were reached. Out of these, 235 completed the survey in its entirety.

The reached sample consists of individuals belonging to four distinct age generations, namely: 21% belonging to the "Baby Boomers" generation, born between 1946 and 1964, aged between 60 and 78 years. 34% belong to Generation X, born between 1965 and 1979, aged between 43 and 59 years. 20% belong to Generation Y (also known as "Millennials"), born between 1980 and 1996, aged between 28 and 44 years. Finally, 25% belong to Generation Z (also known as "Centennials"), born between 1997 and 2009, aged between 15 and 27 years.

Regarding gender, 54% of the sample is comprised of women, while the remaining 45% is comprised of men, with one participant opting not to respond.

The distribution of the sample appears to be evenly spread, accurately representing the reference population - a circumstance that should help avoid systematic errors due to gender distribution that could influence the analysis results.

Regarding the origin, the questionnaire was administered to individuals of Italian nationality, who were asked to indicate whether they hailed from the North, Central, or Southern Italy. For each classification, the complete list of associated Italian regions was provided, as reported by the 2024 ISTAT data. Specifically, 28% of the sample is from Northern Italy, 45% from Central Italy, and 27% from Southern Italy.

Regarding occupation, 33% of respondents are employees, 29% are self-employed professionals, 22% are students, 10% are unemployed, and 5% are workers and artisans.

Before proceeding with the specific survey questions, the *Familiarity* control variable was introduced. Specifically, respondents were asked if they had ever heard the term "recommender system." The data reveals that the majority of respondents, namely 61%, are not familiar with the term.

Q4

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	No	144	61.3	61.3	61.3
	Yes	91	38.7	38.7	100.0
	Total	235	100.0	100.0	

3.3 Questionnaire analysis and results

The collected data was analyzed using the statistical software SPSS (Statistical Package for Social Science), and the analysis outputs can be consulted in Appendix C. Upon launching the analysis on SPSS, the first step involved checking consistency and verifying the reliability of the scales used. For the three variables of interest (*Intention to use, Persuasion Knowledge,* and *Perceived Value*), Cronbach's alpha was respectively 0.982, 0.599, and 0.966. The only scale with an unacceptable Cronbach's alpha is *Persuasion Knowledge*. However, by removing question Q25_3, the Cronbach's alpha increases to 0.946, rendering this scale reliable (see section 3.4).

With this done, we were able to proceed with the actual data analysis to test the research hypotheses.

H1: *A greater level of persuasion knowledge among users is associated with a lower intentionto use recommender systems.*

To test the first hypothesis, a linear regression model was adopted, with *Persuasion Knowledge* as the independent variable and *Intention to Use* (recommender systems) as the dependent variable.

To assess Model fit, it was verified whether at least one coefficient was different from zero and thus statistically significant. The results of the F-test, considering a significance level of 5%, confirm the significance of the regression (p-value < 0.05, F 382.7). Therefore, it is possible to reject the null hypothesis H0, which states that all regression coefficients are equal to zero.

The R^2 of 0.617 indicates a good fit of the model, which can explain 61% of the variability in the dependent variable *Intention to use* (recommender systems).

Through the T-test, a significant (p-value < 0.05, t=-19.5) and negative effect of the independent variable *Persuasion Knowledge* on *Intention to use* was observed, indicating that an increase in users' knowledge about the persuasive nature of recommender systems is associated with a decrease in the intention to use such technologies.

Therefore, it is possible to accept hypothesis H1.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	T	Sig.
1	(Constant)	28.956	.710		40.771	<.001
	Persuasion knowledge	-.779	.040	-.785	-19.562	<.001

a. Dependent Variable: Intention to use

H2: *A greater level of perceived value is correlated with a greater intention to use recommender systems.*

To test the effect described by hypothesis 2, a linear regression model was fitted, with *Perceived value* as the independent variable and *Intention to use* (recommender systems) as the dependent variable.

To assess Model Fit, it was verified whether at least one coefficient was different from zero and thus statistically significant. The results of the F-test, considering a significance level of

5%, are significant (p-value < 0.05, F=803.5). Therefore, it is possible to reject the null hypothesis H0, which states that all regression coefficients are equal to zero.

The R^2 of 0.773 indicates an excellent fit of the model, according to which *Perceived value* can explain 77% of the variability in *Intention to use* (recommender systems).

Through the T-test, it can be observed that the variable *Perceived value* has a significant (p-value < 0.05, t=28.3) and positive effect on *Intention to use*, highlighting that as the perceived value by users about recommender systems increases, their intention to use them also increases.

Therefore, it is possible to accept hypothesis H2.

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	T	Sig.
1	(Constant)	-.033	.664		-.050	.961
	Perceived value	.907	.032	.880	28.346	<.001

a. Dependent Variable: Intention to use

H3: *Perceived value positively moderates the relationship between persuasion knowledge and users' intention to use recommender systems.*

Finally, the third hypothesis aims to identify a possible positive moderation effect of the *Perceived Value* associated with recommender systems in the relationship between *Persuasion Knowledge* and *Intention to use*.

To test the moderation effect, a linear regression model was used, with *Persuasion Knowledge* and *Perceived Value*, and their interaction as independent variables, and *Intention to Use* as the dependent variable.

Due to the presence of strong multicollinearity (VIF>10), the variables were centered, and an additional model was fitted with these centered variables and their interaction.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	T	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	-.911	2.310		-.394	.694		
	Perceived value	1.071	.086	1.039	12.446	<.001	.106	9.405
	Persuasion knowledge	.142	.090	.143	1.577	.116	.090	11.099
	Interaction	-.019	.004	-.309	-5.441	<.001	.230	4.342

a. Dependent Variable: Intention to use

In the regression, a significant effect of the interaction is observed.

To assess Model Fit, an F-test was conducted. The results, considering a significance level of 5%, are significant (p-value < 0.05, F=372.3). Therefore, it is possible to reject the null hypothesis H0, which states that all regression coefficients are equal to zero.

The R^2 of 0.827 indicates an excellent fit of the model, which can explain 82% of the variability in Intention to use.

Through the T-test, it can be observed that the variables *Perceived Value* and *Persuasion Knowledge* have significant effects consistent with what was observed previously.

The interaction term was found to be significant (p-value < 0.05, t=-5.4) but negative, indicating that *Perceived Value* has a negative effect on *Persuasion Knowledge*. This suggests that for those who attribute more value to recommender systems, knowledge of their persuasive nature has an even more negative impact on the intention to use such technologies.

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	T	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	4.641	1.654		2.805	.005		
	Perceived value	.776	.049	.753	15.783	<.001	.325	3.076
	Persuasion Knowledge	-.219	.045	-.221	-4.835	<.001	.354	2.822
	Interaction2	-.019	.004	-.161	-5.441	<.001	.846	1.182

a. Dependent Variable: Intention to use

Therefore, given the negative – rather than positive – moderation effect, it is not possible to accept H3.

3.4 Limitations and future research

The paper has provided an empirical framework on past and emerging studies and research on the topic of hypernudges and recommendation systems. As seen in previous chapters, the literature and research on the aforementioned topics are still rather sparse, and even scarcer is the level of users' familiarity with the implications of such technologies. Regarding the limitations of the study, there are many avenues and points of inquiry that this research has opened. Firstly, regarding the quantitative analysis conducted, it was particularly challenging to find a pre-validated scale in the literature that addressed the topic of persuasion. In fact, as described earlier, the independent variable *Persuasion Knowledge* was extrapolated from a model by Ham, C. D. et al. (2015), which combines pre-validated scales from various authors, each with different denominations: some refer to "Inference of Manipulative Intent," others to "Perceived Intent to persuade," and other related denominations concerning persuasion or the potential manipulative effect of advertising (adapted to recommendation systems). Additionally, no other scales addressing perceived persuasion, perceived manipulation, or perception of influence were found in the literature. Therefore, building new and specific constructs to probe these themes more specifically, relating them to emerging technologies such as artificial intelligence, hypernudges, and recommender systems on major online platforms, could be considered.

Secondly, in testing the reliability of the scales, *Persuasion Knowledge* initially appeared insignificant. The cause of the insignificance of Ham et al.'s (2005) scale lies in question Q25_3 and, more specifically, in its structure: it was posed after exposing respondents to the login scenario on the Amazon.com platform, which featured personalized product recommendations based on past purchases. The question contains two distinct statements to evaluate: on the one hand, it is stated that "I don’t mind this picture," and immediately afterward, in the same question, that "The advertiser tried to be persuasive without being excessively manipulative." Probably, having to answer to two distinct statements within the same question may have confused the respondents.

As for hypothesis testing, the moderation hypothesis H3 could not be accepted, as the effect of the moderating variable was opposite to what was expected. Indeed, in testing the moderating role of *Perceived Value* in the relationship between *Persuasion Knowledge* and *Intention to use*, one would expect that perceiving greater value from recommender systems would attenuate the negative effect of *Persuasion Knowledge*. However, the data show that this variable is so influential that it cannot even be countered by increased *Perceived Value*. This result further emphasizes the importance of *Persuasion Knowledge* in influencing users' opinions on recommender systems. Essentially, although a high *Perceived Value* may increase users’ intention to use recommender systems when considered individually, when compared to a persuasive or manioulatory risk, the latter is the determining factor in influencing consumers' final attitudes toward such technologies.

Considering the survey sample, it is observed that out of 275 respondents, only 235 actually completed the questionnaire. Another limitation of the research concerns the nationality of the interviewees. Indeed, the questionnaire was only administered to individuals of Italian nationality. Expanding the survey to other nationalities or conducting a survey at a European or extra-European level could be interesting to acquire new perspectives and further delve into the subject under examination. Finally, it would be interesting to replicate the research from a business perspective – examining to what extent and under what circumstances businesses choose to implement hypernudge techniques and recommender systems, how they promote them, and how they address the issue of persuasive nature among their customers.

3.5 General discussion and contribution of the research

Recommender systems and hypernudge have assumed a central role in corporate marketing as companies constantly seek new methods to shape user behavior online. Despite their increasing adoption, current research presents significant gaps concerning the effects and implications of these technologies, especially considering the complexity of online dynamics and the diversity of user experiences.

These platforms are effectively transforming the marketing landscape, offering companies a powerful tool to personalize user experiences and improve conversions through targeted and highly customized recommendations. However, ethical and social concerns, such as the potential persuasive and manipulative nature of these technologies, along with user privacy protection and transparency in data usage, raise important issues that can influence business strategies.

In this context, it is crucial to deeply understand consumers' opinions and attitudes toward these technologies. Following this, the importance of the present research on recommender systems with its main contributions is outlined.

Theoretical Contributions

This study contributes to existing literature in several ways. Firstly, it expands the understanding of the interaction between the knowledge of the persuasive nature inherent in recommender systems, perceived value, and users' intention to use them within the context of behavioral economics and digital marketing. By empirically testing these relationships, the research adds empirical evidence to the theoretical framework of digital nudges, hypernudge, and recommender systems.

Furthermore, the study sheds light on the nuanced dynamics of user perceptions and attitudes toward these technologies, highlighting the importance of considering both cognitive factors (such as knowledge of the persuasive nature) and perceived benefits (perceived value) to understand users' behavioral intentions.

Managerial Implications

The research was conducted with the aim of providing insights for companies employing hypernudge and recommender systems to influence user behavior. The results suggest that, although these technologies offer advantages in improving user experience and stimulating engagement, implementing such technologies requires transparency and greater attention to ethical issues.

The findings of the quantitative study have identified a significant relationship between user awareness of persuasive tactics and their intention to use recommender systems. This underscores the importance for companies to strike a balance between exploiting persuasive techniques and delivering genuine value to users.

Recommendations for Companies

It's crucial for companies to ensure that users have a full understanding of how hypernudge and recommender systems operate. Transparency is key in the utilization of these technologies, necessitating clear communication regarding the use of user data and the objectives driving the implementation of such systems. Educating individuals about the underlying mechanisms of these technologies can facilitate heightened awareness and foster trust.

Instead of solely concentrating on engaging users, companies should prioritize crafting recommendation systems that provide genuine and meaningful value to them. This entails making the goal of offering relevant and useful recommendations the focal point of design strategies, rather than simply aiming to capture attention in the short term. By focusing on value, companies can foster a stronger and more enduring relationship with their customer base.

Finally, it is essential for companies to operate in compliance with regulations and ethical guidelines, such as GDPR, the Digital Services Package, and the AIA. This entails not only ensuring legal compliance but also adopting an ethical perspective in the implementation of hypernudge and recommender systems. Respecting users' rights to privacy and autonomy is crucial for building trust and fostering acceptance of these technologies.

Conclusions

This study has sought to shed light on the relationship between consumers and recommender systems, starting from the principles of behavioral economics and reaching digital marketing.

Understanding consumers, their needs, and their predisposition to purchase a particular product or use a service is indeed the starting point for defining effective marketing strategies. In this context, nudge is a theory of behavioral economics that, through the design of the decision-making context, attempts to influence people's decisions without limiting their freedom of choice. Its application to the digital world is defined as "digital nudge," differing from its analog counterpart for the customization of choices. Hypernudge represents the ultimate evolution of digital nudge, using artificial intelligence and algorithms to offer consumers even more personalized experiences, such as targeted advertising or virtual assistants. In particular, I decided to focus on a specific type of hypernudge, recommender systems. The latter suggest choice options based on users' past experiences, thus integrating principles of behavioral economics into digital marketing.

The evolution of increasingly advanced technologies brings with it characteristics and potential far superior to traditional nudge techniques. Like any innovation, recommendation systems are accompanied not only by enthusiasm but also by skepticism and concerns. Indeed, while these digital tools simplify and accelerate the user decision-making process—bypassing cognitive biases such as choice overload—they also carry significant influencing power that could undermine one of the key principles of traditional nudge: the preservation of freedom of choice.

I wondered, therefore, whether the persuasive capacity inherent in recommender systems could influence users' perception of their utility and willingness to use them. The quantitative analysis conducted led to interesting considerations: it is true that the perceived value of recommendations leads to increased usage by consumers, but, conversely, awareness (not always present) of a possible manipulative intent significantly limits their scope.

In summary, as much as consumers may appreciate products, services, and technologies, considering them of high added value, when they perceive a possible threat to individual freedom and decisional autonomy, there is no advantage or value that holds. The above reflections can provide support for all those companies that implement—or intend to implement—hypernudge and recommendation systems within their digital strategy. In order for a user to derive the maximum value from a technology, it is necessary first and foremost that they understand its purpose and potential, and that the relationship with the company utilizing it is built on mutual trust and transparency from the outset.

Today, consumers prefer dialogue with companies and recognize initiatives that contribute to the well-being not only of individuals but of a community as a whole. To allow this to happen, the participation of all stakeholders involved is necessary. It is no longer sufficient, therefore, for a product or service to be "effective"; it must be satisfying in a broader perspective, based on long-term benefits and the physical and mental well-being of those who use it.

Appendix

Appendix A - Qualtrics: questionnaire design

Introduction

Hello! The following questionnaire will focus on the use of hypernudge and recommendation systems on digital platforms. I kindly ask for a few minutes of your time to answer some questions. Your contribution is very important, and your answers will remain anonymous. The responses will be used for my Master's thesis in Marketing. Thank you in advance!

Before we begin, let me provide you with a brief definition of "hypernudge": In behavioral and digital economics, hypernudge focuses on the use of data and advanced algorithms to provide highly personalized suggestions or targeted interactions. These tools are designed to intelligently adapt to users' preferences and behaviors, aiming to simplify their digital choices.

Familiarity with recommender systems

Have you ever heard of the term "***recommender system***"?

- ◯ Yes
- ◯ No

Recommender systems are algorithms used by digital platforms to suggest content based on your interests and past behaviors. For example, on Netflix, they recommend movies based on what you've already watched; on Amazon, they show you products similar to ones you've purchased, and on Spotify, they suggest songs based on your previous musical tastes.

Short definition of recommender systems (only provided to those who answered "No" to the previos question)

Intention to use (recommender systems)

Please rate the questions regarding recommendation systems on a scale from 1 (completely negative) to 7 (completely positive).

How likely are you to be influenced by recommendation systems when making an online purchase decision?

1=Improbable	2	3	4	5	6	7=Probable
○	○	○	○	○	○	○

To what extent do you consider it possible to rely on recommendation systems in your purchasing decisions?

1=Impossible	2	3	4	5	6	7=Possible
○	○	○	○	○	○	○

Your reliance on recommendation systems in daily choices on online platforms is:

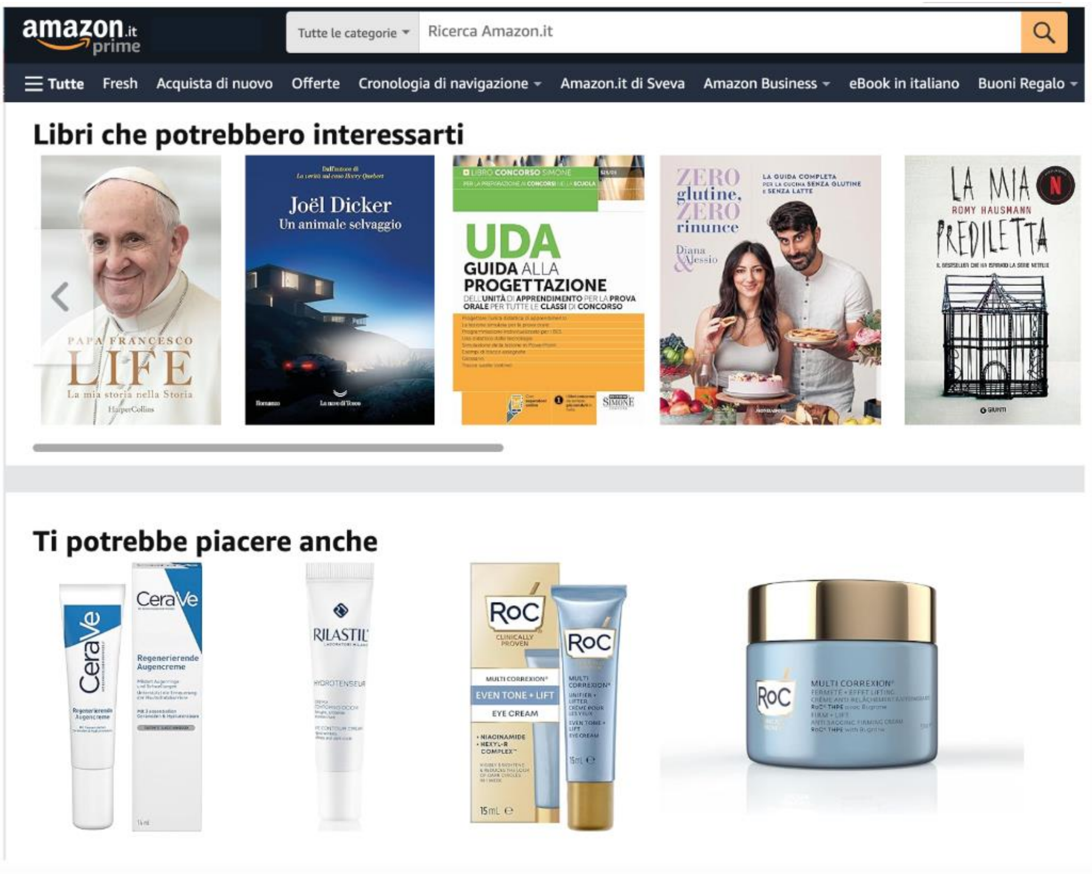
1=Uncertain	2	3	4	5	6	7=Certain
○	○	○	○	○	○	○

If a new recommendation system were implemented on the main platforms you use online, what would you do?

1=Definitely would not use	2	3	4	5	6	7=Definitely would use
○	○	○	○	○	○	○

Persuasion knowledge

Imagine wanting to make a purchase on Amazon. Upon entering the platform, you see the following screen. I ask you to immerse yourself as much as possible in the proposed scenario.



Note that the image is in Italian as it represents a screenshot of Amazon Italy. The two captions that appear on the screen mean, respectively: "Books you might be interested in" (top) and "You might also like" (bottom).

Based on the scenario just presented, please express your honest opinion on a scale from 1 (strongly disagree) to 7 (strongly agree).

	1=Strongly disagree	2	3	4	5	6	7 = Strongly agree
I know when a marketer is pressuring me to buy	○	○	○	○	○	○	○
I was annoyed by this picture because the advertiser seemed to be trying to innapropriately manage or control the consumer audience	○	○	○	○	○	○	○
I don't mind this picture; the advertiser tried to be persuasive without being excessively manipulative	○	○	○	○	○	○	○
I don't mind this picture; the advertiser tried to be persuasive without being excessively manipulative	○	○	○	○	○	○	○
The aim of this picture is to influence my opinion	○	○	○	○	○	○	○
The picture is created to persuade	○	○	○	○	○	○	○

Perceived value (of recommender systems)

Overall, how do you evaluate recommendation systems? (on a bipolar scale with the two opposite extremes)

Unpractical	○	○	○	○	○	○	○	Practical
Useless	○	○	○	○	○	○	○	Useful
Unefficient	○	○	○	○	○	○	○	Efficient
Unproductive	○	○	○	○	○	○	○	Productive

Domande demografiche

Specificy your gender

- ○ Male
- ○ Female
- ○ Prefer not to specify

Specify your year of birth

- ○ 1946-1964
- ○ 1965-1979
- ○ 1980-1996
- ○ 1997-2009

Specify your occupation

- ○ Student
- ○ Employee
- ○ Craftsman/artisan
- ○ Freelancer
- ○ Unemployed

Where do you come from?

- ○ Northern Italy (Valle d'Aosta, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna)
- ○ Center Italy (Lazio, Marche, Toscana, Umbria)
- ○ Southern Italy (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna)
- ○ Extra Italy

Appendix B – References pre-validated questionnaire scales

Variable	*Reference*
Familiarity	Mrazek, A. J., Mrazek, M. D., Calcagnotto, L. A., Cloughesy, J. N., Holman, A. M., Masters-Waage, T. C., & Schooler, J. W. (2020). Familiarity, attitudes, and self-regulatory challenges related to mindfulness. *Mindfulness*, *11*, 1218-1225.
Intention to use	Kleijnen, M., De Ruyter, K., & Wetzels, M. (2007). An assessment of value creation in mobile service delivery and the moderating role of time consciousness. *Journal of retailing*, *83*(1), 33-46.
Persuasion Knowledge	Ham, C. D., Nelson, M. R., & Das, S. (2015). How to measure persuasion knowledge. *International Journal of Advertising*, *34*(1), 17-53.
Perceived value	Kleijnen, M., De Ruyter, K., & Wetzels, M. (2007). An assessment of value creation in mobile service delivery and the moderating role of time consciousness. *Journal of retailing*, *83*(1), 33-46.

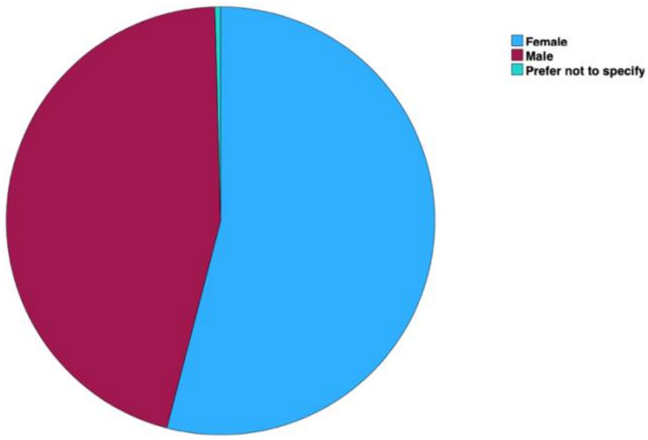
Appendix C – SPSS analysis of questionnaire data

Demographics

Gender

Q14

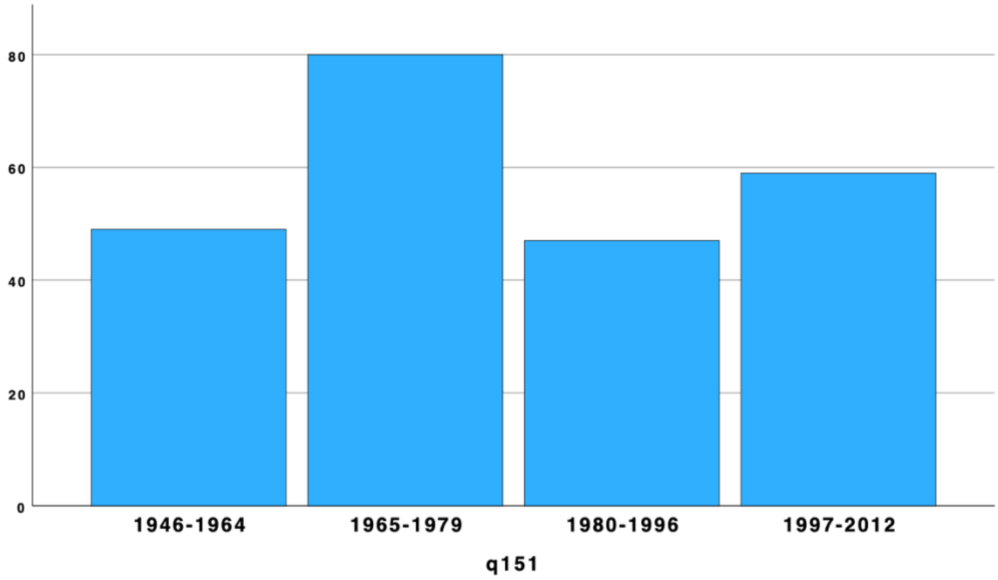
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		40	14.5	14.5	14.5
	Female	127	46.2	46.2	60.7
	Male	107	38.9	38.9	99.6
	Prefer not to specify	1	.4	.4	100.0
	Total	275	100.0	100.0	



Age (classified by age group)

Q15

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		40	14.5	14.5	14.5
	1946-1964	49	17.8	17.8	32.4
	1965-1979	80	29.1	29.1	61.5
	1980-1996	47	17.1	17.1	78.5
	1997-2012	59	21.5	21.5	100.0
	Total	275	100.0	100.0	



Occupation (Q16)

Q16

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Employee	78	33.2	33.2	33.2
	Freelance	69	29.4	29.4	62.6
	Student	51	21.7	21.7	84.3
	Unemployed	24	10.2	10.2	94.5
	Worker/craftsman	13	5.5	5.5	100.0
	Total	235	100.0	100.0	

Origin (for part of Italy)

Q17

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		40	14.5	14.5	14.5
	Central Italy (Lazio, Marche, Toscana, Umbria)	106	38.5	38.5	53.1
	Northern Italy (Valle d'Aosta, Liguria, Lombardia, Piemonte, Trentino-Alto Adige, Veneto, Friuli-Venezia Giulia, Emilia-Romagna)	66	24.0	24.0	77.1
	Southern Italy (Abruzzo, Molise, Campania, Puglia, Basilicata, Calabria, Sicilia, Sardegna)	63	22.9	22.9	100.0
	Total	275	100.0	100.0	

Reliability analysis of scales

Familiarity (Q4)

Having selected a single item from this scale, no scale reliability analysis was performed.

Intention to use (Q_42, Q_43, Q_44, Q_45)

Case Processing Summary

		N	%
Cases	Valid	248	90.2
	Excluded[a]	27	9.8
	Total	275	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.982	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q42	12.65	44.311	.953	.976
Q43	12.61	44.789	.972	.971
Q44	12.81	43.974	.959	.975
Q45	12.60	45.642	.932	.982

Persuasion Knowledge (Q25_1, Q25_2, Q25_3, Q25_4, Q25_5)

Case Processing Summary

		N	%
Cases	Valid	240	87.3
	Excluded[a]	35	12.7
	Total	275	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.599	5

Persuasion Knowledge with Q25_3 item elimination

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q25_1	15.89	27.578	.833	.238
Q25_2	16.45	31.789	.689	.354
Q25_3	15.40	81.203	-.770	.946
Q25_4	15.73	26.456	.874	.201
Q25_5	15.67	26.615	.878	.202

Perceived value (Q51_1, Q51_2, Q51_3, Q51_4)

Case Processing Summary

		N	%
Cases	Valid	237	86.2
	Excluded[a]	38	13.8
	Total	275	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.966	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Q51_1	14.11	43.466	.904	.958
Q51_2	14.22	42.178	.908	.957
Q51_3	14.13	42.190	.931	.950
Q51_4	14.16	43.059	.916	.954

Regression Analysis Output for H1

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	persuasion[b]	.	Enter

a. Dependent Variable: intention

b. All requested variables entered.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	28.956	.710		40.771	<.001
	persuasion	-.779	.040	-.785	-19.562	<.001

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	(Constant)		
	persuasion	1.000	1.000

a. Dependent Variable: intention

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.785[a]	.617	.615	5.54809

a. Predictors: (Constant), persuasion

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11779.633	1	11779.633	382.688	<.001[b]
	Residual	7325.951	238	30.781		
	Total	19105.583	239			

a. Dependent Variable: intention

b. Predictors: (Constant), persuasion

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	persuasion
1	1	1.864	1.000	.07	.07
	2	.136	3.696	.93	.93

a. Dependent Variable: intention

Regression Analysis Output for H2

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	perception[b]	.	Enter

a. Dependent Variable: intention

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.880[a]	.774	.773	4.25734

a. Predictors: (Constant), perception

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	14563.267	1	14563.267	803.492	<.001[b]
	Residual	4259.366	235	18.125		
	Total	18822.633	236			

a. Dependent Variable: intention

b. Predictors: (Constant), perception

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.033	.664		-.050	.961
	perception	.907	.032	.880	28.346	<.001

Coefficients[a]

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions	
				(Constant)	perception
1	1	1.909	1.000	.05	.05
	2	.091	4.583	.95	.95

a. Dependent Variable: intention

Regression Analysis Output for H3

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	interaction, perception, persuasion[b]	.	Enter

a. Dependent Variable: intention

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.910[a]	.827	.825	3.73412

a. Predictors: (Constant), interaction, perception, persuasion

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15573.753	3	5191.251	372.301	<.001[b]
	Residual	3248.879	233	13.944		
	Total	18822.633	236			

a. Dependent Variable: intention

b. Predictors: (Constant), interaction, perception, persuasion

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.911	2.310		-.394	.694
	perception	1.071	.086	1.039	12.446	<.001
	persuasion	.142	.090	.143	1.577	.116
	interaction	-.019	.004	-.309	-5.441	<.001

Coefficients[a]

Model		Collinearity Statistics Tolerance	VIF
1	(Constant)		
	perception	.106	9.405
	persuasion	.090	11.099
	interaction	.230	4.342

a. Dependent Variable: intention

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions (Constant)	perception	persuasion	interaction
1	1	3.450	1.000	.00	.00	.00	.00
	2	.386	2.989	.00	.02	.03	.00
	3	.158	4.670	.02	.00	.01	.27
	4	.005	25.944	.98	.98	.96	.72

a. Dependent Variable: intention

Regression Analysis Output for H3 with centered predictors

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	interaction2, persuasion, perception[b]	.	Enter

a. Dependent Variable: intention

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.910[a]	.827	.825	3.73412

a. Predictors: (Constant), interaction2, persuasion, perception

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15573.753	3	5191.251	372.301	<.001[b]
	Residual	3248.879	233	13.944		
	Total	18822.633	236			

a. Dependent Variable: intention

b. Predictors: (Constant), interaction2, persuasion, perception

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.641	1.654		2.805	.005
	perception	.776	.049	.753	15.783	<.001
	persuasion	-.219	.045	-.221	-4.835	<.001
	interaction2	-.019	.004	-.161	-5.441	<.001

Coefficients[a]

Model		Collinearity Statistics	
		Tolerance	VIF
1	(Constant)		
	perception	.325	3.076
	persuasion	.354	2.822
	interaction2	.846	1.182

a. Dependent Variable: intention

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions		
				(Constant)	perception	persuasion
1	1	3.064	1.000	.00	.00	.01
	2	.566	2.327	.00	.02	.00
	3	.357	2.931	.00	.05	.15
	4	.014	14.902	1.00	.93	.84

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