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## Article

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## RISKS OF OBSERVABLE AND UNOBSERVABLE BIASES IN ARTIFICIAL INTELLIGENCE USED FOR PREDICTING CONSUMER CHOICE

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### Abstract

Companies are increasingly adopting Artificial Intelligence (AI) today. Recently however debates started over the risk of human cognitive biases being replicated (and scaled) by AI. Research on biases in AI predicting consumer choice is incipient and focuses on *observable* biases. We provide a short synthesis of cognitive biases and their potential risk of being replicated in AI-based choice prediction. We also discuss for the first time the risk of *unobservable* biases, which affect choice indirectly, through other biases. We exemplify this by looking at looking at three prevalent, most frequently investigated biases in consumer behaviour: extremeness aversion, regret aversion and cognitive regulatory focus (prevention- versus promotion-focus). Based on a sample of 1747 respondents, through partial least squares structural equation modelling and significance testing, we show that regret aversion (unobservable bias) significantly reduces extremeness aversion (observable bias) and mediates the influence of cognitive regulatory focus (unobservable bias).

**Keywords:** cognitive bias, artificial intelligence, choice prediction, consumer choice behaviour, regret aversion, extremeness aversion, regulatory focus.

**JEL Classification:** D91, D80, D01

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## Introduction

AI is increasingly being adopted today in business and commerce. Hopes that it can help predict better consumer choice, to the benefit of both companies and consumers, are high. There is however an increasing debate on whether human cognitive biases may be adopted and replicated in AI, and even scaled by AI, leading to suboptimal predictions and outcomes for both stakeholders. The current research literature is still incipient on how cognitive biases can be reflected in data and further *copied* by machine learning – based AI models, and how this risk should be managed. Moreover, there is currently little to no research on whether human cognitive biases can be traced through (big) data, and on what happens when some biases influence choice differently through other biases than on their own – multiplicative effects. In such cases, the risk of AI replicating biases, and being unaware of this, or wrongly estimating the effect on each bias on choice, could potentially increase to unknown levels.

We have two goals in this paper. First, we provide a synthesis of examples of cognitive biases and their potential risks, should they be undesirably replicated and scaled by AI. Our second goal is to test the relationships between observable and unobservable biases and show whether unobservable biases can, beyond simply influencing choice, mediate the effect of other observable or unobservable biases. As such, we separate for the first time in research these cognitive biases into two categories, observable and unobservable, and we discuss how unobservable biases pose a double threat to AI: on the one hand, they cannot be detected; on the other hand, they could in fact mediate (or be mediated by) other biases, observable or unobservable in their own right. This could have tremendous implications for research on biases in AI and in fact could represent a new paradigm of research in the field.

To study these relationships, we chose three prevalent, most frequently investigated biases in consumer behaviour: extremeness aversion, regret aversion and regulatory focus. Extremeness aversion (the tendency to avoid extremes and choose the middle option) is one of the most prevalent biases in choice behaviour, an outcome of purchasing behaviour, and thus observable through off-the-shelf (big) data (like historical purchasing data). Regret aversion is one of the strongest and most prevalent anticipated emotions in consumer buying; thus, it is a driver, and very likely unobservable through off-the-shelf data. Cognitive regulatory focus is twofold. On the one hand, promotion- or a prevention-focused cognition can be a driver of behaviour and therefore unobservable. On the other hand, cognitive focus leads to either regret minimisation or utility maximisation behaviour, but this is likely unobservable as well, as it is well related to regret aversion and in fact an underlying motivation of the behaviour.

Our hypotheses for the quantitative study are as follows:

**H1.** Regret aversion reduces extremeness aversion in consumer choice, in the consumer's attempt to reduce the potential regret after choosing.

**H2.** Prevention regulatory focus reduces regret aversion, unlike promotion regulatory focus.

**H3.** Regret aversion mediates the relationship between regulatory focus and extremeness aversion; in other words, prevention regulatory focus combined with regret aversion reduces extremeness aversion.

To test these hypotheses, we use the results from a comprehensive survey of 1747 respondents, which we analyse through partial least squares structural equation modelling (PLS-SEM) and statistical significance testing.

The paper is structured as follows. We first offer a background on the state of AI in the consumer context today, biases in AI, and the further analysed biases: extremeness aversion, regret aversion and regulatory focus. We then describe our research hypotheses and framework, the research method and survey questions used, as well as methodological aspects of data analysis in this context. Finally, we show the results, focused on (a) how choice from a set of low-medium-high alternatives is influenced by regret aversion, (b) how choice is influenced by consumer cognitive regulatory focus (prevention-focused or promotion-focused cognition), and (c) the mediation effect of regret aversion on the relationship between cognitive regulatory focus and choice and extremeness aversion.

## 1. Background and research opportunity

### 1.1. The state of artificial intelligence today in consumer context

Kearney, recently stated that companies must “embrace AI to survive” (Kearney, n.d.). AI is therefore a must for survival in business today, no longer just a nice-to-have on the CEO’s agenda, something a company can afford to leave aside. While the first AI algorithms appeared in the 1960s with pre-programmed and rule-based learning (if-then reasoning), AI has moved along the spectrum of intelligence into various kinds of supervised and unsupervised learning – figure 1 below provides a summary of where AI has been used until today and expectations of its use over the next decade, along the four main domains of AI and machine learning: natural language processing, computer vision, pattern recognition, and reasoning and optimisation.

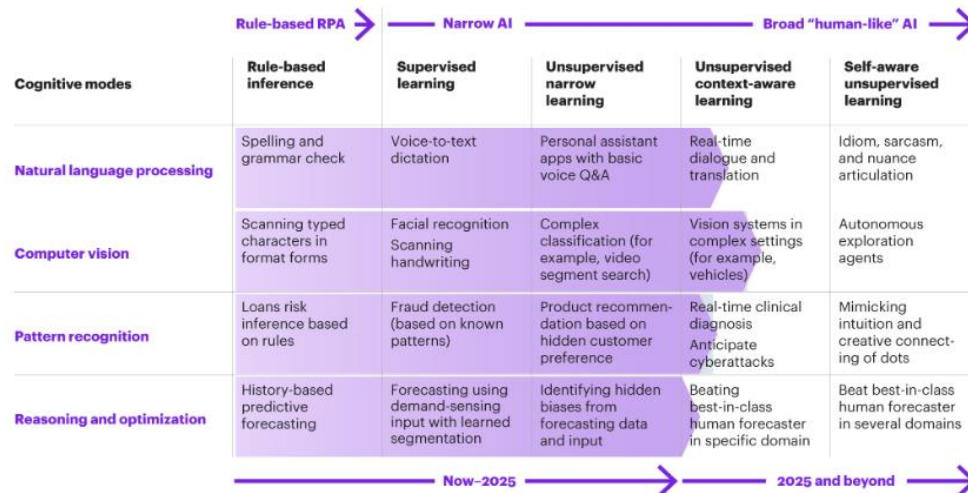


Figure no. 1. The use of artificial intelligence today and beyond

Source: Kearney, n.d.

AI today is expected to dramatically affect how different corporate functions in business, and commerce in particular, accomplish their goals, especially in marketing (Davenport, et al., 2020), marketing personalisation (Kumar, et al., 2019) and advertising (Kietzmann, Paschen and Treen, 2018), as well as back-end functions like product development, sourcing, supply chain management and manufacturing. AI applications in commerce are technically focused on pattern recognition. Practically, beyond offering insights on the target customer audience and revealing complex patterns in consumer choice data, the focus is on predicting consumer choice, from analysing hidden customer preferences to making product recommendations. The benefits should be positive and clear: customers will spend more, will become more loyal, will trust brands more, or will adopt behaviours (e.g., shifting to channels) that optimise costs for companies.

## 1.2. Biases in AI

Recently, however, there has been significant debate over the risk of human cognitive biases being replicated (and scaled) in machine learning – based AI models, as such biases are reflected in the (big) data that AI models learn from, in applications ranging from courts and law enforcement to medicine to business. As Manyika, Silberg and Presten (2019) show: “Over the past few years, society has started to wrestle with just how much these human biases can make their way into artificial intelligence systems — with harmful results”. One great recent example is Apple’s being accused of sexism in 2019 because the company’s new credit card seemed to offer men more credit than women (BBC, 2019). Another is the case of COMPAS, the computer program used to calculate the likelihood of prisoners reoffending, coming under serious scrutiny because it was found to be biased against African-American defendants (Dressel and Farid, 2018). IBM research states that “within five years, the number of biased AI systems and algorithms will increase” (IBM Research, 2018). Tackling bias in AI is therefore one of the priorities on the AI research frontier (Silberg and Manyika, 2019). But while much of the focus (and concern) of research related to biases in AI is on building fairness and equity in machine learning (and in particular areas like medicine, on the correctness of prediction), in prediction of consumer choice in commerce, the risk of misprediction can have negative consequences such as providing consumers with products or services that do not bring them the required or needed value. That can have as a spill-over effect negative consequences on companies’ revenues and profitability due to decreasing customer satisfaction and loyalty. Especially since one of the expected next uses of AI is mimicking intuition and creative connecting of dots, as well as beating human forecasting in several domains (see Figure 1), managing cognitive biases and avoiding their replication and scaling in AI models are critical.

We list below in Table 1 some of the most notable cognitive biases researched in psychology and behavioural economics and explain the potential risk they pose should they be replicated (and scaled) in AI predicting consumer choice. We also classify them into two categories: observable and unobservable. To understand the difference, take the example of a retailer that would like to understand its customers’ biases by analysing large datasets of customers’ purchases over the last 3 years; these datasets contain information about which products consumers bought, product attributes, product availability, even competitive intelligence – observable data, in other words. There are cognitive biases that are expected to be easily identified in AI/machine learning through analysing only the mentioned datasets and employing the right analysis techniques. An example could be extremeness

aversion in a choice set (defined below). By analysing the choice patterns and controlling for factors such as price and product attributes, such a bias can likely be easily isolated. There are, however, biases or attitudes that are not observable in this way, i.e., nearly impossible to detect solely based on analysis of purchase (big) data. To detect regret aversion (defined below), for example, in consumer purchase data, additional customer research would likely be required on specific samples, and then extrapolation to the entire data through specific methods. We do not imply this is impossible, yet it would be much more difficult than identifying biases directly observable in actual purchase data.

**Table no. 1. Cognitive biases and potential risks in being replicated (and scaled) in AI predicting consumer choice**

Cognitive bias (and alike)	Potential risk in being replicated (and scaled) in AI predicting consumer choice	Observable/unobservable
Different utility types (transaction utility, procedural utility, etc.)	While people experience pleasure from finding a good 'deal', or from the fairness of the transaction, this could be picked up by AI as a key driver of consumer choice, underestimating the importance of other factors and putting too much focus on promotion/discounting. This could be detrimental to both the company (margin erosion) and consumers (making them buy products of less value to them just because they have a good price).	Observable
Satisficing behaviour (and alike)	Any brand choice behaviour that deviates from the utility maximisation theory does so because consumers do not have the cognitive power, patience or access to all relevant information. More than 25 distinct models of brand choice behaviour deviating from traditional utility theory exist. AI could 'learn' to replicate this behaviour as being optimal and start predicting choices or recommending products that are not really optimal to consumers.	Observable
Heuristics thinking	All choices made based on heuristics such as anchoring, availability, representativeness, recognition, are not, in most cases, optimal for the consumer in long run. As above, AI however could 'learn' to replicate this behaviour start predicting or recommending suboptimal choices.	Observable
Pain of paying	Some consumers are tightwads, not liking to spend money, often buying cheaper than is optimal. Spendthrifts however like to spend money and often spend more than is optimal. An AI model which does not isolate this 'pain of paying' might simply propose the wrong price level to the wrong segment.	Observable
Variety seeking, try-new bias	The fact that consumers might sometimes have a tendency to switch products or brands simply because of a 'try-new' bias might not be in their best economical/utilitarian interest but only satisfy an impulsive emotional need. AI however could 'learn' this as a beneficial rule and predict choices that are not optimal for consumers instead of helping reduce that bias.	Observable
Choice architecture	The way choices are designed and framed leads to various biases (extremeness aversion, attraction/decoy effect choice overload, evaluability hypothesis, distinction bias, less is better effect, etc.). An AI model however needs to be actively taught to 'detect' these as such, not as a direct preference.	Observable
Information avoidance	The fact that people might avoid some information (consciously or not) is, again, because of limited cognitive power or patience, not because it's in their best interest. AI could however 'learn' that this is desirable behaviour.	Unobservable
Diversification bias	The fact that people prefer more choices or features that are not needed today, 'just in case' they are needed in the future, is a serious psychological aspect. AI might nonetheless not detect if a preference for diversity or some features is triggered by such a bias or by actual in-the-moment preference and again may lead to predictions that are inaccurate or not optimal for the consumer.	Unobservable
Hyperbolic discounting, planning fallacy, dual-self model	When consumers deal with intertemporal choices, they tend to focus on the short rather than the long term and discount the value of a later utility/benefit by a factor that increases with the length of the delay. That is however suboptimal for them, yet AI could interpret it as a rational, beneficial choice.	Unobservable
Social norms, proof, herd behaviour, reason-based choice	When choice is influenced by social aspects (how others see it, what others do, how to justify it to others, how to justify it to yourself and against your values/beliefs), choice deviates from expected utility theory. AI could 'learn' to interpret this as rational, even if it may not be beneficial to the consumer.	Unobservable
Emotions, feelings, deeper motivations	Anticipated emotions such as regret aversion, or even unconscious feelings or motivations of consumer behaviour, influence consumer choice yet may 'fool' AI into attributing the choice to the observable product and context attributes (price, product specifications, environment, etc.).	Unobservable

Unobservable cognitive biases (which cannot be directly observed through off-the-shelf data) pose another, more serious risk to AI/machine learning, which has been undiscussed and unexplored until now: it is not only their direct effect on consumer choice which goes unnoticed, but they can also mediate the effects of other biases, whether observable or not on their own.

### 1.3. Extremeness aversion in dealing with multiple choices

Research on multiple choices and choice in context has been at the centre of behavioural economics. Among other things, it shows that people tend to avoid choosing the extreme options in a choice set. Simonson and Tversky introduced the term “extremeness aversion” in their famous 1992 paper (Simonson and Tversky, 1992). Extremeness aversion states that the attractiveness of an option is enhanced if it is an intermediate option in a choice set and diminished if it is an extreme option. Extremeness aversion is highest when the middle alternative is exactly at the centre in the choice set (equal distances from the extremes) (Padamwar, Dawra and Kalakbandi, 2018). A recent meta-analysis (Neumann, Bockenholt and Sinha, 2016) showed that extremeness aversion is one of the most robust phenomena in consumer behaviour, and that its strength varies: it is weaker when employing price-quality trade-offs, nondurable categories or binary-trinary choice-set comparisons, and stronger when using a large number of trade-off dimensions, non-numeric attributes, high-quality extensions, or utilitarian products. Simonson, Sela and Sood (2017) showed that people are in general unaware of their tendency to avoid extremes, and when made aware of it, they may deny it and find counter-examples or other explanations – avoiding extreme options is thus likely considered as a weakness and inconsistent with a person’s self- and other-image as a decisionmaker.

### 1.4. Regret aversion or fear of a better option in making product and brand choices

Regret theory in economics was initially formulated, simultaneously, by Loomes and Sugden (1982), Bell (1982), and Fishburn (1982), and has been researched since then. Regret aversion, or fear of a better option in more ‘commercial’ terms, is generally defined as a negative cognitively determined emotion appearing when comparing an obtained decision outcome to outcomes that might have been, had one chosen differently (Rosenzweig and Gilovich, 2012; Van Dijk and Zeelenberg, 2005). In economic rather than psychological terms, regret is the “disutility an individual experiences from the value gap between an actual outcome and the best possible outcome that one could have attained” (Braun and Muermann, 2004). In regret *per se*, literature differentiates between experienced regret and anticipated regret. Experienced regret (or rejoice) can lead to risk-averse behaviour (Creyer and Ross, 1999) and may affect the anticipation of regret (Coricelli, et al., 2005; Cooke, Meyvis and Schwartz, 2001; Creyer and Ross, 1999). It can lead consumers to switch to a different product (Zeelenberg and Pieters, 2004) or brand (Zeelenberg and Rik, 2007), and it can (directly and indirectly) negatively influence customer satisfaction and repurchase intentions (Tsiros and Mittal, 2000). Anticipated regret on the other hand is a stronger emotion than experienced regret. Research shows people do not necessarily want to avoid making the same mistake twice as much as they do not want to experience the same negative emotion twice (Raeva, Mittone and Schwarzbach, 2010). Anticipated regret therefore tends to be overestimated compared to actual experienced regret (Gilbert, et al., 2004; Sevдалис and Harvey, 2007), and it strongly affects purchase or choice-making behaviour. Anticipated regret can lead for example to purchase of a currently available item on sale rather than waiting for a better sale, or to preference for

a higher-priced, well-known brand over a less expensive, lesser-known brand (Simonson, 1992). In some instances, it can even lead to complete inertia (or status quo option selection) and ambiguity-driven indecisiveness (Sautua, 2017). Anticipation of regret can even augment other cognitive biases, such as herding behaviour as a rational response to regret aversion (Arlen and Tontrup, 2015) (i.e., observing the choices of many others or professionals, who are perceived as less likely to be biased by regret). Anticipated regret can also induce an endowment effect; for example, owners resist selling houses or increase selling prices because they experience more anticipated regret over selling in error than over failing to make a deal when they should have (Thaler, 1980). As a note, though often confused, regret aversion and risk or loss aversion are different cognitive and emotional responses. Regret aversion has been shown to be even stronger than risk aversion; experiments show people choosing regret-minimising gambles over risk-minimising gambles in both gain and loss contexts and in both relatively high-risk and low-risk pairs of gambles (Zeelenberg, et al., 1996). Regret aversion has been demonstrated to be a more powerful predictor of behaviour than many other types of anticipated negative emotions or risks (Brewer, et al., 2016). In fact, most purchase decisions are frequently a source of regret for most consumers (Rosenzweig and Gilovich, 2012); they often compare their purchase outcomes with what they could have bought differently (Abendroth and Diehl, 2006) and often experience second thoughts and anxiety (Inman and Zeelenberg, 2002).

### **1.5. Cognitive regulatory focus**

According to recent research, consumers may have different appetites for minimising regret or maximising the utility of their choice from a set of alternatives, also depending on their regulatory focus typology: chronically prevention-focused consumers are more likely to be regret minimisers, and chronically promotion-focused consumers are more likely to be utility maximisers (Lim and Hahn, 2019). Moreover, research has shown that people with an ingrained preference for moderation in their lives also tend to have extremeness aversion in experiments with sets of three alternatives (Simonson, Sela and Sood, 2017). It is therefore evident that studying the relationship between regret aversion and choice and extremeness aversion needs to be done, accounting also for consumers' regulatory focus (prevention- versus promotion-focus) and their regret minimisation versus utility maximisation goals as well.

### **1.6. Missing link, and risk of unobservable risks (biases)**

According to Connolly and Butler (2006), numerous studies have investigated how choice can be influenced by anticipated regret or disappointment with the choice. However, the effect of fear of a better option or anticipated regret on extremeness aversion in making a choice from a set of "low-medium-high" alternatives has not been researched so far, let alone with respect to cognitive regulatory focus types. In other words, do consumers who generally have a fear of a better option when making choices between products or brands tend to have a reduced extremeness aversion (compared to those that do not typically think of better options or potential regret of their choice)? If so, in the hypothetical retailer example we discussed previously, the retailer might detect extremeness aversion from its off-the-shelf customer purchase data, and potentially even promotion- versus prevention-focused cognition (potentially, however unlikely, as this is determined through customer research, not based on purchase data); however, we highly doubt off-the-shelf data can reveal consumers' (anticipated) emotions like regret aversion.



## 2. Research framework and methodology

### 2.1. Research framework and hypotheses

Based on the discussed gap between regret aversion and extremeness aversion, we formulate our first hypothesis:

**H1:** Consumers who typically exhibit regret aversion, or fear of a better option, will tend to have a lower extremeness aversion and select the high product alternative in a set of three product alternatives in an attempt to reduce their potential regret of the choice to be made.

Based on the previously discussed understanding that consumers exhibit different behaviours of minimising their regret or maximising the utility of their choice depending on their cognitive regulatory focus typology (prevention-focused or promotion-focused), we formulate the second and third hypotheses of our research:

**H2:** Consumers that are prevention-focused tend to be regret minimisers and thus have a lower extremeness aversion than those who are promotion-focused (who will tend to select the middle option).

Finally, we are able to formulate our third hypothesis and explore the effects of unobservable biases on observable biases and their influence on choice. As such:

**H3:** The relationship between cognitive regulatory focus typology and extremeness aversion is mediated by regret aversion. Consumers who are typically prevention-focused and exhibit regret aversion will tend to have lower extremeness aversion and select the high product alternative in a set of three product alternatives more often than those that typically have lower fear of a better option.

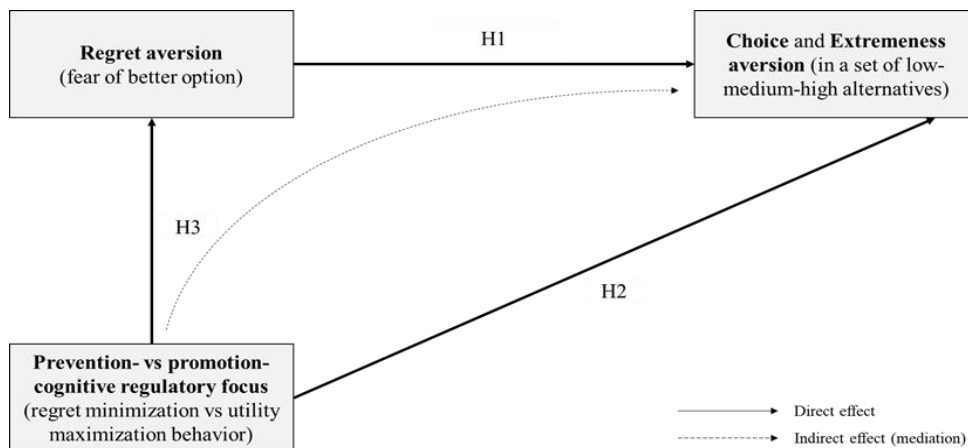


Figure no. 2. Research framework and hypotheses

### 2.2. Research method, survey design, raw data transformation – methodological aspects

To test these hypotheses and effects, we use a comprehensive quantitative survey deployed online through a specific professional online survey instrument and based on a random sampling approach. The survey was deployed as part of a professional consulting project by one of the authors in the retail banking industry in Romania. Data collection was monitored

frequently based on age and income quotas to ensure representativity of the sample for the population. 1747 complete responses were collected, as further described, and the results are statistically representative of the adult (24+) population owning a current account in a bank in the respective country.

The set of product alternatives tested through the survey is depicted in the following figure 3. Prices construction (the middle option being placed at equal distances from the extremes in terms of price) and the additional remarks provided to respondents in terms of potential savings through those prices were designed to ensure sufficient attractiveness of each option on its own. The answers to this question are coded as 1, 2 or 3, depending on which package was chosen (basic, standard or premium, respectively).

Features / Option	Basic	Standard	Premium
Free monthly administration of the current account and Debit Card	✓	✓	✓
Debit Card	✓ Standard Debit Card	✓ Standard Debit Card	✓ Gold Debit Card
Free ATM withdrawals (own ATMs)	✓	✓	✓
Free incoming transactions in the current account	✓	✓	✓
Free monthly administration of mobile payment app	✓	✓	✓
Free monthly administration of Internet & Mobile Banking services		✓	✓
Free death & invalidity insurance OR phone & tablet insurance		✓	✓
Free travel insurance			✓
Priority in Call Center			✓
Access to Business Lounge			✓
<b>Package price (m.u., per month)</b>	<b>0</b> By choosing this option you save 10 m.u. (purchasing each feature separately costs 10 m.u. in total)	<b>7</b> By choosing this option you save 13 m.u. (purchasing each feature separately costs 20 m.u. in total)	<b>14</b> By choosing this option you save 22 m.u. (purchasing each feature separately costs 36 m.u. in total)
<b>Which current account package would you choose?</b>	Basic ○	Standard ○	Premium ○

**Figure no. 3. Set of alternatives tested**

To quantify respondents' regret aversion, or fear of a better option, we asked them choose between *never*, *sometimes* and *always* to the question: *After you have chosen a product or service and purchased it, how often do you think or feel you might have found a better offer or option, in terms of quality and/or price, if you had looked more?* – see figure 4 below. The way the question is formulated is highly relevant for the purpose of this study, better than directly asking a question like *Do you typically regret your choices* or *Do you typically fear a better option could exist?* because it offers a reference point regarding when the feeling under question occurs, i.e., *after you make your choice and purchase*, it offers a reference point regarding how the feeling exactly is experienced, i.e., *if you had looked more*, and finally it offers a simple scale to measure the feeling without any confusion.

<i>After you made your choice upon a product or service and purchased it, how often do you think or feel you might have found a better offer or option, in terms of quality and/or price, if you had looked more?</i>		
Never	Sometimes	Always
1○	2○	3○

**Figure no. 4. Question for determining regret aversion (fear of a better option)**

To segment the respondents between prevention-focused and promotion-focused cognitive regulatory focus types (i.e., regret minimisation versus utility maximisation behaviour), we asked them to evaluate each of the five key statements as shown in the below figure 5.

<i>Please express your agreement or disagreement with the below statements, when making purchases</i>	I totally disagree	I partially disagree	I partially agree	I totally agree
1. I always look for discounts and promotions, looking at the immediate benefits I can obtain	1○	2○	3○	4○
2. I always look for transparency and correctness from the seller regarding prices	1○	2○	3○	4○
3. I always look for best quality-price ratio for that product or service ideal for me	1○	2○	3○	4○
4. I look for offers rather from sellers that I know or I am used to, including where I am part of the loyalty program	1○	2○	3○	4○
5. I look rather for convenience, to finish shopping rather quickly and cover my needs fast	1○	2○	3○	4○

**Figure no. 5. Question to determine cognitive regulatory focus**

We classify between promotion- and prevention-focused consumers as such:

- Respondents with a score of 4 on both statements 1 and 3 and without a score of 4 on statement 5, as a clearly promotion-focused segment (coded with 3)
- Respondents with a score below 4 on both statements 1 and 3 and without a score of 1 on statements 2 and 4, as a clearly prevention-focused segment (coded with 1)
- The rest of respondents as a 'balanced' segment (coded with 2)

This approach to classifying promotion and prevention cognitive regulatory focus is similar in principle to the original method of Higgins, et al. (2001) and further utilised by Lim and Hahn (2019) to study its influence on regret minimisation behaviour, but has been adapted for the purposes of the original consulting project in which the survey was deployed and to tailor it toward purchasing, not general instances.

We believe the above indirect way of constructing the questions and statements to be evaluated is a better method for isolating promotion-focused and prevention-focused consumers than simply asking a direct choice question (i.e., "Do you consider yourself this type or this type? Choose."), as often in research, consumers are not cognitively able to specify their preferences correctly or may be unwilling to disclose real motivations or preferences (fear of appearing superficial or influenced by social norms). Likewise, as aiming to understand whether specific consumer typologies influence another variable is not a statistically optimal way to segment consumers based on characteristics or outcomes, this approach is also preferred, instead of approaches like cluster analysis or PLS (partial least squares) prediction-oriented segmentation.

We used several ex-ante mechanisms to reduce the risk of common method bias or variance (CMV). The online survey tool provided big visible indications at the beginning of the survey about anonymity and confidentiality and that responses should be as honest as

possible. We ordered the questions in such a way that no question could have a priming effect on a subsequent question. We formulated the questions in a simple way so respondents wouldn't have to expend too much cognitive effort in answering them. Commonality in scale endpoints (or anchor effects) is not very likely to affect responses, as there are only a few questions using same scale. As an ex-post check, we ran Harman's single factor test across all variables (except those for basic profiling like age) using SPSS's factor analysis procedure, with principal axis factoring as the extraction method: one single fixed factor could not be extracted; therefore we have no indication that CMV might exist (only if a single factor can be extracted and it explains above 50% of variance in the sample is there an indication that CMV might exist; see more in Podsakoff, et al., 2003, or Chang, van Witteloostuijn and Eden, 2010).

### 3. Data analysis – methodological aspects

The relationships presented in our framework (figure 1) can naturally be analysed through regression analysis; therefore they can be described using the following regression equations and remarks.

In the following equations below, the main outcome variable "Choice" is measured on a scale from 1 to 3 (as per figure 3, where 1 denotes choice of the Basic package, 2, the Standard package, and 3, the Premium package). Variable FOBO\_seg denotes the level of fear of a better option (regret aversion) and is measured on a scale from 1 to 3 (see remarks after figure 4).

**For H1:**  $\text{Choice} = B_{10} + B_1\text{FOBO\_seg} + e$

In the next equation for H2, Cognitive\_seg denotes the cognitive typology and is measured on a scale from 1 to 3 (as per the remarks after figure 5).

**For H2:**  $\text{Choice} = B_{20} + B_2\text{Cognitive\_seg} + e$

Analysing the mediation effect of 'fear of a better option' on the relationship between 'cognitive typology' and 'extremeness aversion' requires coefficients from two linear regressions:

**For H3 – part 1 of 2:**  $\text{FOBO\_seg} = B_{3a0} + B_{3a}\text{Cognitive\_seg} + e$ , and

**For H3 – part 2 of 2:**  $\text{Choice} = B_{3b0} + B_{1-2}\text{FOBO\_seg} + B_{3b}\text{Cognitive\_seg} + e$

More specifically, we will utilise the so-called Sobel product of coefficients approach (Sobel, 1982), where coefficients  $B_{3a}$  and  $B_{1-2}$  are multiplied to obtain the indirect effect of FOBO, i.e., the mediation effect.

$$B_{\text{indirect}} = B_{3a} * B_{1-2}$$

In case  $B_{3a} * B_{1-2}$  is significant and  $B_2$  (from equation for H2) is not, the indirect effect is considered as full mediation. In case  $B_2$  is significant, the indirect effect is considered only partial mediation (complementary if  $B_{3a} * B_{1-2} * B_2$  is positive, or competitive if  $B_{3a} * B_{1-2} * B_2$  is negative).

Advanced procedures (and software) exist to model efficiently and correctly equations like above, such as partial least squares structural equation modelling – PLS-SEM. We use SmartPLS 3.2.9 software for this purpose, which enables both path modelling for the

structural equation model (all our hypotheses combined, as our framework depicts in figure 1) and bootstrapping for testing whether path coefficients are statistically significant. In this case, the path coefficients are interpreted as standardised regression coefficients (i.e., the effect of one standard deviation increase in a predictor variable on the outcome).

In this analysis, because our dependent variable is ordinal (it receives the values of 1, 2 and 3), a significant positive coefficient of any independent variable implies nothing about extremeness aversion. It can explain an effect on the overall choice pattern, i.e., if a 'larger' account package is selected in this case, which we are still interested in studying, but not on the tendency to choose the middle 'standard' package.

Therefore, to truly understand the influence on extremeness aversion (beyond the influence on choice), we use standard significance testing of the differences between various groups of respondents (grouped by their defining characteristics: fear of a better option, cognitive segment) in terms of extremeness aversion: for example, the difference in extremeness aversion between respondents with high fear of a better option, medium fear of a better option, and low fear of a better option.

For this approach, we use two tests. We use the standard Student's t-test to determine if each individual choice percentage is statistically significant. Each group is compared to the opposite one based on its characteristics. For example, if we analyse the choice pattern of those with high FOBO, we compare it with the choice patterns of those with low and medium FOBO. We also use the chi-square test as a non-parametric test for determining if the actual distribution of choice percentages is statistically significant. For example, if we analyse the choice pattern of those with high FOBO, we compare it with the choice patterns of those with low and medium FOBO.

#### 4. Results

Table 2 below shows the distribution of choice percentages in the set of alternatives. As is easily seen, extremeness aversion appears to exist, on average, across all respondents, with more than half of them choosing the middle option (Standard package). The table also summarises respondents' patterns of fear of a better option and their cognitive segment.

**Table no. 2. Choice patterns and respondents' characteristics**  
(% of total, # of respondents)

Distribution of choices		Distribution of respondents by fear of a better option segment		Distribution of respondents by cognitive segment	
Choice 3 (Premium package)	22% (384)	FOBO_seg – low	44% (762)	Cognitive_seg – prevention-focused	16% (271)
Choice 2 (Standard package)	57% (996)	FOBO_seg – medium	42% (741)	Cognitive_seg – balanced	60% (1055)
Choice 1 (Basic package)	21% (367)	FOBO_seg – high	14% (244)	Cognitive_seg – promotion-focused	24% (421)

Figure 6 below represents the actual output from SmartPLS (organised visually as per our research framework in figure 1), which shows the path coefficients for each relationship hypothesised and their p-values in parentheses (derived from running bootstrapping on 5000 samples). Fear of a better option has a statistically significant effect on the choice made from the set of product alternatives, whereas Cognitive\_seg does not (at least at the 5% level, although p-value indicates an effect at the 10% level). Cognitive\_seg appears to have a positive influence on fear of a better option on the other hand. Moreover, fear of a better option appears to have a full mediation effect on the relationship between cognitive typology and choice (as the coefficient of Cognitive\_seg on choice is not significant, at least at the same significance level) – this mediation (indirect) effect is 0.002 (or using the Sobel product of coefficients,  $0.044 * 0.047$ ). Overall, effects' sizes still appear small, however, measured here in standard deviations.

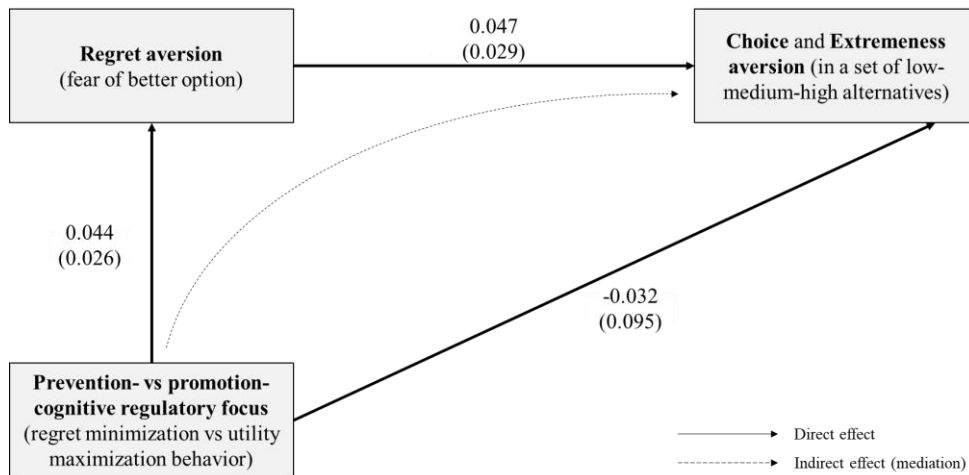


Figure no. 6. Smart-PLS output results (consistent PLS algorithm and bootstrapping)

#### 4.1. Standard significance testing across groups of respondents and their choice patterns

Below, table 3 shows the distribution of choice percentages for different groups of respondents. Groups are organised by lines, and their defining characteristics mapped on the first columns with tick-marks. For example, line 1 shows all respondents (no filters or tick-marks); line 2 shows only respondents with a low fear of a better option; line 10 only those with low fear of a better option and prevention-focused cognition. The following columns show the percentages of respondents selecting choice 1 (basic package), choice 2 (standard) and choice 3 (premium), and in parentheses, the calculated t-statistics, whereas the last column shows the calculated  $\chi^2$  values. Percentages statistically different from the comparison groups are marked with an asterisk (\*) – see table legend – and bolded for easier visualisation. Where two test statistics appear one below the other, the first (top value) is the test statistic (t-stat or  $\chi^2$ ) value calculated when compared to the group one line above (the same where only one test statistic appears), while the second (bottom value) is the test statistic value calculated when compared to the group two lines above.

**Table no. 3. Distributions of choice percentages and standard significance testing results**

Line no.	Fear of better option (FOBO)			Cognitive typology (Cognitive_seg)			Distribution of choice percentages (t-stat values)			$\chi^2$ values
	Low	Medium	High	Prevention-focused	Balanced cognition	Promotion-focused	% choice 1	% choice 2	% choice 3	
1							21%	57%	22%	
2	X						19%	63%	18%	
3		X					20% (0.47)	<b>56%</b> <b>(-3.71**)</b>	<b>23%</b> <b>(4.22**)</b>	2.69
4			X				<b>26%</b> <b>(2.23**)</b> <b>(2.53***)</b>	<b>42%</b> <b>(-4.47***)</b> <b>(-6.72***)</b>	<b>32%</b> <b>(3.13***)</b> <b>(5.90***)</b>	<b>8.26**</b> <b>20.72***</b>
5				X			22%	58%	20%	
6					X		<b>18%</b> <b>(-2.81***)</b>	59% (0.42)	<b>23%</b> <b>(2.36***)</b>	1.02
7						X	<b>26%</b> <b>(4.09***)</b> <b>(2.05**)</b>	<b>54%</b> <b>(-2.04**)</b> <b>(-1.77**)</b>	<b>20%</b> <b>(1.36*)</b> (0.07)	4.00 1.09
8	X			X			22%	63%	15%	
9	X				X		<b>16%</b> <b>(-3.04***)</b>	66% (1.01)	<b>18%</b> <b>(2.18**)</b>	2.38
10	X					X	<b>27%</b> <b>(3.68***)</b> <b>(1.53*)</b>	<b>55%</b> <b>(-2.77***)</b> <b>(-2.14**)</b>	18% (-0.12) (1.12)	<b>8.60**</b> 2.82
11		X		X			20%	57%	23%	
12		X			X		19% (-0.81)	57% (0.01)	25% (0.75)	0.23
13		X				X	<b>23%</b> <b>(1.54*)</b> (0.94)	56% (-0.15) (-0.14)	21% (-1.22) (-0.74)	1.60 0.59
14			X	X			29%	42%	29%	
16			X		X		<b>23%</b> <b>(-1.71**)</b>	42% (0.04)	<b>35%</b> <b>(1.67**)</b>	2.64
16			X			X	<b>31%</b> <b>(1.65**)</b> (0.39)	43% (0.24) (0.27)	<b>25%</b> <b>(-1.70**)</b> (-0.68)	<b>5.97*</b> 0.72

Note: \*\*\*significant at 1% level or below, \*\*significant at 5% level or below, \*significant at 10% level or below

Some of these results confirm what previous PLS-SEM modelling revealed. For example, the results on line 4 are highly statistically significant, showing that consumers with a high fear of a better option have a different choice behaviour, and choice pattern, from the set of product alternatives – they avoid the middle option more frequently, in favour of either of the extremes, and therefore display a significantly lower extremeness aversion. Even those with a medium fear of a better option tend to avoid the middle option in favour of at least the highest alternative (line 3 results). These results show a major influence of fear of a better option on the choice behaviour and extremeness aversion, influence which previous PLS-SEM modelling indicated to be statistically significant but rather low.

Cognitive typology, however (lines 5-7), appears to play a role unconfirmed by the previous PLS-SEM modelling (at least not at the 5% level in the latter case). Those who are

promotion-focused tend to favour the basic alternative more often, and the middle option less often, compared to those who are prevention-focused or balanced; therefore, they show lower extremeness aversion in favour of only one extreme (the lowest one).

These behaviours seem to be different between those with high and medium fear of a better option and those with low fear of a better option. With low fear of a better option, promotion-focused consumers display lower extremeness aversion compared to balanced or prevention-focused consumers, and a higher inclination to favour the cheapest alternative compared to prevention-focused consumers. With medium or high fear of a better option, extremeness aversion stays similar between different cognitive typologies (and the preference for either of both extremes does not change significantly). It seems therefore that once fear of a better option settles in and is especially high, cognitive typology no longer plays a major role in influencing consumers' extremeness aversion or the attractiveness of either of the extremes. This indicates that this fear of a better option (or regret aversion) is stronger than consumers' cognitive regulatory focus.

As a closing remark, there is one intriguing behaviour specific to those with a balanced cognition, in other words, not prevention- or promotion-focused. Even if they seem to have the same extremeness aversion level compared to prevention-focused segment (percentage of choice 2), they clearly favour more the expensive alternative over the cheapest one compared to both other segments. Even more, this happens with different levels of fear of a better option, but again, when fear of a better option is high, the effect is bigger. It appears that cognitive indecisiveness (having no tendency to either minimise regret or maximise the utility/value of choice) makes consumers more prone to favour the higher/highest product alternatives, and this effect is also augmented by regret aversion.

## Conclusions

Regret aversion, or fear of a better option, has a major influence on consumers' choice patterns from a set of low-medium-high alternatives and their extremeness aversion. Hypothesis H1 is therefore confirmed. This influence has been unexplored or unexplained until now, yet with important implications for brands and retailers. Regret aversion significantly reduces extremeness aversion. It doesn't lead only to the high alternative being chosen, however, as initially expected. Extremeness aversion is reduced in favour of either one of the extremes; therefore, other factors may influence which extreme is chosen, when and why, and they should be researched further.

Cognitive regulatory focus in purchasing (being prevention- or promotion-focused, or balanced) also plays a role in influencing consumers' choice and extremeness aversion. Hypothesis H2 is therefore confirmed. Promotion-focused consumers tend to have a lower aversion to extremes, especially in favour of the cheapest option, yet this is somewhat expected, as they are more likely to perceive a low (or zero) priced option as a bargain. When regret aversion is higher, cognitive regulatory focus typology no longer significantly influences consumers' extremeness aversion or their choice pattern. A strong mediation effect of regret aversion is visible. Therefore, Hypothesis H3 is also confirmed. Regret aversion, as an anticipated emotion, appears overall to be stronger in influencing choice and extremeness aversion than consumer cognitive regulatory focus on its own, and to mediate its effect.



These insights bring important implications for how to study biases in AI and establish an important research agenda for differentiating and anticipating unobservable biases in addition to observable ones, as well as their multiplicative effects. In our example case, through understanding what influences consumers' choice patterns and their extremeness aversion, an AI model could design a better choice architecture with improved business results (sales and profitability); product alternatives could be better designed through different features and price levels and better displayed in store or online to shift consumers towards more premium alternatives. However, an AI model would need to differentiate very well between (a) the 'first-order' effect of extremeness aversion, which is observable, (b) unobservable effects like those of regret aversion and cognitive regulatory focus, and (c) the 'second-order' indirect effects (multiplicative effects) like the one regret aversion has in fully mediating the role of regulatory focus.

An additional point on the research agenda should be drawn beyond only predicting what consumers will choose: predicting/understanding how they choose, i.e., which brand choice behaviour models consumers adopt, when, why and how. This is also not currently explored. Existence of unobservable biases and of their multiplicative effects on observable biases should be studied in relation also to how complex the adopted brand choice behaviour model is (i.e., from the simplest heuristics-based choice models, to attribute-based sequential elimination models like elimination-by-aspects, to conjunctive, disjunctive or lexicographic rules, up to the fully fledged utility maximisation model from neoclassical economics).

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