Ostfalia
Hochschule für angewandte Wissenschaften

Wolfsburg
Fakultät Wirtschaft

WWP

Wolfsburg Working Papers

No. 22-02

Impact of the Decoy Effect on Algorithm Aversion

Marco Lorenz, July 2022

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Abstract: Limitations in the human decision-making process restrict the technological potential of algorithms, which is also referred to as "algorithm aversion." This study uses a laboratory experiment with test subjects to investigate whether a phenomenon known since 1982 as the "decoy effect" is suitable for reducing algorithm aversion. For numerous analog products, such as cars, drinks, or newspaper subscriptions, the decoy effect is known to have an immense influence on human decision-making behavior. Surprisingly, the decisions between forecasts by humans and robo-advisors (algorithms) investigated in this study are not affected by the decoy effect at all. This is true both a priori and after observing forecast errors.

Keywords: Algorithm aversion, decoy effect, robo-advisors, technology adoption, human-computer interaction, experiments, behavioral economics.

JEL classification: D81, D83, D91, G41, O30.

Funding: This research project was funded by the grant „Reinhard Selten-Stipendium“ of the German non-profit association "Gesellschaft für experimentelle Wirtschaftsforschung e.V." The funding was used exclusively to remunerate the subjects in the laboratory experiment.

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1. Introduction

Considerable progress in the field of artificial intelligence (AI) is currently paving the way for numerous promising business models. However, many people have reservations about the automated processes they rely on. These reservations are also referred to as "algorithm aversion.”[1]

Algorithms or AI that work with stochastic processes cannot make exclusively accurate predictions, e.g., about the development of capital markets. As soon as users realize this, they often distrust the technology and refrain from using it (Dietvorst, Simmons & Massey, 2015). This problem also occurs when users must decide whether to trust an algorithm or their own judgment. Many users tend to trust themselves even when there is clear evidence that they are unlikely to make better predictions than an algorithm in the long run.

Algorithm aversion means that promising technologies do not succeed in the market as one would expect, given their performance and cost advantages. In finance, for example, many users find it difficult to develop trust in automated asset managers, so-called "robo-advisors," even though their use can help avoid costly mistakes (Back, Morana & Spann, 2021). To mitigate this issue, measures to reduce algorithm aversion need to be identified and taken.

An experimental study focusing on this topic investigates what happens when users are given the possibility to manipulate an algorithm’s output. Dietvorst, Simmons & Massey (2018) give some subjects the ability to adjust an algorithm's predictions downward or upward by a few percent in post-processing. This ability to influence an algorithm significantly increases willingness to use. Interestingly, the effect occurs even when the opportunities for adjustment are kept low. The article suggests that algorithm aversion can be mitigated by giving people opportunities to influence the algorithm's predictions, even if only to a limited extent (Dietvorst, Simmons & Massey, 2018).

Other studies have identified shortening response times (Efendić, Van de Calseyde & Evans, 2020) or making the algorithm take into account the predictions of knowledgeable humans (Kawaguchi, 2021), among others, as measures by which algorithm aversion can be reduced. In addition, a more precise representation of the algorithmic output, e.g., by adding additional decimal places (Kim, Giroux & Lee, 2021) or providing information about the procedure and accuracy of an algorithm (Ben David, Resheff & Tron, 2021) also seem to be suitable for this purpose.

However, the listed measures reduce algorithm aversion only to a limited extent. Moreover, many of them include the risk that the prediction quality of the algorithm decreases after human influence (cf. Kawaguchi, 2021; Dietvorst, Simmons & Massey, 2018). Consequently, it remains an important research task to uncover effective ways to reduce algorithm aversion that do not involve degradation of the algorithm's prediction quality.

Therefore, this study takes up an idea of Huber, Payne & Puto (1982), who studied the human decision-making process under uncertainty using economic experiments. Their study shows that the possibility of comparing multiple options can massively influence the human decision-making process. Under certain circumstances, an option finds significantly greater appeal if a comparable but recognizably inferior option is added. This phenomenon is also known as the "decoy effect" (see chapter 2.1). In

[1] For a detailed review of the literature on algorithm aversion, see e.g. Mahmud et al. (2022), Burton, Stein & Jensen (2020), or Jussupow, Benbasat & Heinzl (2020).

numerous replications, the decoy effect has been shown to cause subjects to change their decision behavior when choosing between different consumer goods (Ariely & Wallsten, 1995), services (Park & Kim, 2005), and even lotteries (Kroll & Vogt, 2012; Herne, 1999). These findings suggest that the decoy effect may have an impact on other decision-making situations as well.

In previous studies on algorithm aversion, decision makers were usually provided with only one algorithm, which they could either rely on or refrain from using (e.g., Dietvorst, Simmons & Massey, 2015). As technology advances, the transferability of this experimental design to practice decreases. In fact, in practice we can already choose between several algorithms that differ in their performance for many tasks, not least asset management.

The possibility to choose between several algorithms could lead to a decoy effect whenever one algorithm is obviously better than another in at least one criterion and not worse than that same algorithm in any other criterion. In this case, the objectively superior algorithm would gain additional attractiveness from the user's point of view, even compared to alternative methods in which no algorithm is used.

The great advantage of this approach over measures already identified for reducing algorithm aversion is that the superior algorithm would not have to be manipulated at all. This means that the willingness of decision makers to use the algorithm could be increased without having to compromise the performance or user-friendliness of the algorithm. Therefore, in this study, an economic experiment will be conducted to investigate whether the decoy effect can be used to reduce algorithm aversion. The influence of the decoy effect on the willingness to use an algorithm is investigated both from the outset and after observing errors in the algorithm.

2. Literature Overview

2.1 Decoy Effect

The decoy effect (or asymmetric dominance effect) was first discovered about 40 years ago. In an economic experiment, Huber, Payne & Puto (1982) let 150 students choose between different cars, restaurants, types of beer, lotteries, movies, and TVs. They found that the addition of a so-called *decoy*, which is comparable to and clearly inferior to the offer referred to as the *target*, can lead to the target being selected significantly more often than a third option, the so-called *competitor*.

The decoy effect is illustrated by Ariely (2009) using the example of subscription offers of the magazine "The Economist." The author divides 200 students into two groups (conditions) and asks them each to estimate which newspaper subscription they would choose if they had to decide between several offers. In the first condition (control), students can choose between the "Digital" ($59) and "Print + Digital" ($125) offers. It turns out that 68 students prefer the "Digital" offer and the remaining 32 study participants prefer the "Print + Digital" offer. If these 100 students actually took out the subscriptions, this would result in total revenue of $8,012 for The Economist (see Table 1).

Table 1: Distribution in the control group in Ariely (2009)

Offer	Digital	Print + Digital
Price	$59	$125
Number of buyers	68	32
Volume of sales per offer	$4,012	$4,000
Total volume of sales		**$8,012**

In the second condition (decoy), the offer "Print" ($125) is added to the already known offers "Digital" ($59) and "Print + Digital" ($125). Although the "Print" offer is not selected even once, it has a massive influence on the theoretically achieved sales of "The Economist." In the second group, only 16 students choose the "Digital" offer, while 84 students prefer the "Print + Digital" offer. The total revenue would now be $11,444 (see Table 2).

Table 2: Distribution under the influence of the decoy effect in Ariely (2009)

Offer	Digital	Print + Digital	Print
Price	$59	$125	$125
Number of buyers	16	84	0
Volume of sales per offer	$944	$10,500	$0
Total volume of sales			**$11,444**

The "Print" offer is added in the second condition to steer decision-making behavior towards the "Print + Digital" offer. In this context, it is therefore referred to as the *decoy*, while the "Print + Digital" offer, which gains in popularity after the decoy is added, is called the *target*. The "Digital" offer is in turn the *competitor* of "Print." In this context, the target is also said to *asymmetrically dominate* the decoy.

Ariely attributes the massive differences in choice behavior between the "Digital" and "Digital + Print" offers to the addition of the decoy "Print." In the first condition, students had to compare two options in which each choice offered a distinct advantage. The name of the "Print + Digital" option already suggests that this option offers additional consumption possibilities. However, it is obviously inferior to the "Digital" option in terms of price. The individual has to infer whether the added value in the "consumption possibilities" dimension of the "Print + Digital" option should be rated higher than the added value in the "price" dimension of the "Digital" option. Accordingly, the results of consumer preferences vary.

In the second condition, the comparability of the "Print + Digital" and "Print" offers leads the subjects to apply a heuristic. Although here, too, all decisions are exclusively in favor of the "Digital" and "Print + Digital" options, subjects replace the question of which of the two options is advantageous with a comparison of the "Print + Digital" and "Print" options. At the same price, the target "Print + Digital" clearly offers more consumption possibilities than the decoy "Print." Since the target is clearly superior to the decoy, its appeal is seemingly enhanced, and this also compared to the competitor "Digital", whose relative advantage over other options still cannot be determined.

Park & Kim (2005) raise the question whether the decoy effect works in the same way when two decoys are offered. In this case, the first decoy is only asymmetrically dominated by the target. It cannot be easily compared with the competitor. The second decoy, on the other hand, is asymmetrically dominated by both the target and the competitor. It turns out that, with two decoys involved, the target only gains in attractiveness if the participants are asked to first evaluate each of the four options for themselves. If they are asked to compare the options immediately, the decoy effect does not work as usual any longer.

Frederick, Lee & Baskin (2014) raise the question of which measures are most effective in eliciting a decoy effect. They compare the effectiveness of three ways of presenting product dimensions: representation in numerical form, representation in pictorial form, and physical experience of the differences by the subjects themselves (e.g., through the sense of taste). They find that the decoy effect occurs only when the product dimensions are represented as written-down numbers, for example in the form of numerical ratings. Yang & Lynn (2014) also conclude that qualitative-verbal descriptions as well as pictorial representations are not particularly well suited to create an asymmetric dominance effect. The two measures studied lead to significant decoy effects in only 11 of 91 comparisons across 23 different product classes.

Crosetto & Gaudeul (2016) investigate the robustness of the decoy effect. For this purpose, they introduce the so-called "monetary indicator" as an additional dimension. The authors design the monetary indicator in such a way that selecting the target entails higher costs than selecting the competitor. They vary how much higher the cost of selecting the target is compared to the competitor. It turns out that the preference for the target remains as long as it is up to 8% more expensive than the competitor.

Last but not least, the decoy effect has also been shown to have an impact on individuals' risk preference and social behavior. Kroll & Vogt (2012) let subjects choose between different types of lotteries. It is shown that adding a decoy in all cases leads to an increase in participants' risk taking. Wang et al. (2018) have their subjects play a modified form of the "Prisoner’s Dilemma" in which the third option "reward" is added as a decoy to the well-known options "cooperate" and "defect." It can be observed that the decoy leads to subjects cooperating significantly more often and thus also increases their average gain compared to a control condition.

2.2 Algorithm Aversion

Differences in the performance of algorithms and humans in dealing with similar tasks have been studied since the 1950s (Meehl, 1955). In recent years, the interaction between humans and algorithms has been examined more closely, as automated algorithmic activity increasingly shapes online information and economic systems. In an experimental study, Önkal et al. (2009) found that the same recommendations are followed to a lesser extent when subjects are led to believe that they come from an algorithm than when they are told that the recommendations come from a competent human. Even though the term “algorithm aversion” was not yet established at the time, the study was subsequently widely interpreted as evidence of algorithm aversion.

Six years later, Dietvorst, Simmons & Massey (2015) found that errors by an algorithm lead to a greater loss of confidence than errors by a human. Their subjects could delegate a prediction task to either an algorithm or a human. The subjects who were able to watch the algorithm commit errors in trial rounds showed an increasingly dismissive attitude towards the algorithm in the subsequent compensated rounds. To describe this phenomenon, the term "algorithm aversion" was coined. Nowadays, the term is used both to generalize humans' rejection of algorithms and to describe the dramatic diminishment of human trust in algorithmic efficiency upon observing the errors of an algorithm. (Filiz et al., 2021a).

Further studies have shown that algorithm aversion is equally observable in different disciplines, such as law (Ireland, 2020), asset management (Niszczota & Kaszás, 2020), medicine (Lennartz et al., 2021), or poetry (Köbis & Mossink, 2021). Its extent nevertheless seems to depend on the context of the task settings (Filiz et al., 2021a; Castelo, Bos & Lehmann, 2019).

Algorithm aversion can occur regardless of whether the users can execute a task themselves or delegate the task to another expert or layperson as opposed to entrusting the work solely to an algorithm (Germann & Merkle, 2020). Unrealistic expectations about the accuracy of an algorithm have been identified as one of the main causes of algorithm aversion (Rebitschek, Gigerenzer & Wagner, 2021). Respondents often assume the error rates of algorithms to be in ranges that are so low that they cannot be achieved in practice. This also partly explains why trust in algorithms drops so rapidly after erroneous predictions (Dietvorst, Simmons & Massey, 2015).

Furthermore, it has been shown that decision makers have reservations about algorithms because, unlike humans, they do not trust them to learn over time and gradually improve their prognosis quality (Berger et al., 2020). Consistent with this is the finding that the so-called "uniqueness neglect" can also be a driver of algorithm aversion. Uniqueness neglect describes the phenomenon in which humans believe each meaningful decision is accompanied by unique circumstances and the intrinsic nature of the decision and surrounding context is unable to be grasped fully by an algorithm (Pezzo & Beckstead, 2020; Longoni, Bonezzi & Morewedge, 2019). Furthermore, humans tend to form stronger emotional bonds with fellow humans than with algorithms, which also leads them to feel hesitant in solely trusting algorithms during collaborative sensemaking processes (Leyer & Schneider, 2019).

Yeomans et al. (2019) also attribute algorithm aversion in part to an overestimation of people's own predictive abilities (overconfidence). By overestimating the likelihood of success when performing a task themselves, people also misjudge the value added by using an algorithm. It has been shown that learning effects, induced by repetitive tasks as well as clear feedback about one's own performance and that of an algorithm, can help to slightly reduce the aversion (Filiz et al., 2021b). Fittingly, algorithm aversion has been observed to decrease with increasing digital literacy of decision makers (Wang, Harper & Zhu, 2020), but to increase with increasing expertise of decision makers in the field of the particular prediction task (Allen & Choudhury, 2021; Gaube et al., 2021).

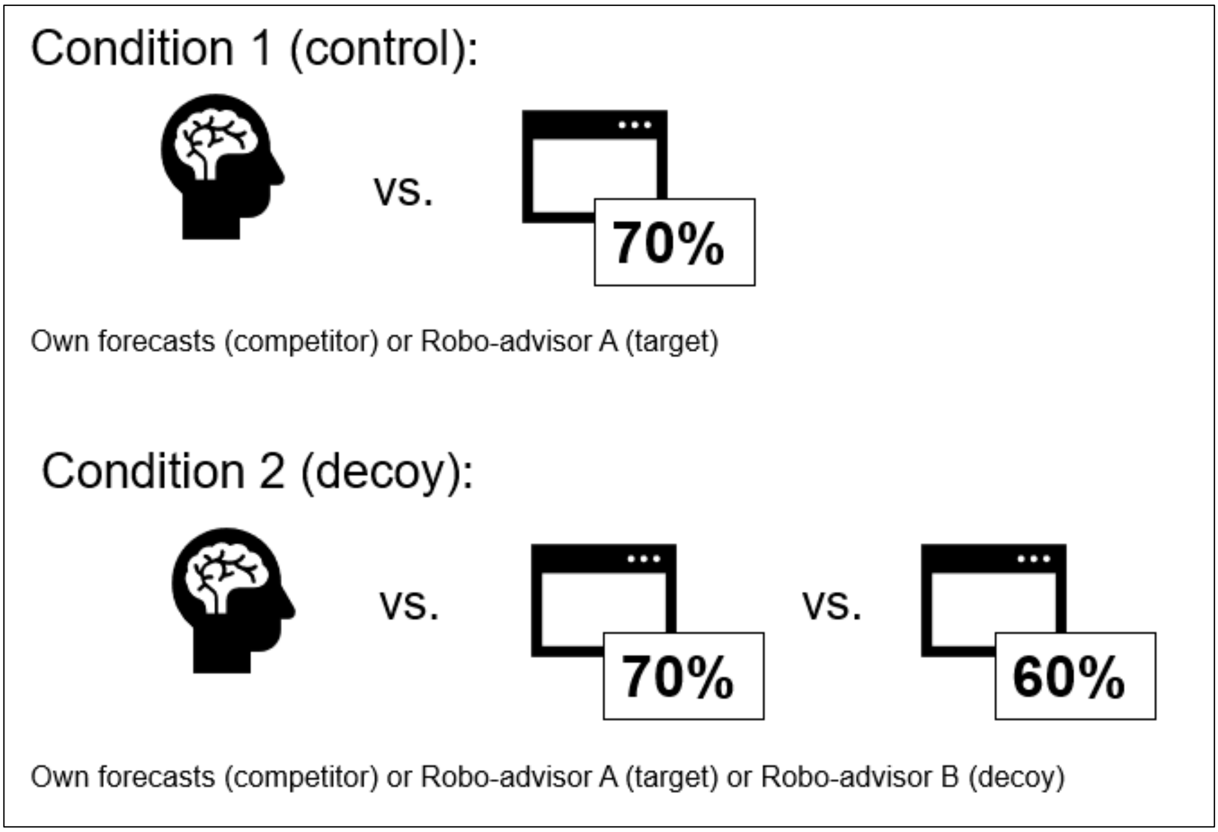
In practice, algorithm aversion means that promising innovations based on the use of algorithms and AI do not establish themselves on the market as one would expect in view of their advantages. If algorithm aversion can be overcome, extensive cost savings or the development of new digital business models can be made possible. In recent years, therefore, research has increasingly been devoted to finding measures that are likely to increase decision-makers' confidence in technology and thus their willingness to use it (Ben David, Resheff & Tron, 2021; Kawaguchi, 2021; Kim, Giroux & Lee, 2021; Efendić, Van de Calseyde & Evans, 2020; Dietvorst, Simmons & Massey, 2018). However, the identified measures only reduce algorithm aversion to a small extent and also introduce new problems, such as a deterioration in prediction quality (Kawaguchi, 2021; Dietvorst, Simmons & Massey, 2018).

2.3 Hypotheses

The example of an investment experiment is used in order to investigate whether a decoy effect can influence the decision for or against the use of an algorithm. The experimental design of Ariely (2009) described in chapter 2.1 is transferred to the context of an investment decision with automated asset managers, so-called robo-advisors. In condition 1 (control), subjects can perform the forecasting task independently or delegate it to an algorithm with a success rate of 70%. In condition 2 (decoy), subjects can perform the prediction task independently, delegate to an algorithm with a success rate of 70%, or delegate to a second algorithm with a success rate of 60%. The algorithm with a success rate of 70% will be referred to as "Robo-advisor A" or "Algorithm A" and the algorithm with a success rate of 60% will be referred to as "Robo-advisor B" or "Algorithm B."

By adding the second algorithm, a decoy effect is produced (Figure 1). In this study, Algorithm A acts as the *target*. Algorithm B represents the *decoy* that could increase the attractiveness of the target (Algorithm A). The independent accomplishment of the prediction task by the subjects themselves is the *competitor* in this case. The experiment lasts ten rounds (see chapter 3.2).

Figure 1: General design of the experiment



Prior research has shown that subjects tend to prefer human judgment over the advice of an algorithm (cf. e.g., Alemanni et al., 2020; Promberger & Baron, 2006). When deciding between algorithms and one's own judgment, this effect can be additionally amplified by an overestimation of one's own forecasting abilities, which is also referred to as “overconfidence” (cf. Filiz et al., 2021b). This is interesting insofar as the probability of achieving a result by human judgment that even comes close to that of a specialized algorithm is extremely low. In view of the previous research results, it can nevertheless be expected that in this study, too, a large proportion of the subjects will rely on their own performance of the task, irrespective of the advantages of the algorithm.

Hypothesis 1: Not all subjects choose to always use an algorithm.

The participants in condition 1 (control) must decide between the better-performing Robo-advisor A with a success rate of 70% (*target*) and the independent asset management by themselves (*competitor*). In condition 2 (decoy), Robo-advisor B with a success rate of 60% is added as a *decoy*, which is comparable to Robo-advisor A and clearly inferior to it.

From a purely mathematical point of view, the decision situation is identical in both cases. It only depends on whether the chances of success are estimated to be higher when performing the prediction task independently than when choosing Robo-advisor A. Robo-advisor B should not have any influence on the decisions of a subject acting as a strictly rational utility maximizer because of the lower probability of success.

If the decoy effect sets in analogous to the form observed by Ariely (2009), the comparability of Robo-advisor A with Robo-advisor B with respect to the dimension "success rate" in the second condition will, however, lead to a significantly higher number of decisions in favor of delegation to the superior algorithm and against independent performance of the prediction task.

Hypothesis 2: The proportion of decisions in favor of the target algorithm is higher if another algorithm is introduced as a decoy.

A crucial aspect of algorithm aversion lies in the reaction to flawed predictions. As in this study, the subjects of Dietvorst, Simmons & Massey (2015) are faced with the choice whether to perform a prediction task independently or to delegate it to an algorithm. Some of the subjects have the opportunity to observe the algorithm in advance as it performs its task (and consequently, inevitably, as it commits errors). The authors investigate to what extent this influences the decision behavior of the subjects. They find that subjects who were able to observe the algorithm making inaccurate predictions actually rely significantly more often on their own judgment than on the algorithm in subsequent rounds, even though the algorithm still has the higher success rate. Interestingly, the effect does not occur to the same extent after observing unsuccessful predictions by a human. This finding is confirmed by Bogert, Schecter & Watson (2021), who also conclude that subjects are more sensitive to errors made by an algorithm than to errors made by a human.

In this study, it will be investigated whether algorithm aversion following erroneous forecasts also occurs when multiple algorithms are available. Adding another algorithm in condition 2 (decoy) could lead to a weakening of the effect, since the subjects now have an additional alternative to choose from. Even if they no longer have sufficient confidence in the algorithm that made an inaccurate prediction, they do not necessarily have to abandon the use of algorithms altogether but can simply use the second algorithm. In addition, the resulting distrust in the algorithm could be weakened by the additional information that it is nevertheless a high-performing algorithm relative to the other algorithm. This would mean that the rejection of algorithms as decision-making aids after an incorrect forecast is no longer so pronounced if several algorithms are available.

> **Hypothesis 3:** The proportion of subjects who subsequently use an algorithm after an incorrect prognosis of an algorithm is significantly higher in condition 2 (decoy) than in condition 1 (control).

Based on this, the reaction to one's own inappropriate predictions could also vary if several algorithms are available as alternatives. In contrast to the study by Dietvorst, Simmons & Massey (2015), a broader range of options and additional information on relative performance could increase the willingness to abandon the initial rejection attitude of algorithms after experiencing the difficulty of a prognosis task firsthand.

> **Hypothesis 4**: The proportion of subjects who subsequently switch to an algorithm after making an incorrect prognosis themselves is significantly higher in condition 2 (decoy) than in condition 1 (control).

3. Experimental Design

3.1 Participants

To answer the research questions, an economic experiment was conducted with students of the Ostfalia University of Applied Sciences in Wolfsburg, Germany. A total of 160 students came to the university's research laboratory between April 20, 2022 and April 28, 2022. They had signed up independently for one of 28 sessions, each lasting approximately half an hour. The subjects appeared concentrated during the experiment. They received an average payment of €5.95, which seems to have created an effective incentive for meaningful decision-making.

The subjects were on average 23.6 years old and in the fifth semester of their studies. For 123 participants (78%), it was their first time partaking in an economic experiment, and the remaining 37 participants (22%) had already engaged in other economic experimental studies. The subjects were equally divided into two groups: a treatment condition, in which a decoy is introduced, and a control condition. To avoid bias of the results, an equal distribution with respect to faculty and gender was taken into account (Figures 2 and 3).

Figure 2: Distribution of the subjects' faculties in the conditions

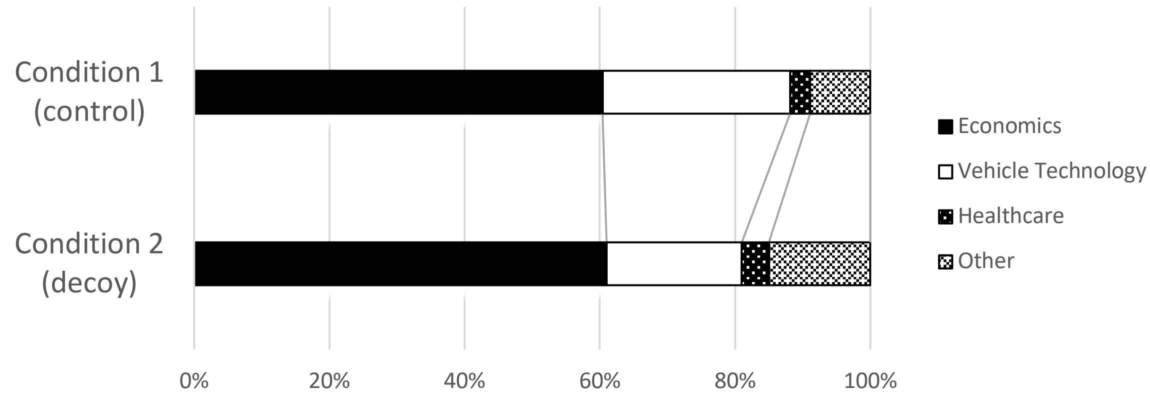
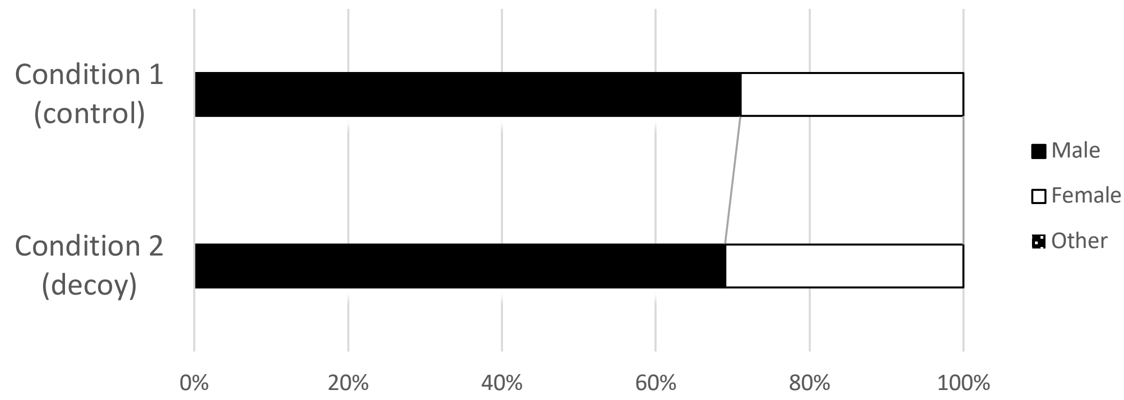


Figure 3: Distribution of the subjects’ genders in the conditions



3.2 Task

The subjects have to cope with a task from the field of asset management. In the course of ten game rounds, each subject must decide whether to invest an allocated initial budget of 10 experimental currency units (ECUs) in the so-called “Z Share" or to save the budget. In each game round, subjects have to invest or save the full amount of 10 ECUs. It is not possible to split the budget within a game round. At the end of the game, the accumulated profit in ECUs from the individual game rounds is converted and paid out to the participants as compensation.

The participants' goal is therefore to maximize their credit. To do this, in each of the ten rounds of the game, they can either manage their budget themselves or entrust it to a robo-advisor (control condition) or one of two robo-advisors (decoy condition), who invest or save the budget in their place. The detailed instructions are in Appendix A.

When the budget is invested in the share, the round profit may be above or below the initial budget of 10 ECUs due to price fluctuations. For example, if the price of the share increases by 10% within a round, and 10 ECUs have been invested in the share, 11 ECUs will be credited to the balance. If the share price falls by 10% in one round and 10 ECUs are invested in the share, the balance is credited with 9 ECUs. If, on the other hand, the decision is made to save, the subjects' balance is always credited with exactly 10 ECUs.

Before making the investment decision, the subjects should therefore get an idea of whether they think the share price will rise or fall in the respective round. If the price rises, it is the profit-maximizing strategy to invest in the share. If the price falls, the profit-maximizing strategy is to save.

As an aid, before each game round, the current values of four fundamental influencing factors are announced. In combination with a fifth influencing factor (the so-called "random influence"), the four fundamental influencing factors determine the share price trend. The instructions describe in detail in which ranges the values of the influencing factors can vary. In addition, the subjects receive insight into the distribution of the values of the fundamental influencing factors and the random influence in ten rounds of share price history. Based on this information, they can get an approximate picture of the correlations and the current development. The values of the influencing factors in each round were generated once as a random process and are identical for each subject.

The participants in condition 1 (control) are given the choice of performing the asset management task independently or delegating it to Robo-advisor A with a success rate of 70%. That is, the algorithm makes the decision that maximizes the subjects' assets (invest or save) in an average of 7 out of 10 rounds. In the second condition (decoy), in addition to the independent execution and the Robo-advisor A, the subjects also have the Robo-advisor B with a success rate of 60%.

The success probabilities of the algorithms are presented in a table in the instructions, along with other product dimensions. This follows the recommendation of Frederick, Lee & Baskin (2014), who found that the presentation of product dimensions in number form is particularly well suited to elicit a decoy effect.

3.3 Procedure

The experiment is implemented in the experimental software z-Tree (cf. Fischbacher, 2007) and is conducted in the laboratory of the Ostfalia University of Applied Sciences. Subjects participate in the experiment from a computer workstation and receive instructions in paper form. The experiment is moderated throughout by a game leader. This ensures that participants actually take the necessary time, do not use any unauthorized aids, and are not disturbed while they have to focus on the task.

The participants first read the instructions for their respective condition. Subsequently, control questions appear on the screen to check whether they have understood the task and correctly recorded all relevant information (see Appendix B). In the second condition, this also ensures that a decoy effect can occur.

The experiment starts with the subjects being given an insight into ten rounds of share price history as well as the values of the four fundamental influencing factors for the current round for orientation purposes (see Appendix C). At this point, the subjects decide for the first time whether they want to perform the investment task in the current round independently or delegate it to Robo-advisor A (condition 1) or either Robo-advisor A or Robo-advisor B (condition 2). If the subjects decide to complete the task independently, they must also decide whether to invest their budget in the Z Share in the current round (expectation: share price rises) or save it (expectation: share price falls). This concludes the first round of the game.

At the beginning of each new game round, the subjects are given an insight into the development of the share price and the influencing factors in the past ten game rounds, as well as the current values of the fundamental influencing factors. In addition, the change in their cumulative balance in the previous game round is always displayed. This allows the subjects to recognize whether the optimal investment decision was made in the past game round or whether there was a forecast error. In each game round, the subjects can decide again whether they want to perform the investment task independently or use the algorithm (condition 1) or one of the two algorithms (condition 2).

After completion of the tenth game round, the subjects are informed of their total compensation. Next, they answer a short questionnaire asking for demographic information. Subsequently, the payout takes place. From the accumulated balance at the end of the tenth game round, 95 ECUs are deducted. The remaining ECUs are exchanged in the ratio of 1 ECU = 1 Euro and paid out to the participants as compensation. The higher the accumulated credit from the ten rounds of play, the higher the payout for the subjects.

3.4 The Algorithms

The two robo-advisors use the values of the fundamental influencing factors to make a prognosis of how the share price will develop. If their model predicts a rising price, they invest the subjects' budget in the share; otherwise, they save it. The formula that the algorithms rely on is designed to make the decision that is favorable to the subjects in the majority of the rounds of the game, but they also occasionally miss the mark. In order to analyze the subjects' reactions to incorrect predictions, it is crucial that the experiment uses algorithms whose predictions are not always correct.

Robo-advisor A uses exactly the equation behind the share price formation mechanism. It always enters the current values of the fundamental influencing factors into the formula and makes a forecast on this basis. Only the amount of the random influence, which acts as the fifth influencing factor, is not known to Robo-advisor A. It therefore always calculates with the expected value of the random influence (0). The random influence leads to the fact that the forecasts of the algorithm only in 70% of the cases lead to the financially advantageous decision (invest or save). In 30% of the cases, the random influence reverses the direction of the share price development suggested by the four known fundamental influencing factors.

Robo-advisor B uses the same approach. However, this algorithm has no access to the values of fundamental influencing factor B. Therefore, it always calculates with the mean value of the range of fundamental influencing factor B, which is 15 (see instructions in Appendix A). The use of approximate formulas to predict future values is an established procedure when algorithms lack relevant information (cf. Rencher & Schaalje, 2008).

The formula behind the Z Share price development mechanism is:

$$0.8 \times \textit{Fundamental Influencing Factor A} + 0.2 \times \textit{Fundamental Influencing Factor B} - 0.4 \times \textit{Fundamental Influencing Factor C} + 0.04 \times \textit{Fundamental Influencing Factor D} + \textit{Random influence}$$

The formula used by Algorithm A is:

$$0.8 \times A + 0.2 \times B - 0.4 \times C + 0.04 \times D + 0$$

The formula used by Algorithm B is:

$$0.8 \times A + 0.2 \times 15 - 0.4 \times C + 0.04 \times D + 0$$

The price formation mechanism and the procedure of the algorithms are shown in table 3. They are illustrated below using the example of game round 5. In game round 5, the value of fundamental influencing factor A is 12, fundamental influencing factor B is 9, fundamental influencing factor C is 7, fundamental influencing factor D is 30, and the random influence is -1 (see Table 3 – section "Influencing Factors"). Thus, the price of the Z Share takes the following value:

$$0.8 \times 12 + 0.2 \times 9 - 0.4 \times 7 + 0.04 \times 30 + (-1) = 8.80 \text{ ECUs}$$

Subjects who invest their round budget in this game round will be credited 8.80 ECUs. Subjects who save their round budget will always be credited 10.00 ECUs. So, in this round it is advisable to save the round budget of 10 ECUs instead of investing it in the Z Share. The delta is -1.20 ECUs (see Table 3 – section "Yield in ECU").

Algorithm A uses the following equation in this round of the game:

$$0.8 \times 12 + 0.2 \times 9 - 0.4 \times 7 + 0.04 \times 30 + 0 = 9.80 \text{ ECUs}$$

Thus, its model predicts that no higher round profit can be achieved by investing (+9.80 ECUs) than by saving (+10.00 ECUs). The predicted delta between investing and saving is -0.20 ECUs. If this delta is negative or exactly 0, i.e., a share price of ≤ 10 ECUs is predicted, the algorithm saves the subjects' round budget. Their balance is therefore credited with 10 ECUs when choosing Algorithm A in game round 5.

Algorithm B uses the following equation in this round of the game:

$$0.8 \times 12 + 0.2 \times 15 - 0.4 \times 7 + 0.04 \times 30 + 0 = 11.00 \text{ ECUs}$$

Thus, its model predicts that a higher round profit can be achieved by investing (+11.00 ECUs) than by saving (+10.00 ECUs). The predicted delta between investing and saving is +1.00 ECUs. If this delta is positive, i.e., a share price of > 10 ECU is predicted, the algorithm invests the subjects' round budget in the Z Share. However, the actual share price at the end of the round is only 8.80 ECUs. The credit balance of the subjects who bet on Algorithm B in game round 5 is consequently credited with 8.80 ECUs (see Table 3 – section "Algorithm Success").

Table 3: Price formation mechanism, forecasts of algorithms, and remuneration depending on chosen strategy

Game Round	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Sum**	**Remuneration***
Influencing Factors												
Influencing Factor A	13	11	6	8	12	11	6	11	10	15	-	-
Influencing Factor B	15	13	17	18	9	14	20	18	16	11	-	-
Influencing Factor C	6	8	2	1	7	6	5	8	5	9	-	-
Influencing Factor D	19	27	35	32	30	23	24	22	23	21	-	-
Random Influence	0	1	0	-2	-1	0	2	1	-1	0	-	-
Yield in ECU												
Invest	11.76 ECU	10.28 ECU	8.80 ECU	8.88 ECU	8.80 ECU	10.12 ECU	9.76 ECU	11.08 ECU	9.12 ECU	11.44 ECU	100.04 ECU	-
Save	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	100.00 ECU	-
Delta (Invest - Save)	+1.76 ECU	+0.28 ECU	-1.20 ECU	-1.12 ECU	-1.20 ECU	+0.12 ECU	-0.24 ECU	+1.08 ECU	-0.88 ECU	+1.44 ECU	-	-
Optimal Strategy	Invest	Invest	Save	Save	Save	Invest	Save	Invest	Save	Invest	-	-
Algorithm Success												
Price Forecast (Algorithm A)	11.76 ECU	9.28 ECU	8.80 ECU	10.88 ECU	9.80 ECU	10.12 ECU	7.76 ECU	10.08 ECU	10.12 ECU	11.44 ECU	-	-
Price Forecast (Algorithm B)	11.76 ECU	9.68 ECU	8.40 ECU	10.28 ECU	11.00 ECU	10.32 ECU	6.76 ECU	9.48 ECU	9.92 ECU	12.24 ECU	-	-
Forecast of Delta (Alg. A)	+1.76 ECU	-0.72 ECU	-1.20 ECU	+0.88 ECU	-0.20 ECU	+0.12 ECU	-2.24 ECU	+0.08 ECU	+0.12 ECU	+1.44 ECU	-	-
Forecast of Delta (Alg. B)	+1.76 ECU	-0.32 ECU	-1.60 ECU	+0.28 ECU	+1.00 ECU	+0.32 ECU	-3.24 ECU	-0.52 ECU	-0.08 ECU	+2.24 ECU	-	-
Decision of Algorithm A	Invest	Save	Save	Invest	Save	Invest	Save	Invest	Invest	Invest	-	-
Decision of Algorithm B	Invest	Save	Save	Invest	Invest	Invest	Save	Save	Save	Invest	-	-
Remuneration												
Only Incorrect Forecasts	10.00 ECU	10.00 ECU	8.80 ECU	8.88 ECU	8.80 ECU	10.00 ECU	9.76 ECU	10.00 ECU	9.12 ECU	10.00 ECU	95.36 ECU	€0.36
Only Correct Forecasts	11.76 ECU	10.28 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.12 ECU	10.00 ECU	11.08 ECU	10.00 ECU	11.44 ECU	104.68 ECU	€9.68
Always Saving	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	10.00 ECU	100.00 ECU	€5.00
Always Investing	11.76 ECU	10.28 ECU	8.80 ECU	8.88 ECU	8.80 ECU	10.12 ECU	9.76 ECU	11.08 ECU	9.12 ECU	11.44 ECU	100.04 ECU	€5.04
Choosing Algorithm A	11.76 ECU	10.00 ECU	10.00 ECU	8.88 ECU	10.00 ECU	10.12 ECU	10.00 ECU	11.08 ECU	9.12 ECU	11.44 ECU	102.40 ECU	€7.40
Choosing Algorithm B	11.76 ECU	10.00 ECU	10.00 ECU	8.88 ECU	8.80 ECU	10.12 ECU	10.00 ECU	10.00 ECU	10.00 ECU	11.44 ECU	101.00 ECU	€6.00

Game rounds in which an algorithm does not make the profit-maximizing decision are highlighted in gray.

*Remuneration is calculated from the cumulative balance at the end of the 10th game round minus 95 ECU, exchanged in the ratio 1 ECU = 1 EUR (see Appendix A).

3.5 Strategies

The subjects have three main strategies at their disposal. They can choose to neglect the robo-advisors and carry out the investment task independently in all ten rounds of the game. Their compensation is then strongly dependent on the success of their forecasts. Based on the values of the fundamental influencing factors generated by a random process, it will range from €0.36 (in the case of ten incorrect forecasts) to €9.68 (in the case of ten correct forecasts).

If subjects save in all ten rounds, their compensation is €5.00 (10 rounds × 10 ECUs - 95 ECUs). If subjects invest in the Z Share in all ten rounds, they receive €5.04. In three out of ten rounds, the share price trend suggested by the fundamental influencing factors is reversed by the random influence, the amount of which is unknown in advance. Consequently, it cannot be assumed that the subjects will succeed in earning the maximum possible compensation. If subjects always make the investment decision implied by the course of the fundamental influencing factors, their compensation for the ten randomly designed price rounds is €7.40. Thus, the compensation for independent forecasting will presumably be on average in the range between €5.00 (random asset management) and €7.40 (structured asset management based on the fundamental influencing factors).

Furthermore, subjects can use Robo-advisor A in all ten rounds of the game. In this case, their compensation is €7.40 because the algorithm optimally exploits the information content of the fundamental influencing factors.

In the second condition (decoy), the subjects can also use Robo-advisor B throughout. In this case, their compensation is below the compensation when choosing the superior Robo-advisor A and amounts to €6.00 (see Table 3 - section "Remuneration").

While human subjects can only roughly estimate the price formation mechanism on the basis of historical data on price development, the algorithms know the exact price formation mechanism and also have substantial advantages in linking the given information. In order to achieve the success probability of Algorithm A, participants would have to evaluate all information from the ten rounds of price history optimally. To do this, they would have to analyze the effects of each of the four fundamental influencing factors as well as the random influence on the share price and derive the price formation mechanism by an extremely complex regression equation. They would then have to enter the values of the fundamental influencing factors in each of the remunerated game rounds into the formula of the price formation mechanism and, on the basis of the result, make a decision as to whether to save or invest their budget.

But even if they succeed in doing so, the expected value of their remuneration would only be the same as when using Algorithm A, which also makes optimal use of all the information available in advance. In order to exceed the probability of success of Algorithm A, on top of that, the subjects would have to guess correctly in which rounds of the game the random influence, the amount of which is unknown in advance, would cause a change in the sign of the share price. To beat the algorithm in this experiment, therefore, not only outstanding analytical skills are required, but also a large amount of luck. This is exactly why algorithm aversion has attracted the interest of behavioral economists. Decisions against an algorithm that is so superior, and that are also associated with financial disadvantages, are often placed in the context of cognitive biases.

3.6 Methods

To test hypothesis 1 (Not all subjects choose to always use an algorithm), the decisions in favor of the target algorithm and decoy algorithm in all ten game rounds are added up for each subject, regardless of the treatment. Then, using the one-sample t-test, it is checked whether the number of game rounds in which an average subject relies on an algorithm is significantly different from 10 out of 10 game rounds (100%). In addition, the Z-test is used to determine whether the proportion of subjects who consistently bet on the algorithm differs significantly from 100% of the subjects (160 out of 160).

To test hypothesis 2 (The proportion of decisions in favor of the target algorithm is higher if another algorithm is introduced as a decoy), the mean value of the decisions in favor of the target algorithm is determined in both conditions. Using the Wilcoxon rank sum test, it can be checked whether there is a significant difference between the conditions.

Hypothesis 3 is: The proportion of subjects who subsequently use an algorithm after an incorrect prognosis of an algorithm is significantly higher in condition 2 (decoy) than in condition 1 (control). Here the chi-square test is used. It checks whether the proportion of decisions in favor of the algorithms differs significantly between the conditions. For hypothesis 3, all situations are selected in which a subject delegated the decision to an algorithm in any round between game round 1 and game round 9 and the algorithm did not make the profit-maximizing decision (invest or save), i.e., the algorithm made an error. Subsequently, for both conditions it is separately recorded in how many cases an algorithm was selected again in the following game round and in how many cases the subjects made the investment decision themselves in the following game round. The resulting 2x2 contingency table (condition 1 vs. condition 2; own execution vs. algorithm) is subjected to the chi-square test.

In addition, the same procedure is applied solely to the responses to the first (second, ..., n-th) error of an algorithm that a subject observes. Again, the chi-square test is used to check whether the decisions in the follow-up round differ significantly between the treatments. This additional procedure has the advantage that each subject is included only once in each chi-square test. This can lead to possible biases in the results, e.g., due to differentially pronounced learning effects, being less significant.

Hypothesis 4 is: The proportion of subjects who subsequently switch to an algorithm after making an incorrect prognosis themselves is significantly higher in condition 2 (decoy) than in condition 1 (control). To test this hypothesis, the same procedure is used as for hypothesis 3, with the only difference that now only the game rounds after incorrect predictions by the subjects themselves (instead of incorrect predictions by the algorithms) are taken into account.

4. Results

4.1 General

160 subjects each make 10 decisions between independent asset management and delegation of the task to an algorithm. In total, 1,600 decisions are observed. Of these, 899 (56.188%) are for independent asset management and only 701 (43.813%) are for one of the two algorithms. Subjects who manage their assets independently invest their round budget in Z Shares in 577 cases (64.182%) and save the budget in 322 cases (35.818%).

The 43.813% of decisions for the algorithms are divided into 679 decisions (42.438%) in favor of Algorithm A with a success rate of 70% and 22 decisions (1.375%) in favor of Algorithm B with a success rate of 60%. Age, gender, and faculty of the subjects have no significant influence on the decision between algorithm and independent asset management. Moreover, the distribution remains constant over the course of the experiment. In every single one of the ten rounds of the game, only between 35% (round 4) and 49% (round 10) of the subjects decide to use an algorithm, despite its obvious advantages (see Section 3.5). The participants in the experiment are clearly subject to the phenomenon of algorithm aversion. Only 18 of the 160 subjects consistently rely on an algorithm (p-value Z-test < 0.001). The one-sample t-test supports that subjects are far from selecting an algorithm in all ten rounds of the game ($t = -21.376$, $p < 0.001$). The 95% confidence interval ranges from 3.862 to 4.900 out of 10 decisions per algorithm per subject.

In terms of the number of correct predictions, the subjects are clearly inferior to both algorithms. The independent asset management by the subjects leads to the profit maximizing investment decision in 43.604% of the cases (392 out of 899 decisions) and in 56.396% of the cases (507 out of 899 decisions) not to the profit maximizing investment decision. As expected, the complexity of the task poses considerable problems for the subjects in independent asset management. Their success rate is even below 50%.

In the instructions, the probability of success of Algorithm A was given as 70%. Its predictions are correct in 71.429% of the actual observed cases (485 of 679 decisions). Recommendations of Algorithm B are correct in 63.636% of the actually observed cases (14 out of 22 decisions), which also fits the reported success probability of 60%.

Consistent with these results, subjects who consistently make their own predictions achieve a compensation of €5.12 on average. In comparison, the average compensation of subjects who consistently rely on an algorithm is €7.27 (Table 4). Linear regression analysis shows that the compensation increases on average by 19.793 cents with each additional decision in favor of one of the two algorithms (p-value < 0.001).

Table 4: Average remuneration depending on the frequency with which the algorithm was selected

Number of Rounds in Which an Algorithm Was Selected	Number of Subjects	Ø Remuneration
0	26	€5.12
1	15	€5.65
2	16	€5.91
3	17	€5.60
4	11	€5.16
5	15	€5.14
6	12	€6.16
7	15	€6.79
8	8	€6.84
9	7	€7.08
10	18	€7.27
	160	€5.95

In view of these figures, the rejection attitude toward the algorithm is remarkable. Over the course of ten rounds of play, subjects pay for their algorithm aversion with a reduction in their average remuneration by up to €1.98, or up to 30% on average. This is nevertheless in line with previous studies, in which algorithm aversion also occurs, although the renunciation of the algorithm drastically reduces the expected value of the compensation.

4.2 Differences Between Conditions

Out of 800 decisions in the control condition, 338 (42.250%) are made in favor of the target algorithm and 462 (57.750%) in favor of the independent asset management. In the decoy condition, 341 decisions (42.625%) are made in favor of the target algorithm, 437 decisions (54.625%) are made in favor of the independent asset management, and 22 decisions (2.750%) are made in favor of the decoy algorithm (Figure 4 and Table 5).

Figure 4: Comparison of the conditions

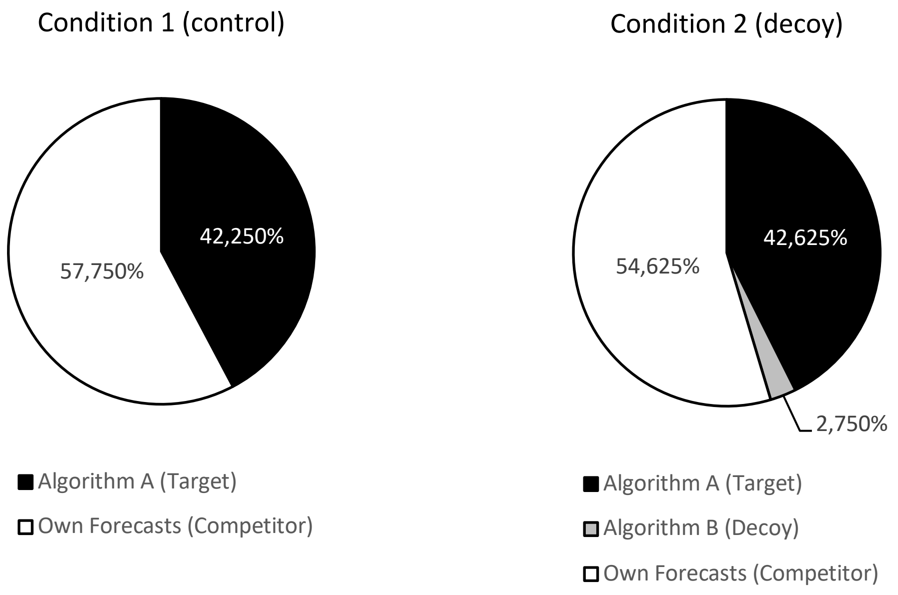


Table 5: Comparison of the conditions

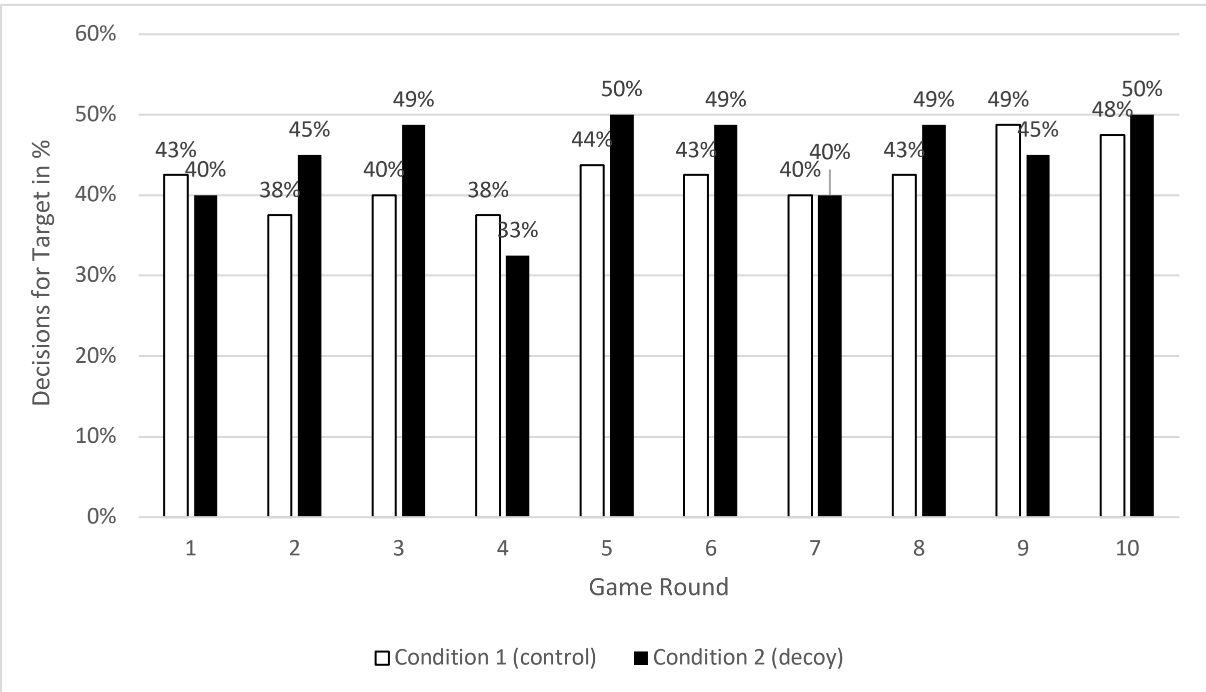
Condition	Own Forecasts	Algorithm A	Algorithm B	Total Algorithm
Control (1)	462 (57.750%)	338 (42.250%)	-	338 (42.250%)
Decoy (2)	437 (54.625%)	341 (42.625%)	22 (2.750%)	363 (45.375%)
Total	899 (56.188%)	679 (42.438%)	22 (1.375%)	701 (43.813%)

The proportion of decisions in favor of own predictions thus decreases slightly in condition 2 (decoy). However, it is by no means the case that subjects now massively select target Algorithm A, as previous research on the decoy effect might have suggested. Of the 25 additional decisions made in favor of the algorithms in the decoy condition, 22 are for Algorithm B (decoy) and only 3 are for Algorithm A (target). The p-value of the Wilcoxon rank sum test of 0.889 proves that the addition of the decoy in the form of Algorithm B in condition 2 does not lead to any significant increase in the use of the target algorithm.

It can be argued just as little that adding a decoy contributes to the reduction of algorithm aversion. Aggregating the decisions in favor of the two algorithms, the difference between the conditions is still far from significant (p-value of the Wilcoxon rank sum test = 0.530). The observed difference of 25 decisions (3.125%) is too small to constitute a significant result. It is rather due to noise in the decisions of the eleven subjects who, despite its lower probability of success, select Algorithm B once or several times.

Further analyses show that the behavior of the subjects is hardly influenced by the introduction of a decoy. Firstly, the number of subjects who consistently follow a certain strategy is almost identical in both conditions. 18 subjects choose the algorithm in all ten rounds of the game. They are evenly distributed between both conditions (9 each). Of the 26 subjects who do not select the algorithm in any single game round, 12 are in condition 1 (control) and 14 in condition 2 (decoy). Secondly, there are no differences in the time course of the game (Figure 5). The difference in the frequency with which the target algorithm is selected is always in the small range of 0% (round 7) to 8.750% (round 3).

Figure 5: Comparison of the decisions in favor of the target algorithm between the conditions per game round



In line with all these findings, the average compensation in the two conditions is also close to each other. The average compensation per subject is €6.02 in condition 1 (control) and €5.89 in condition 2 (decoy). The difference is not significant in the Wilcoxon rank sum test (p-value = 0.371).

4.3 Reaction to Forecast Errors

Of the 1,600 total forecasts made, 891 are correct and 709 are incorrect. The latter are divided into 507 incorrect forecasts by subjects themselves and 202 incorrect forecasts by one of the algorithms. In the following, the reaction to incorrect predictions in the first nine game rounds is examined, since only these game rounds are followed by at least one more game round in which a change in behavior is possible.

The algorithm makes 202 incorrect predictions in the first nine game rounds: 99 in condition 1 (control) and 103 in condition 2 (decoy). In the control group, 69.697% of subjects continue to use the algorithm in the subsequent round regardless. 30.303% of the subjects withdraw their trust in the algorithm immediately after an error and opt to make their own investment decision in the subsequent round. This result is consistent with previous studies that found that human trust in algorithms declines rapidly after erroneous predictions (cf. Dietvorst, Simmons & Massey, 2015).

How will subjects react if not only another algorithm is available but also the decoy effect provides additional evidence for the relatively good performance of the target algorithm? In condition 2 (decoy), only 62.136% of the subjects choose the target algorithm immediately after they observe an error of an algorithm. 4.854% of the subjects subsequently choose the decoy algorithm and 33.010% choose the independent prediction by themselves (Table 6).

Thus, the expected effect does not occur. In fact, the extent of algorithm aversion after forecast errors of an algorithm even seems to slightly increase under the impression of a decoy effect. The p-value in the chi-square test that includes all decisions made after observing an error of an algorithm is 0.679, which is not a significant result. When only the response to the first (second, ..., n-th error) of an algorithm is considered, the difference is also not significant (first error of an algorithm: n = 105, p = 0.781; second error of an algorithm: n = 66, p = 0.421; third error of an algorithm: n = 29, p = 0.453; for more than three errors of the algorithm, the sample size is less than 20 participants).

Table 6: Responses to forecast errors by an algorithm

	Condition 1 (control)			Condition 2 (decoy)		
Selection in next round	Own Forecasts	Algorithm A	Algorithm B	Own Forecasts	Algorithm A	Algorithm B
Total	30	69	-	34	64	5
Percentage	30.303%	69.697%	-	33.010%	62.136%	4.854%

The subjects' own investment decisions lead to 474 errors in the first nine rounds of the game: 230 in condition 1 (control) and 244 in condition 2 (decoy). In the control group, 69.130% of the subjects maintain their strategy of making their own predictions after an error. In contrast, 30.870% switch to the target algorithm after making their own forecast errors in the following round. In condition 2 (decoy), the values are almost identical (Table 7). Here, 69.262% of the subjects continue to give their own forecasts, 29.098% rely on the target algorithm and 1.639% on the decoy algorithm (total algorithm = 30.737%). This difference is also clearly not significant in the chi-square test that includes all decisions made after observing an error of oneself (p-value = 0.975). When only the response to the first (second, ..., n-th error) of a subject itself is considered, the difference between treatments is still not significant (first error of a subject: n = 140, p = 0.601; second error of a subject: n = 120, p = 0.266; third error of a subject: n = 95, p = 0.596; fourth error of a subject: n = 68, p = 0.195; fifth error of a subject: n = 32, p = 0.414; for more than five errors of a subject, the sample size is less than 20).

Table 7: Responses to forecast errors by the subjects themselves

	Condition 1 (control)			Condition 2 (decoy)		
Selection in next round	Own Forecasts	Algorithm A	Algorithm B	Own Forecasts	Algorithm A	Algorithm B
Total	159	71	-	169	71	4
Percentage	69.130%	30.870%	-	69.262%	29.098%	1.639%

It can thus be stated that the decoy is particularly popular when one of the other two options made an error in the previous round. However, the extent of algorithm aversion after prediction errors remains unaffected by the decoy effect both in the case of errors of the algorithm and in the case of errors of the subjects themselves.

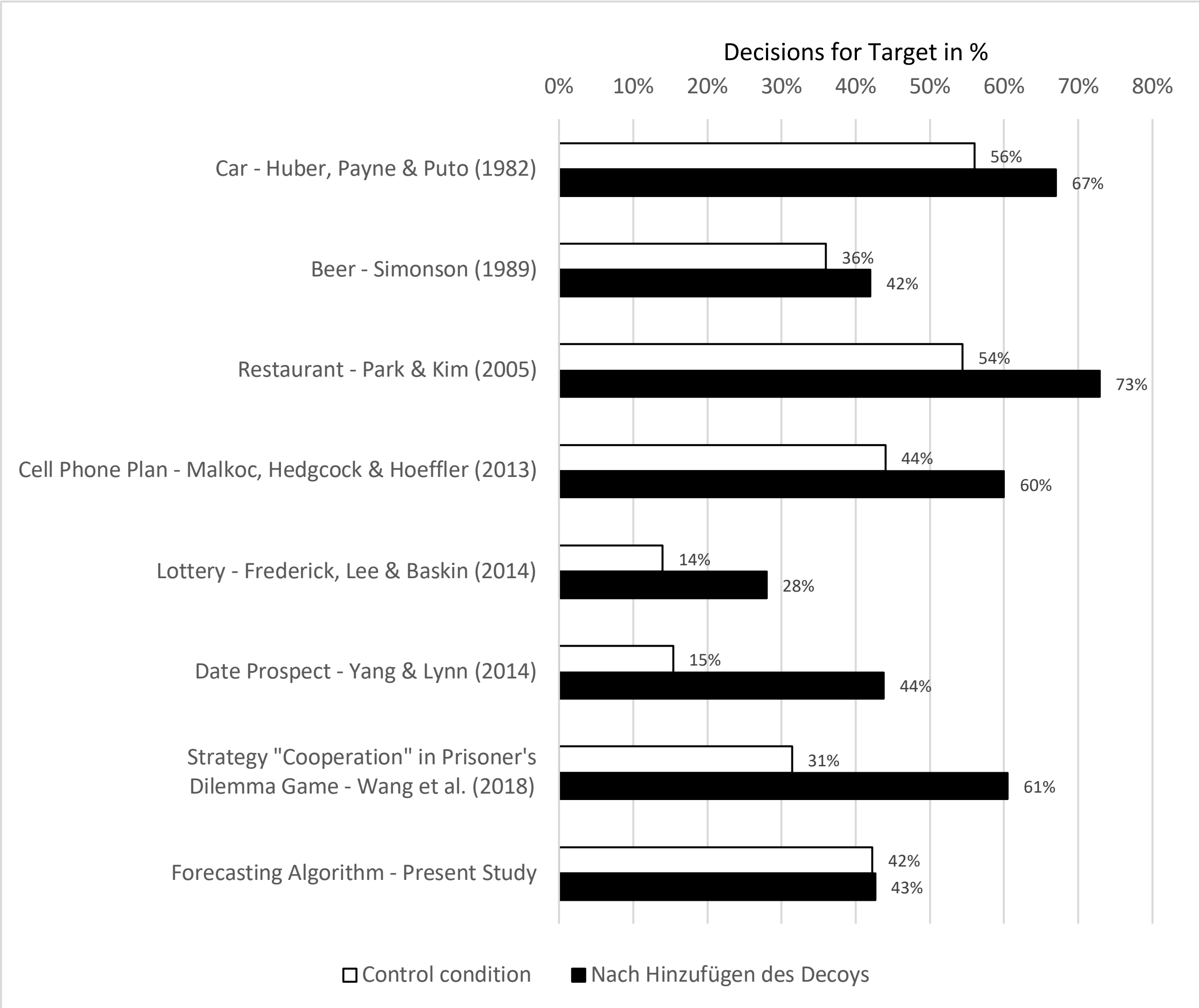
5. Discussion

Imagine you are faced with the decision of whether to entrust your private assets to an innovative robo-advisor that promises to increase your wealth. How easy is it to develop trust in the new technology when so much is at stake? The robo-advisor has been explicitly designed to exploit information from the market to maximize your wealth and seems superior to all alternatives. But will the robo-advisor also succeed in your case, or might you not be better off taking the management of your assets into your own hands?

Now imagine you could compare two robo-advisors available on the market and freely choose between them. It quickly becomes apparent that one of the two robo-advisors seems to be particularly powerful compared to the other. How do you make your initial decision now? Will you succeed in completely ignoring the second robo-advisor in your decision-making process, or will the added option unnecessarily increase the appeal of the superior robo-advisor due to comparison bias?

The results of this study provide initial evidence that the presence of the second robo-advisor makes little difference. The influence of the decoy effect on our decision-making behavior has been demonstrated for numerous products and services from the analog world. The findings so far suggest that adding a decoy should lead to the target gaining greater popularity. Surprisingly, this does not seem to hold true for decoys in the context of novel, complex, digital technologies affected by the phenomenon of algorithm aversion. It has already been shown that emphasizing the statistical superiority of algorithms alone is not sufficient to address algorithm aversion (e.g., Filiz et al., 2021a). The results of this study support the persistence of algorithm aversion. It is apparently so robust that even the otherwise highly reliable decoy effect is unable to mitigate it (Figure 6).

Figure 6: Comparison of decisions in favor of the target product before and after adding a decoy in prior studies



Where multiple experiments with different designs were conducted in the studies, the results from the research design closest to the original design by Huber, Payne & Puto (1982) and the present study are presented here.

In the present study, the decoy effect was made abundantly salient. In the instructions, subjects were given a comparison of the target algorithm with the decoy algorithm in tabular form with easily comparable numbers (Appendix A). Before starting the experiment, all subjects in the decoy condition had to show in the control questions that they understood that two different algorithms were available to them (Appendix B). Last but not least, the success probabilities of the target and the decoy were displayed again in the selection area of the screen in every single round of the game (Appendix C). The fact that the decoy was actually selected in 2.750% of the decisions also fits with the results of previous studies (e.g., Yang & Lynn, 2014; Huber, Payne & Puto, 1982) and suggests that the decoy was noted as a decision option.

However, the presence of the decoy does not lead to an increase in the proportions of the target, as is usually the case. Furthermore, the introduction of the decoy is not suitable for reducing algorithm aversion. Even if the decisions for both algorithms are added together, there is hardly any difference to the control group. This is extremely surprising. On the one hand, the subjects seem to act so rationally that they are hardly influenced by the inferior decoy in their decision between target and competitor. On the other hand, more than half of the decisions are made to perform the prediction task independently, even though the performance in doing so falls significantly short of that of an algorithm.

The main finding of this study is that algorithm aversion prevails over the decoy effect as soon as both have an impact on a decision situation. This is true both throughout the course of the game and explicitly after observing errors of the algorithm. Dietvorst, Simmons & Massey (2015) had uncovered that trust in an algorithm declines rapidly after erroneous predictions, leading to the original coining of the term "algorithm aversion.” The results of the present study suggest that this finding is not only valid in the context of one human vs. one algorithm. When an additional decoy algorithm is available, the willingness to use algorithms after errors still declines to the same extent.

In many application areas for algorithms and AI, we are currently at the point where the first offerings are entering the market. For example, autonomous robo-taxis are expected to be offered to the public in Germany for the first time in 2022. For providers, this raises the question of how to raise their chances of success. Previous theory on the decoy effect had implied that providers should offer a decoy in addition to their target product, which they want to establish on the market in the long term, in order to influence potential customers in favor of the target.

However, the results of this study show that the market share of new technologies cannot be increased so easily. Rather, potential users harbor a great deal of skepticism toward innovative, automated processes, which cannot be remedied by adding a decoy to the offering. The pioneers of digitized and automated business ideas should therefore be advised not to pursue the decoy effect as a sales strategy. Instead, they should rather refer to already identified measures to reduce algorithm aversion, such as influencing algorithmic output (Dietvorst, Simmons & Massey, 2018) or learning effects (Filiz et al., 2021b).

Finally, some aspects should be mentioned that may limit the validity of this study for decisions in practice. In order to follow the established research on the decoy effect, the participants in the economic experiment were provided with only two algorithms (target and decoy). In practice we can often choose between more than two offers that dominate each other in different ways with respect to different dimensions. In particular, the rapid scalability of digital technologies means that the choice usually quickly exceeds two algorithms. Second, it should be mentioned that the results were obtained in the context of robo-advisors. However, asset management is only one small area affected by algorithm aversion. Possibly, different results would be obtained when using other algorithms from areas such as medicine, transportation, or entertainment. Last but not least, this study did not focus on social influences. However, humans are social beings. In our everyday lives, in contrast to a laboratory experiment, there is a great deal of interaction with other people, which influences our decision-making behavior. It must be left to subsequent research to analyze these aspects in more detail.

6. Summary

In this study, the impact of the decoy effect on algorithm aversion is investigated by means of an economic laboratory experiment. Subjects are divided into two groups for an investment game in which they try to maximize their compensation. In the control condition, they have the choice in ten rounds of the game whether to delegate a prediction task to a specialized algorithm with a success rate of 70% (target) or to handle it independently by themselves (competitor). In the treatment condition, they also have a second algorithm (decoy) available to them in addition to the first algorithm and their own predictions. The second algorithm is identical to the first with one exception: it has a significantly lower success rate of just 60%. We speak of the decoy effect if one option (decoy) is inferior to another option (target) in at least one dimension and superior in no other dimension.

The theory of the decoy effect suggests that the first algorithm (target) should be selected significantly more often in the treatment condition than in the control condition. Once the decoy comes into play, decision makers regularly apply a heuristic. They compare target and decoy and decide in favor of the target, since it is clearly superior to the decoy. In this case, the competitor always loses shares in favor of the target, since adding the decoy does not provide any additional information about comparative effectiveness of the competitor, but only about the target.

In contrast to these considerations is the algorithm aversion. It describes users' reservations about automated procedures (algorithms) that cannot be easily remedied. If users are subject to algorithm aversion, they should not be influenced by the presence of a decoy, because algorithms are generally not an attractive option for them.

The first thing that emerges is that the subjects in this study are also affected by algorithm aversion. Although each decision in favor of one of the two algorithms increases their compensation by an average of 19.793 cents, an algorithm is selected in just 43.813% of the decisions.

Further, the presence of a decoy is shown to have no effect on the extent of algorithm aversion. The proportion of decisions in favor of the better performing target algorithm increases by only 0.375 percentage points after the decoy is added, from 42.250% to 42.625%. Another 2.750% of the decisions are now made in favor of the inferior algorithm (decoy). The proportion of own predictions by the subjects themselves decreases slightly from 57.750% to 54.625%. The difference turns out to be not significant.

Finally, the reaction to erroneous forecasts is also examined. In slightly more than 30% of the cases, the reaction to forecast errors of the algorithm is to switch to independent forecasting by oneself in the following game round. However, this proportion differs only minimally between conditions. Behavior after algorithm errors is not affected by the decoy effect. The same is true for the behavior after participants' own erroneous forecasts. The proportion of switches to the algorithm is approximately the same in both conditions.

Whether an additional algorithm (decoy) is present or not does not change the willingness to resort to a specialized algorithm in all cases studied. Algorithm aversion cannot be effectively reduced by the decoy effect.

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Appendix A: Instructions

Instructions for Condition 1 (Control)

<u>The Game</u>

In this game, you are asked to make an investment decision in the course of ten game rounds each. You will be given an initial budget of Experimental Currency Units (ECUs) of 10 ECUs per round. In each of the ten rounds, you can either invest 10 ECUs in Z Shares or save them. You always invest or save the full amount; it is not possible to split the budget within a game round.

If you **invest** the 10 ECUs in Z Shares, you buy the shares at the beginning of the period and sell the shares again at the end of the period. The selling price will be credited to your balance. It may be higher or lower than the initial amount of 10 ECUs you invested, depending on whether the price of the Z Share increased or decreased during the round.

For example, if the price of the Z Share increases by 10% within a round, and you have invested 10 ECUs in the Z Share, your balance will be credited with 11 ECUs. If the price of the Z Share falls by 10% within a round, and you have invested 10 ECUs in the Z Share, your balance will be credited with 9 ECUs. **You can therefore invest in the Z Share specifically in the rounds in which you expect the price to rise.**

The share price of the Z Share always results from **four influencing factors** (see Table 1) plus a **random influence**. The values of the influencing factors are announced to you before each game round.

Table 1: Factors influencing the formation of the Z Share price

Influencing Factor	Span	Influence	Impact on Share Price
A	5 to 15	Positive	High
B	5 to 25	Positive	Medium
C	0 to 10	Negative	Medium
D	15 to 35	Positive	Low
Random Influence	-2 to +2	Positive	Medium

Influencing factors **A**, **B**, **D,** and the **random influence** have a positive effect on the share price. This means that if these influencing factors are in the upper range of their span (i.e., above the average of the previous periods), the share price tends to rise during the upcoming game round.

Influencing factor **C** has a negative effect on the share price. That is, if this influencing factor lies in the upper range of its span (i.e., above the average of the previous periods), the share price tends to fall during the coming round. The influencing factors have varying degrees of impact on the share price (Table 1).

Alternatively, you can **save** the round budget in the amount of 10 ECUs. Your balance will then be credited with 10 ECUs for the round in question.

Your credit will be built up over the 10 rounds of play and used to calculate your pay at the end of the game. Regardless of your decisions in the previous rounds, you can always invest or save exactly 10 ECUs in each new round.

Choice Between Independent Asset Management and an Algorithm

You can also choose in each game round whether you want to manage your round budget independently by yourself or entrust it to a robo-advisor (algorithm).

If you choose the algorithm, it will either invest or save your round budget of 10 ECUs in the respective game round in your place. The algorithm will always decide to invest your ECUs if its model predicts a rising share price. If its model predicts a falling share price, it will save your budget in that round.

In the past, it has been shown that in 7 out of 10 cases (70%) the algorithm makes the decision (invest or save) that leads to a higher return.

Remuneration

The pay structure is the same whether you manage your budget independently or entrust it to the algorithm. At the end of the game, your total cumulative balance earned in the ten game rounds is considered. 95 of the originally allocated 100 ECUs (10 ECUs each in 10 game rounds) will be deducted from your balance. The remaining amount will be exchanged for real money at the ratio of 1 ECU = 1 EUR and paid to you as your remuneration.

Procedure

After reading the instructions and answering the control questions, the first remunerated game round (period 11 of 20) starts on your screen.

At the beginning of each game round, you will see the price development of the Z Share, the development of the influencing factors and the development of the random influence for the last ten game rounds (period 1 to 10), in order to get an idea of the development. In addition, you will always be informed of the current values of the four influencing factors for the respective game round. The value of the random influence, on the other hand, is unknown in advance. Afterwards, you make your decision for the respective game round whether you want to manage your round budget independently or entrust it to the robo-advisor (algorithm).

If you decide to do the investment task on your own, next you will choose whether you want to invest 10 ECUs in Z Shares or save them in the particular round. If you decide to use the algorithm, it will make the decision between investing and saving in your place.

After submitting the decision, you will be informed about the development of the Z Share price in any case, regardless of whether your budget was invested or saved. So, you will receive the full information in any case. The achieved return from the investment in Z Shares or the saved amount will be credited to your balance.

A total of ten rounds will be played. After the experiment is completed, you will receive your remuneration, which is calculated according to the scheme described under "Remuneration."

Remarks

- Please keep quiet during the experiment!
- Do not look at your neighbor's screen!
- Apart from a pen and a pocket calculator, no other aids (smartphones, smartwatches, etc.) are permitted.
- Only use the white sheet of paper provided for your notes.

Instructions for Condition 2 (Decoy)

The Game

In this game, you are asked to make an investment decision in the course of ten game rounds each. You will be given an initial budget of Experimental Currency Units (ECUs) of 10 ECUs per round. In each of the ten rounds, you can either invest 10 ECUs in Z Shares or save them. You always invest or save the full amount; it is not possible to split the budget within a game round.

If you **invest** the 10 ECUs in Z Shares, you buy the shares at the beginning of the period and sell the shares again at the end of the period. The selling price will be credited to your balance. It may be higher or lower than the initial amount of 10 ECUs you invested, depending on whether the price of the Z Share increased or decreased during the round.

For example, if the price of the Z Share increases by 10% within a round, and you have invested 10 ECUs in the Z Share, your balance will be credited with 11 ECUs. If the price of the Z Share falls by 10% within a round, and you have invested 10 ECUs in the Z Share, your balance will be credited with 9 ECUs. **You can therefore invest in the Z Share specifically in the rounds in which you expect the price to rise.**

The share price of the Z Share always results from **four influencing factors** (see Table 1) plus a **random influence**. The values of the influencing factors are announced to you before each game round.

Table 1: Factors influencing the formation of the Z Share price

Influencing Factor	Span	Influence	Impact on Share Price
A	5 to 15	Positive	High
B	5 to 25	Positive	Medium
C	0 to 10	Negative	Medium
D	15 to 35	Positive	Low
Random Influence	-2 to +2	Positive	Medium

Influencing factors **A**, **B**, **D,** and the **random influence** have a positive effect on the share price. This means that if these influencing factors are in the upper range of their span (i.e., above the average of the previous periods), the share price tends to rise during the upcoming game round.

Influencing factor **C** has a negative effect on the share price. That is, if this influencing factor lies in the upper range of its span (i.e., above the average of the previous periods), the share price tends to fall during the coming round. The influencing factors have varying degrees of impact on the share price (Table 1).

Alternatively, you can **save** the round budget in the amount of 10 ECUs. Your balance will then be credited with 10 ECUs for the round in question.

Your credit will be built up over the 10 rounds of play and used to calculate your pay at the end of the game. Regardless of your decisions in the previous rounds, you can always invest or save exactly 10 ECUs in each new round.

Choice Between Independent Asset Management and an Algorithm

You can also choose in each game round whether you want to manage your round budget independently by yourself or entrust it to one of two robo-advisors (algorithms).

If you choose one of the algorithms, it will either invest or save your round budget of 10 ECUs in the respective game round in your place. The algorithms will always decide to invest your ECUs if their models predict a rising share price. If their models predict a falling share price, they will save your budget in that round.

In the past, it has been shown that in 7 out of 10 cases (70%) Algorithm A makes the decision (invest or save) that leads to a higher return. Furthermore, it has been shown that Algorithm B makes the advantageous decision in 6 out of 10 cases (60%).

Table 2: Properties of the algorithms

Property	Algorithm A	Algorithm B
Year of completion	2022	2022
Manufacturer	Ostfalia Analytics	Ostfalia Analytics
Probability of success	70%	60%

Remuneration

The pay structure is the same whether you manage your budget independently or entrust it to one of the algorithms. At the end of the game, your total cumulative balance earned in the ten game rounds is considered. 95 of the originally allocated 100 ECUs (10 ECUs each in 10 game rounds) will be deducted from your balance. The remaining amount will be exchanged for real money at the ratio of 1 ECU = 1 EUR and paid to you as your remuneration.

Procedure

After reading the instructions and answering the control questions, the first remunerated game round (period 11 of 20) starts on your screen.

At the beginning of each game round, you will see the price development of the Z Share, the development of the influencing factors and the development of the random influence for the last ten game rounds (period 1 to 10), in order to get an idea of the development. In addition, you will always be informed of the current values of the four influencing factors for the respective game round. The value of the random influence, on the other hand, is unknown in advance. Afterwards, you make your decision for the respective game round whether you want to manage your round budget independently or entrust it to Algorithm A or entrust it to Algorithm B.

If you decide to do the investment task on your own, next you will choose whether you want to invest 10 ECUs in Z Shares or save them in the particular round.

If you decide to use an algorithm, it will make the decision between investing and saving in your place.

After submitting the decision, you will be informed about the development of the Z Share price in any case, regardless of whether your budget was invested or saved. So, you will receive the full information in any case. The achieved return from the investment in Z Shares or the saved amount will be credited to your balance.

A total of ten rounds will be played. After the experiment is completed, you will receive your remuneration, which is calculated according to the scheme described under "Remuneration.”

Remarks

- Please keep quiet during the experiment!
- Do not look at your neighbor's screen!
- Apart from a pen and a pocket calculator, no other aids (smartphones, smartwatches, etc.) are permitted.
- Only use the white sheet of paper provided for your notes.

Appendix B: Test Questions

Question 1: How many rounds of play does this economic experiment involve?

a) 5.
b) 10. *(Correct!)*
c) 15.

Question 2 (condition 1): What alternatives do you have in each round?

a) I must perform the investment task independently.
b) I can perform the investment task independently or delegate it to a financial expert.
c) I can perform the investment task independently or delegate it to a robo-advisor (algorithm). *(Correct!)*

Question 2 (condition 2): What alternatives do you have in each round?

a) I must perform the investment task independently.
b) I can perform the investment task independently or delegate it to a financial expert.
c) I can perform the investment task independently or delegate it to one of two robo-advisors (algorithms). *(Correct!)*

Question 3: Which influencing factors have a positive effect on the price of the Z Share?

a) Influencing factors A, B, and C.
b) Influencing factors A, B, and D. *(Correct!)*
c) Influencing factors A, C, and D.

Question 4: How is your remuneration calculated?

a) At the end of the game, 100 ECUs will be deducted from my balance. The remaining amount will be exchanged for real money at the ratio of 1 ECU = 0.10 EUR.
b) At the end of the game, 100 ECUs will be deducted from my balance. The remaining amount will be exchanged for real money at the ratio of 1 ECU = 1 EUR.
c) At the end of the game, 95 ECUs will be deducted from my balance. The remaining amount will be exchanged for real money at the ratio of 1 ECU = 1 EUR. *(Correct!)*

Appendix C: Screen Design

Figure A-1: Screen design in condition 1 (control)

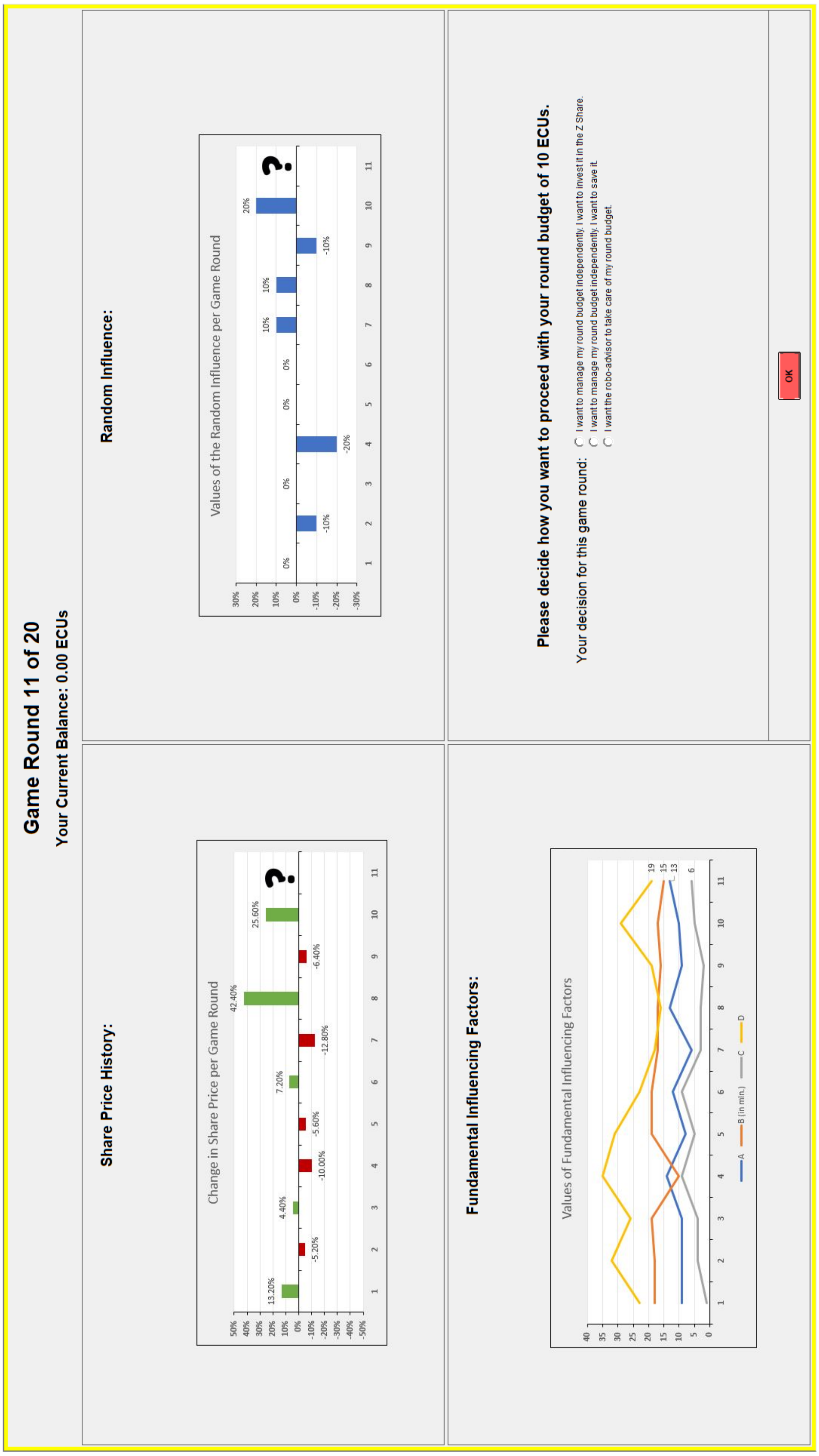

Figure A-2: Screen design in condition 2 (decoy)