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Casting out the devil with Beelzebub? On the interaction of loss aversion and algorithm aversion

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On the interaction of loss aversion and algorithm aversion

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Abstract

The phenomenon of "algorithm aversion" can be defined as a behavioral anomaly whereby individuals exhibit a tendency to distrust the efficacy of algorithmic systems and instead favor the input of human judgment. Consequently, subjects may fail to achieve their optimal potential benefit. The objective of this study is to make a contribution to the question of how algorithm aversion can be reduced. The present study employs a laboratory experiment to investigate the potential contribution of loss aversion, an extensively researched behavioral anomaly, to the reduction of algorithm aversion. Indeed, the opposite seems to be true: the willingness to use an algorithm that is demonstrably more efficient than a human expert actually declines when there is a risk of loss when making a decision. This finding aligns with other research results indicating that algorithm aversion is more prevalent when the potential consequences are more severe. To promote the adoption of algorithm-based systems, it may be more effective to highlight the potential gains associated with their use rather than positioning them as tools for loss avoidance.

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Introduction

The use of algorithmic tools is becoming increasingly prevalent in decision-making processes, as they are capable of evaluating vast quantities of data with greater efficiency and are less susceptible to bias and distortion than humans (see, for example, Sunstein 2023). Nevertheless, there is a prevalent tendency to distrust algorithms and to prefer human judgment instead. This behavioral anomaly was first termed "algorithm aversion" by Dietvorst et al. (2015). It presents a challenge to the adoption of more efficient, algorithm-based decision aids and systems in an increasing number of use cases. Examples include the use of autonomous vehicles (cf. Shariff et al. 2017), the creation of medical diagnoses (cf. Majumdar and Ward 2011), the provision of support in court proceedings (cf. Simpson 2016), or the use of asset-managing robo-advisors (cf. e.g. Filiz et al. 2022). The rejection of such decision-making aids is detrimental to subjects in particular and to society as a whole, as it leaves society below its maximum achievable benefit in the long term. If one acknowledges that algorithm aversion is harmful, it becomes necessary to consider how the occurrence of this behavioral anomaly can be reduced in important decision-making situations.

Kahneman and Tversky (1979) and Tversky and Kahneman (1981) demonstrated that decision-making situations can be interpreted in different ways and that losses often have a greater impact than gains (loss aversion). Also, the benefits of algorithms can be presented differently in decision-making situations: Either the potential gain in benefit is emphasized, or the avoidance of loss of benefit is pointed out. Accordingly, algorithms in autonomous vehicles can, for example, help to enhance the safety of all road users or avoid traffic accidents and associated damage. The application of algorithms to the evaluation of MRI scans can facilitate the restoration of health or avoid further health losses. In legal proceedings, algorithms can assist in securing favorable outcomes or avoid penalties and losing freedom. As a robo-advisor, algorithms can facilitate the generation of risk-adjusted relative gains or avoid risk-adjusted relative losses.

On the one hand, it can therefore be argued that decision-making situations can be perceived differently as opportunities for gain or avoidance of loss, with losses often exerting a stronger influence than gains. On the other hand, it can be posited that the reduction of algorithm aversion represents an important concern both for subjects and society at large. In light of these considerations, the assertion by Lin et al. (2023) that there has been no comprehensive examination of the impact of gain-loss bias on human behavior within the context of computer-based recommendations, despite the pivotal role that gain-loss asymmetry plays in human decision-making, is particularly noteworthy. It is therefore of central importance to investigate in more detail whether the phenomenon of loss aversion, as proposed by Kahneman and Tversky (1979), offers a potential starting point for contributing to a reduction in algorithm aversion.

Literature review

Algorithm aversion

The decision-making processes of subjects are increasingly being supported by algorithms in a wide variety of areas. For example, algorithms are being used in asset management (see, e.g., Méndez-Suárez et al. 2019; Niszczota and Kaszás 2020), in medicine (cf. e.g. Grove et al. 2000; Ægisdóttir et al. 2006; Beck et al. 2011), in police work (cf. e.g. Mohler et al. 2015), in the judiciary (cf. e.g. Simpson 2016; Ireland 2020), and in sport (cf. e.g. Pérez-Toledano et al. 2019). The performance of algorithms frequently surpassed that of humans, as they are better able to recognize complex relationships within vast quantities of data, for example, where humans rapidly reach their cognitive limits (cf. Meehl 1954; Dawes et al. 1989; Youyou et al. 2015; Castelo et al. 2019).

Sunstein (2023) provides an overview of the application and limitations of algorithms in society. He concludes that algorithms already demonstrate superior performance compared to humans in various fields, including justice and medicine. This is due to their increased resilience against bias and other forms of perceptual distortion. Conversely, the capabilities of algorithms are constrained in other domains, such as when insufficient data is available or contextual factors, timing, chance, or emotional state exert unpredictable influences. In some of these domains, he anticipates that algorithms will continue to evolve, whereas in others, it is unlikely that either humans or algorithms will be able to make precise forecasts in the future.

Despite the growing prevalence and superior performance of algorithms in various domains, there remains a tendency for individuals to distrust their output and prefer human judgment (cf. Highhouse 2008; Önkal et al. 2009; Dietvorst et al. 2015). This behavioral anomaly was first termed "algorithm aversion" by Dietvorst et al. (2015). In their study, the researchers observed that subjects reduce the use of a superior algorithm when they realize that it does not always produce error-free results. They also observed that people are less forgiving of errors made by algorithms than those made by humans (see also Prahl and van Swol 2017; Bogert et al. 2021).

Dietvorst et al. (2015) consider this aversion to algorithms to be costly for two reasons. First, it results in financial losses for participants in their study, who demonstrably lost money compared to algorithm-based decisions. Second, it has broader societal implications due to the numerous applications of forecasts. This renders the acceptance and, consequently, the proliferation of more efficacious algorithmic systems more challenging. There is a risk that subjects, in particular, and society at large will fail to realize their maximum achievable benefit over the long term. As part of an experiment, Filiz et al. (2023) and Filiz et al. (2024), for example, demonstrate that the frequency of algorithm aversion is positively correlated with the perceived severity of potential consequences of a decision. This ultimately results in a diminished probability of success, particularly in the case of crucial decisions. Additionally, Sunstein and Gaffe (2024) anticipate that algorithm aversion will have a significant influence on political and legal matters, as well as on public and private institutions. Consequently, a substantial body of scientific literature has been dedicated to investigating the underlying causes and potential mitigating factors associated with this behavioral phenomenon. Comprehensive reviews of the literature on algorithm aversion can be found, for example, in the works of Alvarado-Valencia and Barrero (2014), Burton et al. (2020), Yusupov et al. (2020) and Mahmud et al. (2022).

Sunstein and Gaffe (2024) identify a number of potential causes for the phenomenon of algorithm aversion. These include the desire to retain the capacity to act independently, moral or emotional concerns, the conviction that humans possess unique knowledge that algorithms not, a lack of awareness regarding the source of the algorithms' performance, and a stronger negative reaction to algorithmic than to human errors.

As observed by Dietvorst et al. (2018), subjects in their studies demonstrated a tendency to select an imperfect yet superior algorithm for performing a prediction task when they had the opportunity to slightly influence the algorithm's prediction (cf. also Gubaydullina et al. 2022). The argument is similar to that put forth by Cheng and Chouldechova (2023), discovered in a replication study that process control mitigates algorithm aversion. Watson (2024) did not find that insight into the decision-making process of an algorithm contributes to the reduction of algorithm aversion. However, the provision of information about the reliable performance of an algorithm in the past has been shown to have a positive effect. Additionally, Judek (2024) posits that algorithm aversion is lower when decision-makers are informed about a high level of social acceptance of the algorithm by previous decision-makers.

In a study conducted by Filiz et al. (2021), an experiment was designed to forecast share price movements. The findings indicate that algorithm aversion can be reduced through a learning process involving repetitive tasks, constant feedback, and financial incentives (see also Leffrang et al. 2023). Reich et al. (2023) posit that consumers tend to distrust algorithms because they often incorrectly assume that, unlike humans, they cannot learn from mistakes. Accordingly, it can be argued that emphasizing the ability of algorithms to learn and taking note of their learning progress may serve as a starting point for reducing algorithm aversion (cf. also Berger et al. 2021). Furthermore, Bogert et al. (2021) found that as task difficulty increases, people tend to rely on the recommendations of algorithms to a greater extent. Jung and Seiter (2021) also observed in an experimental study that time pressure when working on a task reduces algorithm aversion.

Efendić et al. (2020) observed that individuals are more inclined to rely on predictions generated by algorithms and perceive them as more accurate when they are produced rapidly. In contrast, human predictions that were generated at a slower pace were perceived as more accurate. As noted by Kim et al. (2021), algorithm-based recommendations are rated more favorably when presented with greater accuracy, as indicated by the inclusion of additional decimal places. This effect is also consistent across different use cases, such as CT scans or music or book recommendations. Zhao et al. (2024) demonstrate that individuals exhibit greater acceptance and sympathy for an algorithm with human-like characteristics, such as a human-like name or communication style, compared to those with mechanical algorithms (cf. also Castelo et al. 2019).

In light of the aforementioned findings, the assertion by Lin et al. (2023) that there has been no comprehensive examination of the impact of gains and losses on human behavior in the context of computer-based recommendations, despite the pivotal role that the gain-loss asymmetry plays in human decision-making, is noteworthy. As part of their own pioneering study, they observed that human trust in algorithm-based recommendations does not appear to be influenced by the phenomenon of "gain-loss asymmetry" when making risky decisions. However, this phenomenon does seem to affect trust in a human recommendation. The authors thus posit that human trust in computer-based advice is more resilient. Their findings lend support to the hypothesis of automation bias (cf. Skitka and Mosier 1994; Skitka et al. 2000), which posits that individuals tend to place greater trust in recommendations from automated systems than in those from individuals (cf. Manzey et al. 2012). This stands in contrast to the phenomenon of algorithm aversion. Consequently, further research is clearly warranted.

Loss aversion

In 1979, Kahneman and Tversky proposed a more realistic alternative to the prevailing expected utility theory in the form of their "Prospect Theory". It provides an empirically validated framework for describing how individuals make decisions in reality, independent of optimal or normative considerations. In their subsequent work, Kahneman and Tversky (1984) introduced the concept of loss aversion. It posits that, based on a subjective reference point, the loss of a given amount of money (x) evokes a stronger aversion than a gain of the same amount of money (x) elicits corresponding pleasure (cf. Kahneman and Tversky 1979; Kahneman and Tversky 1984; Tversky and Kahneman 1991; Tversky and Kahneman 1992).

This reference point, designated as “reference dependence”, represents another significant distinction between the prospect theory and the expected utility theory. In contrast to the latter, which assumes that people derive their benefit from an absolute level (of prosperity, for example), the former postulates that the benefit results from the change in comparison to a reference point (usually the status quo). In this context, positive changes are understood as gains and negative changes as losses (cf. Kahneman 2003). In conjunction with this, Thaler (1980) derives the so-called "endowment effect" from the loss aversion posited by Kahneman and Tversky (1979). It suggests that the loss of goods that are already in one's possession is perceived to have a greater value than the gain of the same goods if they were not previously in one's possession (cf. Thaler 1980).

The phenomenon of loss aversion has been substantiated in a multitude of contexts. For example, regarding the promotion of breast cancer screening in women, a negative, loss-focused communication has been demonstrated to be more persuasive and to lead to better, actual self-examination behavior months later than positive, benefit-focused communication (cf. Meyerowitz and Chaiken 1987; Nagaya 2023). In consumer decision-making, loss aversion has been observed in experiments examining the product selection process of eggs (cf. Putler 1992) and real estate (cf. Genesove and Mayer 2001). Additionally, model calculations have indicated that loss aversion may impede the adoption of sustainable heating technologies (cf. Knobloch et al. 2019).

Furthermore, loss aversion has been observed in children (cf. Harbaugh et al. 2001) and capuchin monkeys (cf. Chen et al. 2006; Lakshminaryanan et al. 2008). The brain regions affected also demonstrate heightened reactivity to losses relative to gains. Consequently, loss aversion is presumed to be an inherent, evolutionary trait of human behavior (cf. Tom et al. 2007; Griskevicius and Kenrick 2013; Knobloch et al. 2019).

In a meta-study conducted by Neumann and Böckenholt (2014), it was determined that losses have, on average, twice the impact of gains of the same size. However, it should be noted that there are considerable differences in the impact of losses and gains in different research contexts. In a meta-analysis of 607 empirical estimates of loss aversion strength from 150 articles spanning economics, psychology, neuroscience, and other disciplines, Brown et al. (2021) identified a mean loss aversion coefficient ranging from 1.8 to 2.1.

Research design and hypotheses

When the two behavioral anomalies of loss aversion and algorithm aversion are considered together, it becomes pertinent to inquire as to the extent to which the former can contribute to the reduction of the latter. The question thus arises as to whether loss aversion can be employed to facilitate the implementation of algorithm-based decision aids. The objective of this study is to investigate this relationship through an experiment conducted under controlled laboratory conditions.

For this purpose, a decision situation is constructed in which subjects can choose whether they want an economic decision to be made by a human expert or by a specialized algorithm. Following Kahneman and Tversky (1984), the subjects are divided into two treatments with different starting points but the same expected value: In treatment 1, the subjects face a potential loss, whereas in treatment 2 there is a chance of a gain.

Both treatments are preceded by a real-effort task adapted from Benndorf et al. (2014) and Filiz et al. (2020). On the one hand, this is intended to provide the subjects in treatment 1 (threat of loss) in particular with capital, some of which they could lose again during the experiment. On the other hand, the subjects' effort should increase their loss aversion and the house money effect should be excluded or reduced as far as possible (see e.g. Thaler and Johnson 1990; Loewenstein and Issacharoff 1994; Weimann and Brosig-Koch 2019).

To this end, the subjects have to match different letter combinations to a correct number combination in 50 rounds of a coding task. In each round, both the letter and number combinations are randomly generated, assigned and placed in the solution table (see Appendix). It is important to work making any mistakes. In addition, a non-binding time limit of 10 minutes is set. These conditions are deliberately chosen so that the subjects experience the task as strenuous and the money they receive as a reward for their own performance.

The test subjects in treatment 1 (threat of loss) earn EUR 5.00 per person, which is first physically paid to them in the form of EUR 5 banknotes after they have completed the coding task. This is intended to strengthen the endowment effect and the effect of loss aversion. In the actual experiment that follows, however, the subjects are now faced with the risk of losing EUR 3.00 of their hard-earned money in the context of an investment decision. To prevent this, they have the option of choosing either an algorithm (robo-advisor) with a loss probability of 30% (alternative 1.1) or a human expert (capital market expert) with a loss probability of 40% (alternative 1.2) (Table 1). The expected value of the algorithm alternative 1.1 is EUR 4.10 (EUR 5.00 - 0.3 · EUR 3.00), while that of the human expert alternative 1.2 is only EUR 3.80 (EUR 5.00 - 0.4 · EUR 3.00).

The test subjects in treatment 2 (chance of gain), on the other hand, initially earn only EUR 2.00 per person through the preceding coding task. In the subsequent actual experiment, however, they have the chance to earn a further EUR 3.00 in the context of an investment decision. They also have the option of choosing either an algorithm (robo-advisor) with a probability of success of 70% (alternative 2.1) or a human expert (capital market expert) with a probability of success of 60% (alternative 2.2) (Table 1). Analogous to treatment 1 (imminent loss), the expected value of the algorithm alternative 2.1 is EUR 4.10 (EUR 2.00 + 0.7 · EUR 3.00), while that of the human expert alternative 2.2 is only EUR 3.80 (EUR 2.00 + 0.6 · EUR 3.00).

In both treatments, therefore, the subjects can earn a minimum of EUR 2.00 and a maximum of EUR 5.00. Despite the different reference points of the decision situations (loss of EUR 3.0 of EUR 5.00 or gain of EUR 3.0 on top of EUR 2.00), the expected values per decision alternative (EUR 4.10 for the algorithm and EUR 3.80 for the human expert) are identical in both treatments. The decision alternative per algorithm is therefore superior to that per human expert (EUR 4.10 > EUR 3.80). A homo economicus would therefore be expected to choose the algorithm in both treatments. Table 1 summarizes the monetary implications and expected values of the different treatments and decision alternatives.

Table 1: Overview of the monetary implications and expected values of the decision alternatives

Treatment	Scenario	Remuneration for coding task	Decision alternative	Probability of loss/gain	Loss/gain amount	Expected value	Min. remuneration	Max. remuneration
1	Threat of loss	5.00 EUR	Algorithm	30 %	-3.00 EUR	4.10 EUR	2.00 EUR	5.00 EUR
			Expert	40 %		3.80 EUR		
2	Chance of gain	2.00 EUR	Algorithm	70 %	+3.00 EUR	4.10 EUR	2.00 EUR	5.00 EUR
			Expert	60 %		3.80 EUR		

Based on the findings of existing literature, the occurrence of algorithm aversion is anticipated in both treatments. Nevertheless, should a notably lower incidence of algorithm aversion be observed in the loss-focused treatment 1 than in the gain-focused treatment 2, this would indicate that loss aversion exerts a more powerful influence over subjects than algorithm aversion. Consequently, a conscious focus on the potential for losses in practical applications may assist in reducing algorithm aversion and, in turn, facilitate the acceptance of algorithm-based decision-making aids.

Hypothesis 1 is therefore: Algorithm aversion occurs significantly more frequently in treatment 2 (chance of gain) than in treatment 1 (threat of loss).

Null hypothesis 1 is therefore: Algorithm aversion does not occur significantly more frequently in treatment 2 (chance of gain) than in treatment 1 (threat of loss).

The experiment is programmed and executed using the software "z-Tree" developed by Fischbacher (2007).

Results

The experimental survey was conducted at the Ostfalia Laboratory for Experimental Economic Research (OLEW) in Wolfsburg between April 24 and May 8, 2024. The survey was completed by 200 students from Ostfalia University of Applied Sciences. A total of 100 subjects completed treatment 1 (threat of loss), and an additional 100 subjects completed treatment 2 (chance of gain).

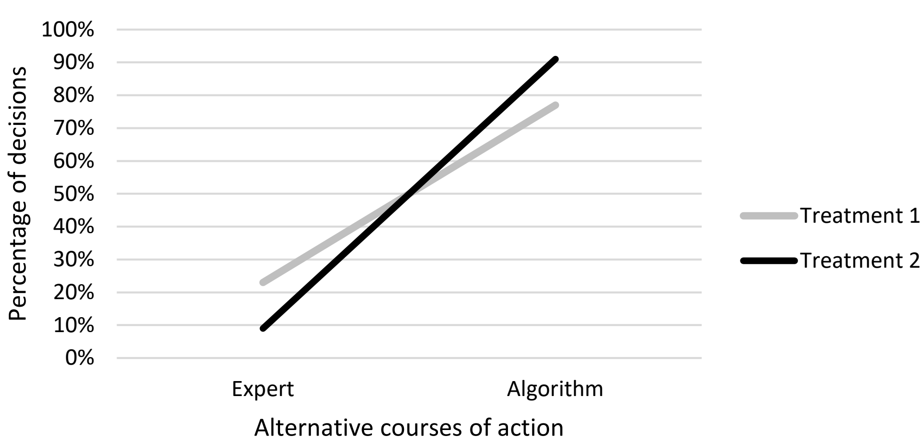
The sample consists of 43.5% female and 56.5% male subjects. The majority of the subjects (67.0%) are enrolled in the Faculty of Business, while 27.5% are in the Faculty of Automotive Engineering and 5.5% are in other faculties. The vast majority of the participants, 97.0%, are enrolled in a Bachelor's degree program, while the remaining 3.0% are pursuing a Master's degree course. On average, the respondents pursuing a Bachelor's degree indicated that they had completed 4.06 semesters of study, while the Master students had completed 3.40 semesters. The average age of the subjects is 22.3 years.

First of all, it is notable that only 16% of the participants exhibited the behavioral anomaly of algorithm aversion (see Table 2 and Figure 1).

Table 2: Decisions in favor of the human expert or the algorithm by treatment

	Decision for		
	Expert	Algorithm	Total
Treatment 1 (threat of loss)	23 (23%)	77 (77%)	100 (50%)
Treatment 2 (chance of gain)	9 (9%)	91 (91%)	100 (50%)
Total	32 (16%)	168 (84%)	200 (100%)

Figure 1: Decisions in favor of the human expert or the algorithm by treatment



A noteworthy distinction emerges when contrasting the outcomes of the two treatments. In the context of an imminent loss (treatment 1), the expert is selected at a significantly higher rate (23%) than in the case of a potential gain (treatment 2) (9%). The difference in the observed frequencies was found to be statistically significant in the Pearson chi-square test, with a probability of error less than 1% (p-value = 0.007). Although the difference is statistically significant, it is contrary to the initial hypothesis. In treatment 1 (threat of loss), algorithm aversion does not occur less frequently, but more frequently than in treatment 2 (chance of gain). This means that null hypothesis 1 cannot be rejected. Therefore, hypothesis 1 is not substantiated.

It appears that triggering loss aversion is not an effective strategy for reducing algorithm aversion. Conversely, loss aversion seems to result in an intensification of algorithm aversion. The results of Filiz et al. (2023) and Filiz et al. (2024) provide a potential explanation for this remarkable finding. In their experiments, the researchers demonstrate that algorithm aversion occurs with greater frequency when the potential consequences of a decision are more severe. As postulated by Kahneman and Tversky (1979) and Thaler (1980), the potential loss of goods already in one's possession (e.g. the possibility of losing three euros from five euros laboriously earned in treatment 1) is perceived as more critical than a gain of the same goods if they were not previously in one's possession (e.g. being able to gain a further three euros on top of two euros in treatment 2). In light of the aforementioned, the potential consequences of the decision in treatment 1 (threat of loss) can be regarded as more severe than those in treatment 2 (chance of gain). These current findings align with the observations of Filiz et al. (2023) and Filiz et al. (2024) that algorithm aversion is more prevalent when the potential consequences of a decision are perceived as more severe. The researchers' hypothesis that this leads to a reduced probability of success can also be supported by this present experiment, as the significantly more frequent choice of the human expert instead of the algorithm is also associated with a lower probability of success (60% instead of 70%). However, the observation by Lin et al. (2023) that human trust in algorithm-based recommendations does not respond to the phenomenon of the gain-loss asymmetry in decisions under risk is not supported by these present findings.

In order to promote the adoption of algorithm-based systems, it seems advisable to highlight the potential benefits associated with their use, rather than promotion them as a means of avoiding losses. To conclude, this study provides further insights into the behavioral anomaly of algorithm aversion and the strategies for reducing it.

Summary

The use of algorithmic tools is becoming increasingly prevalent in decision-making processes across a multitude of domains, offering a means to enhance efficiency in a growing number of scenarios. Nevertheless, it is frequently observed that individuals exhibit a tendency to distrust these algorithms and instead prefer to rely on human judgment. This behavioral anomaly is referred to as "algorithm aversion" (cf. Dietvorst et al. 2015). It impedes the diffusion of more efficient algorithm-based decision-making instruments and systems. Consequently, subjects forgo potential financial gains, and society as a whole risks failing to realize its maximum achievable benefit. Algorithm aversion thus represents a behavioral anomaly that requires further research.

Simultaneously, decision-making scenarios in which algorithms can offer assistance can frequently be interpreted from different viewpoints. To illustrate, algorithms can assist either in generating profits or avoiding losses. This approach is based on the highly regarded research of Kahneman and Tversky (1979), which represents another behavioral anomaly that has already been intensively studied: Loss aversion. This phenomenon has been identified as a strong factor influencing human decision-making, yet there has been no systematic investigation into its impact on computer-aided recommendations, as noted by Lin et al. (2023). Consequently, it is pertinent to ask whether loss aversion can be employed as a means of reducing algorithm aversion.

To investigate this question, an economic experiment was conducted in a controlled laboratory setting. For this purpose, a decision-making scenario was constructed, comprising two treatments for making an investment decision. In treatment 1, the subjects are threatened with a loss, whereas in treatment 2, the subjects have the chance of a gain. The expected value of the payout is identical in both treatments. Due to the frequently demonstrated effect of loss aversion, it is expected that algorithm aversion is suppressed in treatment 1 (threat of loss) and therefore occurs significantly more frequently in treatment 2 (chance of gain) (hypothesis 1).

The results demonstrate that algorithm aversion is observed in only 16% of the participants. With a probability of error of less than 1% (p-value = 0.007), the human expert was also selected significantly more frequently by the subjects in the case of an impending loss (treatment 1) than

in the case of the chance of a gain (treatment 2). Hypothesis 1 was therefore not substantiated. Ultimately, the effect of loss aversion on algorithm aversion can be observed in the context of this experiment in a manner that is opposite to what was previously expected. Loss aversion did not reduce the occurrence of algorithm aversion; rather, it actually increased it.

As postulated by Kahneman and Tversky (1979) and Thaler (1980), the potential loss of goods already in one's possession (e.g. the possibility of losing three euros from five euros laboriously earned in treatment 1) is perceived as more critical than a gain of the same goods if they were not previously in one's possession (e.g. being able to gain a further three euros on top of two euros in treatment 2). In light of the aforementioned, the potential consequences of the decision in treatment 1 (threat of loss) can be regarded as more severe than those in treatment 2 (chance of gain). These current findings align with the observations of Filiz et al. (2023) and Filiz et al. (2024) that algorithm aversion is more prevalent when the potential consequences of a decision are perceived as more severe. The researchers' hypothesis that this leads to a reduced probability of success can also be supported by this present experiment, as the significantly more frequent choice of the human expert instead of the algorithm is also associated with a lower probability of success (60% instead of 70%). However, the observation by Lin et al. (2023) that human trust in algorithm-based recommendations does not respond to the phenomenon of the gain-loss asymmetry in decisions under risk is not supported by these present findings.

The results of this study indicate that to mitigate algorithm aversion and promote the adoption of more efficient algorithm-based decision-making tools and systems, it is advisable to highlight the potential benefits associated with their use, rather than portraying them as a means of loss avoidance. This study, therefore, offers further insights into the behavioral anomaly of algorithm aversion and the strategies for its reduction.

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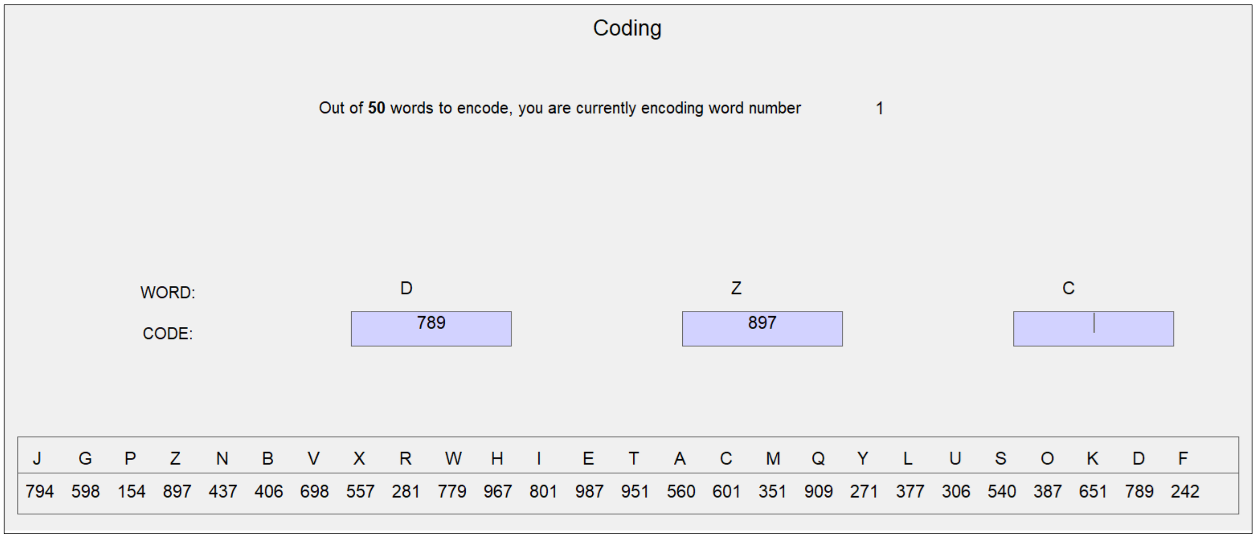
Appendix: Presentation of the economic experiment

Treatment 1 (threat of loss)

Instructions for the initial coding task (real-effort task)



Procedure

In this task you can earn money by correctly coding 50 letter combinations (words) into numbers.

The image above shows an example of the input mask that is available to you once the task has started.

To complete the task, you must assign the randomly generated numbers from the lower table to the letters displayed above the blue fields by clicking with the mouse in the respective blue field under a letter and entering the correct number from the table using the keyboard.

In the example above, the letters D and Z have already been coded correctly with the numbers 789 and 897. For complete and correct coding, the numbers 601 should be entered in the blue field on the right for the letter C.

Once you have entered the correct numbers in all three blue fields, confirm your entry by clicking on OK in the bottom right-hand corner of the screen (not shown in the screenshot above).

If all entries were correct, you will be taken to the next, randomly generated letter combination (word). The table is also completely reshuffled and new numbers are assigned to each letter.

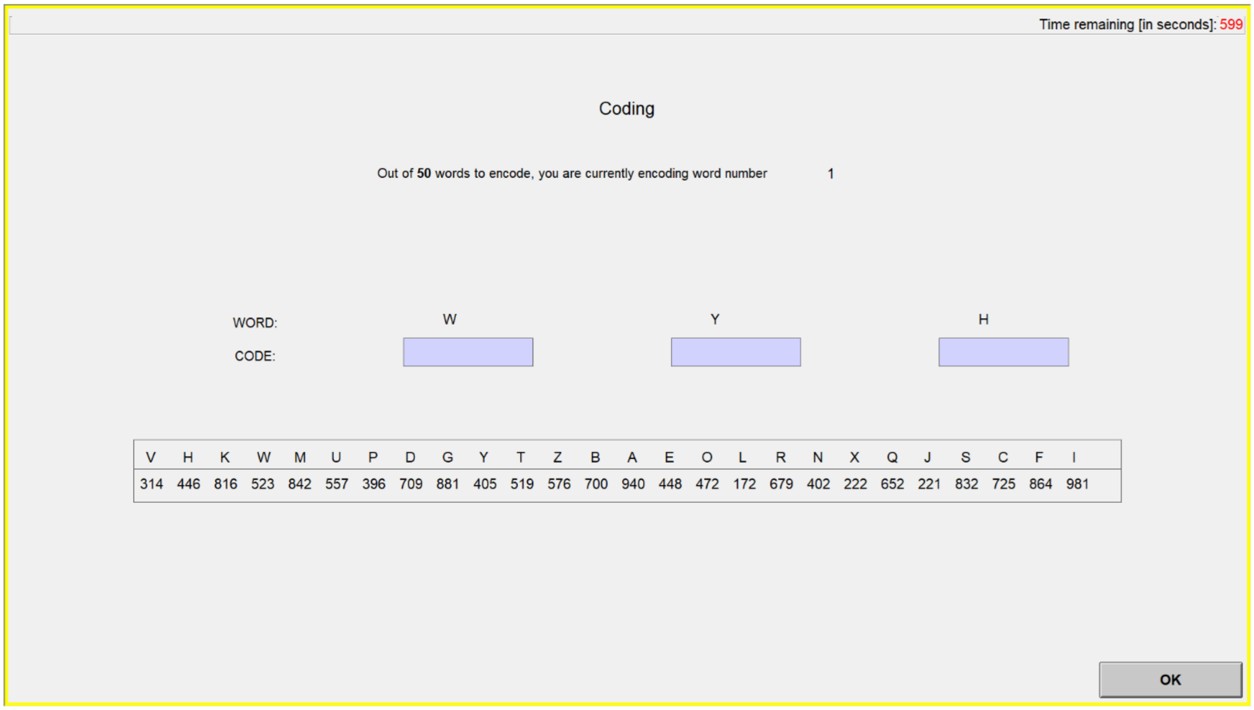
If your entries were incorrect, you will receive a corresponding message in red and must repeat all entries for the current letter combination (word). The table will not change in this case.

If possible, you should not spend more than **10 minutes** coding all 50 letter combinations (words). After starting the task, you can see how much time you have left in the top right-hand corner of the screen.

Payout

For each correctly coded letter combination (word) you will receive a credit of 10 cents. You can earn a total of EUR 5.00 for this task (50 combinations of 10 cents each).

Exemplary input mask of the initial coding task (real-effort task)



Interim payment screen after completion of the initial coding task (real-effort task)

Congratulations!

In the coding task you have just completed, you have earned **5.00 EUR.**

The laboratory supervisor will now gradually come around and make an interim payment for this.

Please wait for this interim payment. Continue to behave quietly, do <u>not</u> talk to your neighbors and do <u>not</u> look at their screens.

The next task will start automatically as soon as all participants have received their interim payment.

Instructions for the actual experiment

Situation

In the previous task, you earned and have been paid EUR 5.00. Of this amount, EUR 2.00 will surely be yours. The remaining EUR 3.00 represent your stake for the new decision situation that now follows. In this situation, you have to choose whether you want to have an investment made by a capital market expert or by a robo-advisor. A robo-advisor is a specialized computer program that continuously analyses the capital markets and independently implements investment decisions tailored to the respective customer. It is known that the capital market expert has a 40% probability of making an unsuccessful investment in this task. It is also known that the robo-advisor has a 30% probability of making an unsuccessful investment in this task. If the investment is unsuccessful, you will lose your stake of EUR 3.00.

Procedure

After reading these instructions and answering the control questions, you will be presented with the decision situation. In this situation, you must select one of the two possible decision options.

Payout

For participating in this task, you will receive a payout depending on the decision you make and a random principle which is based on the above-mentioned probabilities of occurrence. If an unsuccessful investment is made, you will lose your stake of EUR 3.00. Otherwise, you will lose nothing.

Control questions for the actual experiment

<u>Control question 1:</u> Which decision options are available to you for making the investment?

- ☐ I can have the investment made by a robo-advisor or make it myself.
- ☐ I can make the investment myself or have it done by a capital market expert.
- ☐ I can have the investment made by a capital market expert or a robo-advisor. (Correct!)

<u>Control question 2:</u> What is a robo-advisor?

- ☐ A specialized computer program that continuously analyzes the capital markets and independently implements investment decisions tailored to the respective customer. (Correct!)
- ☐ A specialized expert who independently advises companies on the use of robot technology in production systems and also installs them on request.
- ☐ A computer program available on any standard PC that displays the current share prices in the German share index (DAX) at the touch of a button.

<u>Control question 3:</u> What is the probability of an unsuccessful investment made by the robo-advisor?

- ☐ 20%
- ☐ 30% (Correct!)
- ☐ 40%

<u>Control question 4:</u> How much money do you lose if an unsuccessful investment is made?

- ☐ 2.00 EUR
- ☐ 3.00 EUR (Correct!)
- ☐ 5.00 EUR

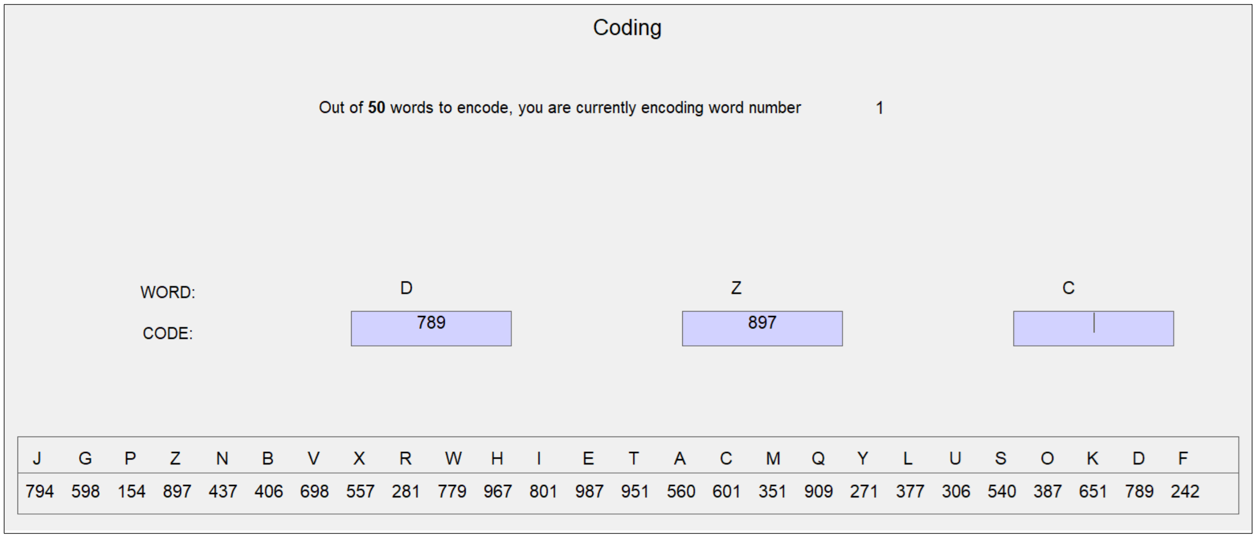
Decision-making situation in the actual experiment

Now make your choice as to who should make the investment!

- ☐ I have the investment made by a capital market expert.
- ☐ I have the investment made by a robo-advisor.

Treatment 2 (chance of gain)

Instructions for the initial coding task (real-effort task)



Procedure

In this task you can earn money by correctly coding 50 letter combinations (words) into numbers.

The image above shows an example of the input mask that is available to you once the task has started.

To complete the task, you must assign the randomly generated numbers from the lower table to the letters displayed above the blue fields by clicking with the mouse in the respective blue field under a letter and entering the correct number from the table using the keyboard.

In the example above, the letters D and Z have already been coded correctly with the numbers 789 and 897. For complete and correct coding, the numbers 601 should be entered in the blue field on the right for the letter C.

Once you have entered the correct numbers in all three blue fields, confirm your entry by clicking on OK in the bottom right-hand corner of the screen (not shown in the screenshot above).

If all entries were correct, you will be taken to the next, randomly generated letter combination (word). The table is also completely reshuffled and new numbers are assigned to each letter.

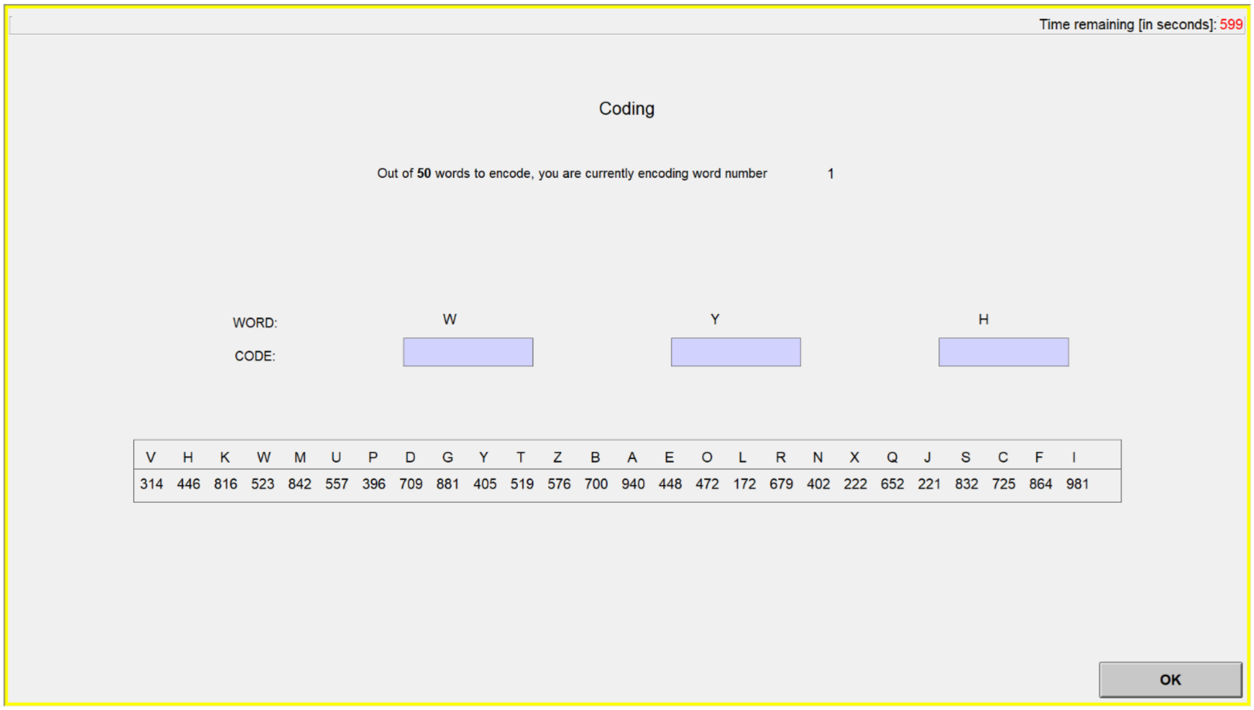
If your entries were incorrect, you will receive a corresponding message in red and must repeat all entries for the current letter combination (word). The table will not change in this case.

If possible, you should not spend more than **10 minutes** coding all 50 letter combinations (words). After starting the task, you can see how much time you have left in the top right-hand corner of the screen.

Payout

For each correctly coded letter combination (word) you will receive a credit of 4 cents. You can earn a total of EUR 2.00 for this task (50 combinations of 4 cents each).

Exemplary input mask of the initial coding task (real-effort task)



Interim payment screen after completion of the initial coding task (real-effort task)

Congratulations!

In the coding task you have just completed, you have earned **EUR 2.00.**

Please click OK to continue with the next task.

Instructions for the actual experiment

Situation

In the previous task, you earned EUR 2.00. This amount will surely be yours. In the following decision situation, you have the chance to win an additional EUR 3.00. To do this, you have to choose whether you want to have an investment made by a capital market expert or by a robo-advisor. A robo-advisor is a specialized computer program that continuously analyses the capital markets and independently implements investment decisions tailored to the respective customer. It is known that the capital market expert has a 60% probability of making a successful investment in this task. It is also known that the robo-advisor has a 70% probability of making a successful investment in this task. If the investment is successful, you will win the additional EUR 3.00.

Procedure

After reading these instructions and answering the control questions, you will be presented with the decision situation. In this situation, you must select one of the two possible decision options.

Payout

For participating in this task, you will receive a payout depending on the decision you make and a random principle which is based on the above-mentioned probabilities of occurrence. If a successful investment is made, you will win the additional EUR 3.00. Otherwise, you will win nothing.

Control questions for the actual experiment

<u>Control question 1:</u> Which decision options are available to you for making the investment?

- ☐ I can have the investment made by a robo-advisor or make it myself.
- ☐ I can make the investment myself or have it done by a capital market expert.
- ☐ I can have the investment made by a capital market expert or a robo-advisor. (Correct!)

<u>Control question 2:</u> What is a robo-advisor?

- ☐ A specialized computer program that continuously analyzes the capital markets and independently implements investment decisions tailored to the respective customer. (Correct!)
- ☐ A specialized expert who independently advises companies on the use of robot technology in production systems and also installs them on request.
- ☐ A computer program available on any standard PC that displays the current share prices in the German share index (DAX) at the touch of a button.

<u>Control question 3:</u> What is the probability of a successful investment made by the robo-advisor?

- ☐ 60%
- ☐ 70% (Correct!)
- ☐ 80%

<u>Control question 4:</u> How much money do you win when a successful investment is made?

- ☐ 2.00 EUR
- ☐ 3.00 EUR (Correct!)
- ☐ 5.00 EUR

Decision situation for the actual experiment

Now make your choice as to who should make the investment!

- ☐ I have the investment made by a capital market expert.
- ☐ I have the investment made by a robo-advisor.