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Creative Drive and Algorithm Aversion –

The Impact of Influence in the Process of Algorithmic Decision-making on Algorithm Aversion

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Abstract: Although algorithms make more precise forecasts than humans in many applications, decision-makers often refuse to resort to their use. In an economic experiment, we examine whether the extent of this phenomenon known as algorithm aversion can be reduced by granting decision-makers the possibility to exert an influence on the design of the algorithm (an influence on the algorithmic input). In addition, we replicate the study carried out by Dietvorst et al. (2018). This shows that algorithm aversion recedes significantly if the subjects can subsequently change the results of the algorithm – and even if this is only by a few percent (an influence on the algorithmic output). The present study confirms that algorithm aversion is reduced significantly when there is such a possibility to influence the algorithmic output. However, exerting an influence on the algorithmic input seems to have only a limited ability to reduce algorithm aversion. A limited opportunity to modify the algorithmic output thus reduces algorithm aversion more effectively than having the ability to influence the algorithmic input.

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1. Introduction

Businesses throughout the world are driving the digital transformation. Progress in the field of artificial intelligence (AI) has wide-ranging effects on our everyday lives and is bringing about fundamental changes in all fields of human life. This enormous potential is also shown by the estimate that AI will contribute up to $15.7 trillion to the global economy by the year 2030 (PriceWaterhouseCoopers, 2019).

Technological progress is also leading to algorithms or algorithmic decision-making systems (ADM systems) being increasingly deployed in a wide range of areas and becoming part of day-to-day life. AI-based algorithms make a considerable contribution towards tasks being completed faster and above all more cheaply (Upadhyay & Khandelwal, 2018). In addition, fact-based algorithms can better the performance of humans (from lay persons to experts) in a multitude of areas and make more precise predictions, including the following examples: forecasts on the performance of employees (Highhouse, 2008), the likelihood of ex-prisoners re-offending (Wormith & Goldstone, 1984), or in making medical diagnoses (Beck et al., 2011; Gladwell, 2007; Grove et al., 2000; Dawes, Faust & Meehl, 1989; Adams et al., 1986).

Nevertheless, in certain fields there is a lack of acceptance for the actual use of algorithms because subjects have reservations about them. This phenomenon, which is known as algorithm aversion, refers to the lack of trust in algorithms which arises in subjects as soon as they recognize that the algorithms are not perfect (Jussupow, Benbasat & Heinzl, 2020; Prahl & Van Swol, 2017; Dietvorst, Simmons & Massey, 2015). We therefore focus on the issue of how algorithm aversion can be reduced and how the level of acceptance of algorithms can be increased.

In their study, Dietvorst, Simmons and Massey (2018) reveal a way in which algorithm aversion can be significantly reduced. In their experiment, the subjects can either choose an algorithm or make their own forecasts. Some of the subjects are – if they choose to use an algorithm – allowed to subsequently change the preliminary forecast of the algorithm by a few percentage points up or down (we describe this in our study as an opportunity to influence the 'algorithmic output'). When they have this opportunity to make retrospective changes to the forecasts, significantly more subjects are prepared to consult the algorithm for their forecasts than otherwise.

As long as the subjects are able to change the results of the algorithm somewhat (i.e., they have an influence on the algorithmic output), algorithm aversion can be significantly reduced. Decisions in favor of a flawed algorithm are made more frequently if the users retain an element of control over it, whereby the extent to which they are able to modify the algorithm is irrelevant. Furthermore, users who can make slight modifications report that they are no less content with the forecasting process than users who can make unlimited changes. To sum up, users will deploy algorithms more often when they have the final say in how they deal with them. So is it decisive for lowering algorithm aversion that users are given an opportunity to influence the algorithmic output, or can algorithm aversion be generally reduced by providing a way of influencing the forecasting process?

Human decision-makers want to influence algorithms instead of being at the mercy of their calculations (Honeycutt, Nourani & Ragan, 2020; Stumpf et al., 2008). In other words, decision-makers need partial control over an algorithm in order to make a decision in favor of its use. Having real or at least perceived control over the decisions to be made satisfies the psychological needs and personal interests of users (Colarelli & Thompson, 2008). This feeling of control can arise either via a real understanding of the efficiency of an algorithm, or via adaptations to the algorithmic decision-making process which have little or no influence on the functioning or level of performance of an algorithm (Burton, Stein & Jensen, 2019). In other words, if a user is granted control over decisions, this leads to a higher level of acceptance: if a recommendation algorithm for hotel rooms is used which only recommends hotel rooms based on the person's previous search and purchasing behavior, the offers made are less readily accepted. However, if less than ideal offers are included, from among which the user can make a choice, levels of acceptance of the algorithm improve (Taylor, 2017). Participation in the decision-making process, or a belief that one can influence the decision-making process, can contribute towards the user exhibiting greater trust in a decision (Landsbergen et al., 1997).

In our study, we therefore grant the subjects the opportunity to participate in the design of an algorithm by giving them a genuine influence on the algorithmic input, although we keep the extent of their intervention in the algorithmic input small. In this way the algorithm can almost reach its maximum level of performance; however, this minor intervention could be of great significance in overcoming algorithm aversion. We examine whether the opportunity to participate in the design of the algorithm has an effect on its acceptance. In addition, we observe whether influencing the algorithmic input can contribute towards a reduction of algorithm aversion in the same way as influencing the algorithmic output does.

2. Experimental design and hypotheses

In this study, the subjects are asked to forecast the exact price of a share in ten consecutive periods. Here, the price of the share is always the result of four influencing factors (A, B, C and D) which are supplemented by a random influence (Ɛ) (see Filiz et al. 2021; Filiz, Nahmer & Spiwoks, 2019; Meub et al., 2015; Becker, Leitner & Leopold-Wildburger, 2009). First of all, the subjects are familiarized with the scenario and are informed that the influencing factors A, C and D have a positive effect on the share price. This means that - other things being equal - when these influencing factors rise the share price will also rise. The influencing factor B, on the other hand, has a negative effect on the share price. This means that - other things being equal - when the influencing factor B rises, the share price will fall (Table 1). In addition, the subjects are informed that the random influence (Ɛ) has an expected value of zero. However, the random influence can lead to larger or smaller deviations from the share price level which the four influencing factors would suggest.

Table 1: Influencing factors in the formation of the share price

Influencing factor	Influence	Strength of the influence
A	Positive	Strong
B	Negative	Strong
C	Positive	Strong
D	Positive	Medium

The subjects are informed of the four influencing factors before each round of forecasting. In addition, they always receive a graphic insight into the historical development of the share price, the influencing factors and the random influence in the last ten periods. In this way, the subjects can recognize in a direct comparison how the levels of the four influencing factors have an effect on the share price during the individual rounds of forecasting.

The payment structure provides for a fixed show-up fee of €4 and a performance-related element. The level of the performance-related payment is dependent on the precision of the individual share price forecasts, whereby the greater the precision of the forecasts, the higher the payment (Table 2). The subjects can thus obtain a maximum payment of €16 (€4 show-up fee plus €12 performance-related payment from ten rounds of forecasting).

Table 2: Performance-related payment for the forecasts

Deviation of the forecast from the actual share price	Payment for the forecast
€0 ≤ $\mid K_t - P_t \mid$ ≤ €5	€1.20
€5 < $\mid K_t - P_t \mid$ ≤ €10	€0.90
€10 < $\mid K_t - P_t \mid$ ≤ €15	€0.60
€15 < $\mid K_t - P_t \mid$ ≤ €20	€0.30
$\mid K_t - P_t \mid$ > €20	€0.00

Whereby K_t = share price at the point of time t, P_t = forecast at the point of time t.

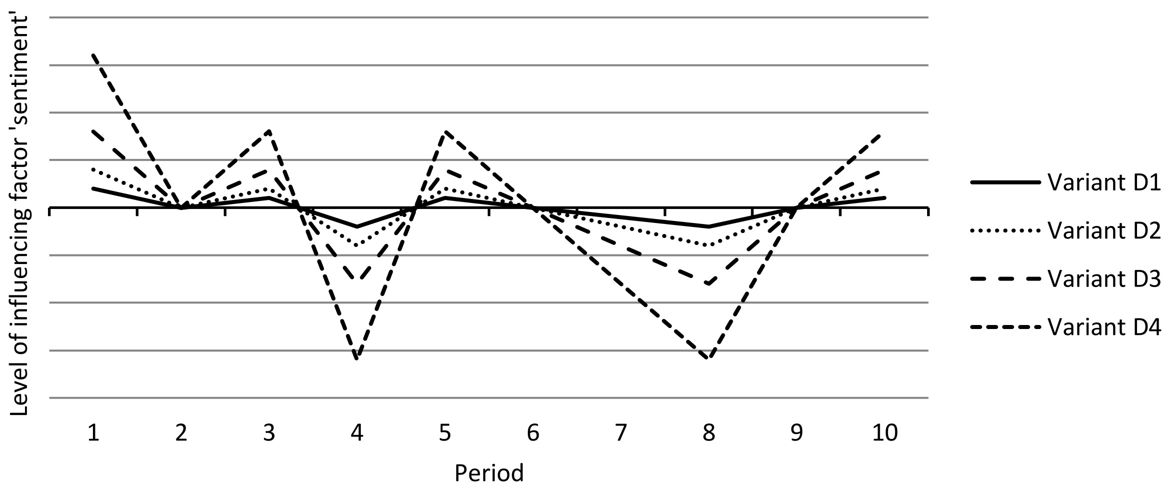
In order to help them make the share price forecasts, a forecasting computer (algorithm) is made available to the subjects. The subjects are informed that in the past the share price forecasts of the forecasting computer have achieved a payment of at least €0.60 per forecast in 7 out of 10 cases. The subjects are thus aware of the fact that the algorithm they are using does not function perfectly. In order to make its forecasts, the algorithm uses the information which it has been given on the fundamental influencing factors, the direction and strength of the influence and the random influence (Ɛ) in an optimal way. In this way, however, it by no means achieves 'perfect' forecasts (for a detailed description of how the algorithm works, see Appendix D). Based on the same information and the historical share prices, the subjects can make their own assessments. They would, however, be wrong to assume that they can outperform the algorithm in this way. Following the suggestions of the algorithm would thus seem to be the more sensible option. Before making their first share price forecast, the subjects make a one-off decision on whether they wish to base their payment for the subsequent ten rounds of forecasting on their own forecasts or on those made by the forecasting computer. Our set-up is oriented towards that used in the study carried out by Dietvorst et al. (2018).

The experiment is carried out in three treatments. The study uses a between-subjects design: each subject is assigned to only one treatment and encounters the respective decision-making situation. In Treatment 1 (no opportunity to influence the algorithm), the subjects make the decision (once only) whether they want to use their own share price forecasts as the basis for their payment or whether they want to use the share price forecasts made by the forecasting computer. Even if the subjects choose the algorithm for determining their bonus, they have to make their own forecasts. The obligation to submit one's own forecasts even when choosing the algorithm is based on the study by Dietvorst et al. (2018). Regardless of this decision, the subjects make their own forecasts without having access to the forecast of the algorithm. (Appendix C-1).

With Treatment 2 (opportunity to influence the algorithmic output), we intend to replicate the results of Dietvorst, Simmons & Massey (2018). To this end, the subjects make the decision (once only) whether they solely want to use their own share price forecasts as the basis for their payment or whether they solely wish to use the share price forecasts made by the forecasting computer (which, however, can be adjusted by up to +/- €5) as the basis for their performance-related payment. The algorithmic forecast is only made available to the subjects if they decide in favor of the forecasting computer (Appendix C-2).

In Treatment 3, we introduce the opportunity to influence the design of the algorithm (algorithmic input). Before handing in their first share price forecast, the subjects again make the decision (once only) whether they want to solely use their own share price forecasts as the basis for their performance-related payment or whether they want to solely use the share price forecasts made by the forecasting computer. If they decide in favor of the share price forecasts of the forecasting computer, the subjects receive a one-off opportunity to influence the design of the algorithm (Appendix C-3). To this end, they are given a more detailed explanation. The algorithm uses data on four different factors which influence the formation of the share price (A, B, C and D). The last of these four influencing factors is identified as the sentiment of capital market participants and can be taken into account to various extents by the forecasting computer. To do so, the subjects can choose from four different levels. Whereas variant D1 attaches relatively little importance to sentiment, the extent to which sentiment is taken into account in the other variants increases continuously and is relatively strong in variant D4 (Figure 1).

Figure 1: Level of the influencing factor 'Sentiment of capital market actors'



Subjects who decide to use the forecasting computer in Treatment 3 and thus receive the opportunity to influence the design of the algorithm have a one-off chance to change the design of the algorithm. This occurs solely by means of their choice of which degree of sentiment should be taken into account (variant D1, D2, D3 or D4).

Önkal et al. (2009) already point out the phenomenon of algorithm aversion in the field of share price forecasts. Humans rely on share price forecasts less when they have been drawn up by an algorithm instead of a human expert. We examine whether algorithm aversion in the field of share price forecasts also occurs when a choice is made between an algorithm and a subject's own forecasts. The strength of the forecasting computer (algorithm) lies in the fact that it uses the information which it is given in an optimal way. The subjects thus have no reason to expect that they can integrate this information into their forecasts in a similarly efficient way. They should therefore suspect that the forecasting computer will be superior to their own forecasts. On the basis of the existing findings (cf. Jussupow, Benbasat & Heinzl, 2020; Burton, Stein & Jensen, 2019), we expect that algorithm aversion will appear nevertheless. Hypothesis 1 is: The algorithm will not always be selected. Null hypothesis 1 is therefore: All of the subjects will select the algorithm.

Algorithm aversion can be reduced by providing the opportunity to modify the algorithmic output, even when the possibilities for modification are modest (Dietvorst, Simmons & Massey, 2018). In order to establish whether these measures can also contribute towards a reduction of algorithm aversion in the field of share price forecasts, we replicate the above-mentioned results in our experiment. Hypothesis 2 is: The proportion of decisions in favor of the algorithm will be significantly higher in Treatment 2 (opportunity to influence the algorithmic output) than in Treatment 1 (no influence possible). Null hypothesis 2 is therefore: The proportion of decisions in favor of the algorithm will not be significantly higher in Treatment 2 (opportunity to influence the algorithmic output) than in Treatment 1 (no influence possible).

The fact that algorithms can provide better results than humans in forecasting processes has already been shown on numerous occasions (Grove et al., 2000; Dawes, 1979; Meehl, 1954). As modification of the algorithmic output can also have a negative overall effect on forecasting performance, it is examined whether there are additional possibilities to decrease algorithm aversion without allowing human modification of the algorithmic output.

In their review of the literature, Burton, Stein & Jensen (2019) pose the question of whether the reduction of algorithm aversion by the modification of the algorithmic output can also be achieved by a modification of the algorithmic input. Even the illusion of having the freedom to act and make decisions can be a possible solution to overcome algorithm aversion (Burton, Stein & Jensen, 2019). Users who interact with algorithms often receive their advice from a black box whose workings are a mystery to them. They thus develop theories about which kinds of information an algorithm uses as input and how this information is exactly processed (Logg, Minson & Moore, 2019). In order to increase the acceptance of algorithms, users need to at least have the feeling that they can exercise a degree of control. This feeling of control can either come from a genuine understanding of how an algorithm works or by making modifications to the algorithmic decision-making process. Whether a genuine influence is exerted on the way the algorithm actually functions is not important here. It is only necessary to allow the user to have real or perceived control over decision-making in order to satisfy their psychological needs (Colarelli & Thompson, 2008).

Some studies have already made changes to the input variables of an algorithm and their weighting in the forecasting process (Kawaguchi, 2021). We also follow this approach and examine how an opportunity to influence the algorithmic input affects algorithm aversion. In this way we are testing an alternative approach to the reduction of algorithm aversion without influencing the algorithmic output. We make an input factor which the computer uses to make its forecasts visible to the subjects. We do not want to deceive the subjects and thus give them – in the form of this input factor – the opportunity to exert an actual influence on the design of the forecasting computer. In this way, the subjects are given freedom to act in a limited way, which actually leads to slight differences in how the algorithm works. We ask ourselves whether a general possibility to influence the algorithmic process is sufficient in order to reduce algorithm aversion, or whether an opportunity to influence the results themselves is necessary. We thus examine whether an opportunity to influence the design of the algorithm (algorithmic input) can contribute towards a similar decrease in algorithm aversion as the opportunity to influence the algorithmic output. Hypothesis 3 is: The proportion of decisions in favor of the algorithm will be significantly higher in Treatment 3 (opportunity to influence the algorithmic input) than in Treatment 1 (no influence possible). Null hypothesis 3 is therefore: The proportion of decisions in favor of the algorithm will not be significantly higher in Treatment 3 (opportunity to influence the algorithmic input) than in Treatment 1 (no influence possible).

3. Results

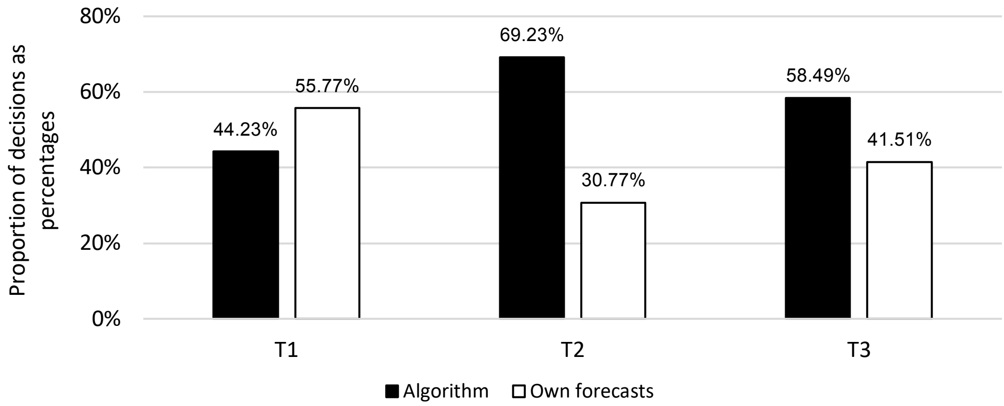
This economic experiment is carried out between 17-27 March 2021 in the Ostfalia Laboratory of Experimental Economic Research (OLEW) of Ostfalia University of Applied Sciences in Wolfsburg. In 51 sessions, a total of 157 subjects take part in the experiment. 118 subjects (75.16%) are male and 39 subjects (24.84%) are female. The subjects are distributed across the faculties as follows: 66 subjects (42.04%) study at the Faculty of Vehicle Technology, 56 subjects (35.67%) at the Faculty of Business, 9 subjects (5.73%) at the Faculty of Health Care and a further 26 subjects (16.56%) at other faculties based at other locations of the Ostfalia University of Applied Sciences. Their average age is 23.6 years. On average, the subjects are between their sixth and seventh semesters and have taken part in an average of 0.9 other economic experiments before this one.

The experiment is programmed with z-Tree (cf. Fischbacher, 2007). In the Ostfalia Laboratory for Experimental Economic Research (OLEW) there are twelve computer workplaces. However, only a maximum of four are used per session. This ensures that in line with the measures to contain the Covid-19 pandemic a considerable distance can be maintained between the subjects. The workplaces in the laboratory are also equipped with divider panels, which makes it possible to completely separate the subjects from each other. The experiments are constantly monitored by the experimenter so that communication between the subjects and the use of prohibited aids (such as smartphones) can be ruled out. Overall a total of 51 sessions are carried out. A session lasts an average of 30 minutes.

The 157 participants are divided up evenly over the three treatments, so that 52 subjects carry out Treatments 1 and 2, and 53 subjects carry out Treatment 3. The distribution of the subjects among the three treatments has similarities to their distribution among the faculties as well as to their gender.

The results show that the various possibilities to influence the forecasting process lead to different decisions on the part of the subjects. In Treatment 1 (no influence possible), 44.23% of the subjects opt for the use of the algorithm. The majority of the subjects here (55.77%) put their faith in their own forecasting abilities. In Treatment 2 (opportunity to influence the algorithmic output) on the other hand, 69.23% of the subjects decide to use the forecasting computer and 30.77% of the subjects choose to use their own forecasts. In Treatment 3 (opportunity to influence the algorithmic input), 58.49% of the subjects decide to use the forecasting computer and 41.51% of the subjects choose to use their own forecasts (Figure 2).

Figure 2: Comparison of the decisions in favor of the algorithm or the subjects' own forecasts per treatment



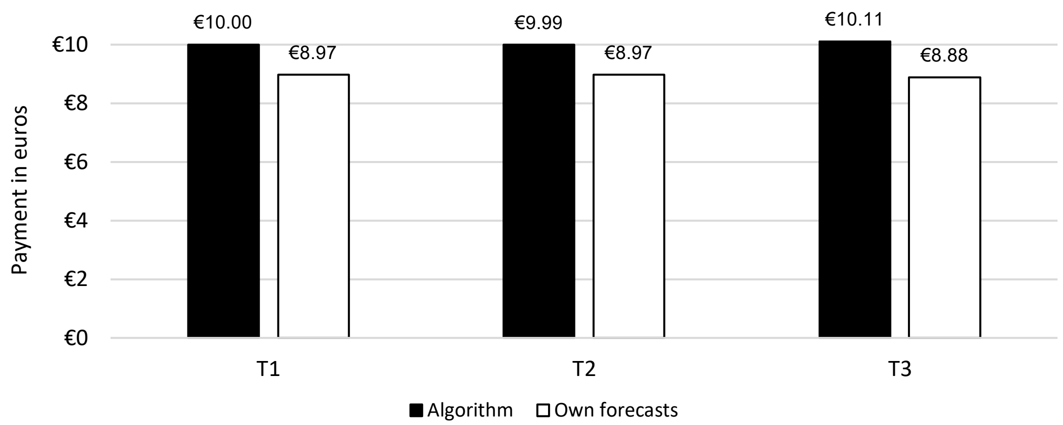
Overall, 67 subjects (42.68%) decide against using the algorithm (Table 3). In our study too, the phenomenon of algorithm aversion in the field of share price forecasts shows itself (Önkal et al., 2009; Castelo, Bos & Lehman, 2019). Null hypothesis 1 thus clearly has to be rejected. Somewhat more than two fifths of the subjects are affected by the phenomenon of algorithm aversion and thus miss out on a higher average payment. The significance of this result is confirmed by the Chi-square goodness of fit test ($p = 0.000$).

We subject the distribution of the participants among the individual treatments to the Chi-square test. Whereas in Treatment 1 a total of 44.23% of the decisions are in favor of the algorithm, 69.23% of the subjects who can make changes to the algorithmic output (Treatment 2) decide to use the forecasting computer (χ^2 (N = 104) = 6.62, $p = 0.010$). Null hypothesis 2 thus has to be clearly rejected; the opportunity to modify the algorithmic output by up to +/- €5 leads to the subjects selecting the forecasting computer significantly more frequently to determine their payment.

When subjects are given the opportunity to influence the algorithmic input (Treatment 3), the majority of the subjects – 58.49 percent – choose to use the forecasting computer (χ^2 (N = 105) = 2.14, $p = 0.144$). Nevertheless, null hypothesis 3 cannot be rejected. The possibility to influence the algorithmic input (via the extent to which the influencing factor D is taken into account) does not lead to the subjects selecting the forecasting computer significantly more often as the basis for their performance-related payment.

On average across all three treatments, the subjects obtain a payment of €9.57. However, there are differences in the amounts of the payment depending on the strategy chosen. Subjects who choose their own forecasts achieve an average total payment of €8.94. When the algorithm is chosen, the average payment in all three treatments is between €9.99 and €10.11. The Wilcoxon rank-sum test shows that the payment – regardless of the treatment – is significantly higher if the algorithm is used as the basis of the forecasts (T1: $p = 0.000$; T2: $p = 0.001$; T3: $p = 0.000$). No matter which treatment is involved, it is thus clearly in the financial interests of the subjects to put their faith in the algorithm.

Figure 3: Average payment in the three treatments depending on the strategy chosen when making the forecasts (own forecast or delegation to the algorithm)



The 67 subjects who, regardless of which treatment they are in, use their own forecasts as the basis of their payment, diverge by an average of €18.2776 from the actual share price and thus achieve an average bonus of €0.4939 per round of forecasting. Subjects who decide to use the forecasts of the forecasting computer exhibit a lower average forecasting error independently of which treatment they are in. The average bonus and the average payment of the subjects who use the forecasting computer are also higher than that of subjects who rely on their own forecasting abilities (Table 3).

In Treatment 2, the subjects are given the opportunity to adapt the algorithmic output in each round of forecasting by up to +/- €5. The subjects do not fully exploit the scope granted to them to exert an influence on the algorithm and make an average change to the algorithmic forecast of €2.11. In Treatment 3 the subjects are given a one-off opportunity via the influencing factor D (sentiment) to exert an influence on the design of the algorithm (input). Eight subjects select variant D1, which takes sentiment into account to a minor extent. Eleven subjects choose to take sentiment into account to a moderate extent, seven to a considerable extent, and five to a great extent.

Table 3: Performance of the subjects in relation to their chosen strategy when making their forecasts (own forecasts or delegation to the algorithm)

	n	Ø Forecast error [in €]*	Ø Bonus per round [in €]	Ø Total payment [in €]
Own forecasts	67	18.2776	0.4939	8.94
Forecasts by the algorithm without the opportunity to influence it *(Treatment 1)*	23	13.4000	0.6000	10.00
Forecasts by the algorithm with an opportunity to influence the output *(Treatment 2)*	36	13.5167	0.5992	9.99
Forecasts by the algorithm with an opportunity to influence the input *(Treatment 3)*	31	13.2968	0.6106	10.11
Total	157	15.4879	0.5566	9.57

* Ø Deviation between the forecasted share price and the actually occurring share price

If the results are viewed in isolation, a similar picture is revealed. Regardless of whether subjects used their own forecasts or the forecasts of the forecasting computer to determine their payment, the average forecast error in Treatment 1 (no influence possible) is higher than in the other two treatments, which offer the subjects the opportunity to influence the algorithm. Whereas the forecasts in Treatment 1 deviate by an average of €16.1788 from the resulting share price, the average forecast error in Treatment 2 is €15.1442 and €15.1472 in Treatment 3. That those subjects who are given the opportunity to influence the algorithm are more successful is shown by their average bonus and higher average overall payment (Table 4).

Table 4: Comparison of the performance of the subjects across all three treatments

	n	Ø Forecast error [in €]*	Ø Bonus per round [in €]	Ø Total payment [in €]
No influence possible *(Treatment 1)*	52	16.1788	0.5423	9.42
Influence on the algorithmic output *(Treatment 2)*	52	15.1442	0.5677	9.68
Influence on the algorithmic input *(Treatment 3)*	53	15.1472	0.5598	9.60
Total	157	15.4879	0.5566	9.57

***** Ø Deviation between the forecasted share price and the actually occurring share price

4. Discussion

Algorithm aversion is characterized by the fact that it mostly occurs when algorithms recognizably do not function perfectly. Even when it is recognizable that the algorithm provides significantly more reliable results than humans (lay persons as well as experts), many subjects are still reluctant to trust the algorithm (Dietvorst, Simmons & Massey, 2018). In our study too, the forecasts of the computer (algorithm) are far from perfect, and the majority of users choose not to use the forecasting computer if there are no opportunities to influence the programme's decision-making process.

Nevertheless, the results show that subjects who are granted an opportunity to influence the algorithmic input or output are more successful on average than subjects who do not have this opportunity. This is because they make the algorithm into the basis for their payment more frequently, and it can be viewed as the success which comes from a reduction in algorithm aversion. On the other hand, forecasters who trust in their own forecasts not only make less precise forecasts overall; they also obtain lower payment for their efforts (Table 3 and Table 4). It can also be seen that the forecasts of the forecasting computer after the changes made to the algorithm by the subjects in Treatments 2 and 3 are almost equally successful to those made without this possibility in Treatment 1 (Table 3). However, the subjects in Treatment 1 (no opportunity to influence the algorithm) put their faith in the forecasting computer relatively seldom and thus reduce their bonus and their overall payment.

In Treatment 2 (opportunity to influence the algorithmic output), we replicate the results of Dietvorst, Simmons and Massey (2018). In our study too, the forecasters tend to rely on the forecasting computer significantly more often if they have at least a small opportunity to influence the algorithmic output.

Even though the subjects do not fully exploit this opportunity to make modifications, it does lead to them being more successful overall, to them making less errors on average, and to them achieving a higher bonus than subjects who are not given the chance to influence the algorithm (Treatment 1) (Table 4). This is not because they make better forecasts - they simply use the (superior) algorithm more frequently.

In Treatment 3 (opportunity to influence the algorithmic input) we obtain similar results. The possibility of influencing the algorithmic input also seems to be suited to reducing algorithm aversion. Nevertheless, the differences in comparison to Treatment 1 are not statistically significant. It is the chance to exert a minor influence on the algorithmic output which reduces algorithm aversion tremendously (Dietvorst, Simmons & Massey, 2018). We ask ourselves whether this major reduction in algorithm aversion is due to the fact that the subjects can exercise an influence on the process of algorithmic decision-making in general, or only because they can influence its results. Here we can see that a general opportunity to influence the algorithm is obviously not sufficient to significantly reduce algorithm aversion. Subjects want to retain control over the results and to have the final say in the decision-making process, even if this intervention is limited by considerable restrictions.

Nevertheless, our study has interesting implications for real-life situations. The overall financial benefit can be maximized by influencing the algorithmic output. Decision-makers tend to trust an algorithm more if they can keep the upper hand in the decision-making process. This even applies when the possibilities to exert an influence are limited. In our study, the average share price is €100 and the maximum amount by which the results can be adjusted is €5. This corresponds to just five percent of the average value of the subject of the forecast, and yet it suffices to significantly shift the grounds on which the decision is based in favor of the algorithm. The average quality of the forecasts is slightly reduced due to the changes made by the decision-maker (Table 3), but this is over-compensated for by a significantly higher utilization rate of the – still clearly superior – algorithm, and in a comparison between the treatments this leads to a higher average total payment (Table 4). The opportunity to influence the algorithmic input has a similar effect with regard to the overall pecuniary benefit. The forecasts made after the subjects have made changes to the algorithm actually exhibit a slightly lower forecast error and a somewhat higher bonus. To a similar degree to which the subjects do not fully take advantage of the opportunity to influence the algorithmic output, they also fail to put their faith in the algorithm. Their average payment is nevertheless significantly higher than that of the subjects who cannot influence the algorithm.

Our study also has some limitations which should be noted. We give the subjects a genuine opportunity to influence the algorithmic input. However, we also make it clear in the instructions that the influencing factor D, which can be taken into account to different degrees, only has a moderate influence on the formation of the share price. The influencing factors A, B and C, on the other hand, have a considerable influence. This circumstance could contribute towards the subjects not developing enough trust in their opportunity to influence the input and thus tending to rely on their own forecasts.

Future research work may wish to investigate further possibilities to reduce algorithm aversion. This study has again shown that granting subjects the opportunity to influence the algorithmic output can effectively reduce algorithm aversion. However, there is a risk that the forecasting performance of the algorithm can deteriorate as a result of the modifications. For this reason, it is important to examine alternative forms of reducing algorithm aversion. Our study has shown that modifying the algorithmic input is only of limited use here. Opportunities to influence the algorithmic input cannot reduce algorithm aversion to the same extent as giving subjects the chance to influence the algorithmic output. We therefore recommend that further research be carried out to search for other alternatives to reduce algorithm aversion. One possible approach could be to merely give users the illusion of having control over the algorithmic process. In this way, algorithm aversion could be decreased without a simultaneous reduction of the forecasting quality.

5. Conclusion

In this study we carry out an experiment to investigate in which ways algorithm aversion can be reduced. It is a well-known fact that providing subjects with an opportunity to influence the algorithmic output is a suitable means of significantly reducing algorithm aversion. We examine whether providing a possibility to influence the algorithmic input also contributes towards decreasing algorithm aversion.

In our experiment, the subjects are asked to make forecasts of share prices. In return, they receive a performance-related payment which increases in line with the precision of their share price forecasts. In three treatments the subjects have a forecasting computer (algorithm) available to them whose forecasts deviate by a maximum of €15 from the actual share price in 7 out of 10 cases. In this way they can earn a bonus of at least €0.60 per forecast. The maximum possible payment per forecast is €1.20. The predictions of the forecasting computer are thus by no means perfect. In Treatment 1 we do not grant the subjects any opportunity to influence the forecasting process. In Treatment 2, on the other hand, the subjects are able influence the algorithmic output, and in Treatment 3 they can influence the algorithmic input.

In agreement with the literature on algorithm aversion, we establish that even a considerably limited opportunity to influence the algorithmic output is able to reduce algorithm aversion significantly. However, being able to influence the algorithmic input does not lead to a significant reduction in algorithm aversion. Granting subjects a general possibility to influence the algorithmic decision-making process is therefore not a decisive factor in reducing algorithm aversion. What does lead to a significantly higher rate of using the forecasting computer, however, is the opportunity to influence the algorithmic output. This remains true even when the opportunity to influence the programme is only a minor one. Subjects want to have the upper hand over the algorithm and to have the final say in the decision-making process.

Nevertheless, we note that the overall financial benefit to the subjects can be increased via the opportunity to influence the algorithmic input. Regardless of whether an opportunity to influence the algorithmic input or output is granted, on average the forecasts exhibit similar forecast errors and similar levels of bonuses per round of forecasting. Overall, the subjects achieve a higher payment. If they have the opportunity to influence the algorithmic output, this effect is reproduced even more strongly than in relation to the algorithmic input, given that in the former the proportion of decisions in favor of the algorithm is highest.

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Appendix A: Instructions for the game

Appendix A-1: Instructions for the game in Treatment 1 (no opportunity to influence the algorithm)

The game

In this game you are requested to make forecasts on the future trend of a share price. You will forecast the price movements of a share (share Z) in 10 periods.

The price of share Z is always the result of four influencing factors (**A**, **B**, **C** and **D**) and a random influence (**Ɛ**). The influencing factors are announced before every round of forecasting. In addition, you receive an insight into the past development of the share price, the influencing factors and the random influence in the last ten periods.

The influencing factors **A**, **C** and **D** have a positive effect on the share price. This means that when these influencing factors rise, the share price will also tend to rise (Table 1).

The influencing factor **B** has a negative effect on the share price. This means that when the influencing factor **B** rises, the share price will tend to fall (Table 1).

Table 1: Influencing factors in the formation of the share price

Influencing factor	Influence	Strength of the influence
A	Positive	Strong
B	Negative	Strong
C	Positive	Strong
D	Positive	Medium

The random influence **Ɛ** has an expected value of 0, but it can lead to smaller or larger deviations of the share price from the level which the influencing factors would suggest.

You can choose whether your own share price forecasts or the share price forecasts of a forecasting computer (algorithm) are used to determine your payment. Regardless of your choice, you will make your own share price forecasts.

You will receive a show-up fee of €4 for participating. In addition, you receive a performance-related payment: the more precise your share price forecasts are, the higher your payment. For each forecast made, you receive…

- €1.20 in the case of a deviation of a maximum of €5 of the forecast from the actual share price;
- €0.90 in the case of a deviation of a maximum of €10 of the forecast from the actual share price;
- €0.60 in the case of a deviation of a maximum of €15 of the forecast from the actual share price;
- €0.30 in the case of a deviation of a maximum of €20 of the forecast from the actual share price.

In the past, the share price forecasts of the algorithm have achieved a payment of at least €0.60 per forecast in 7 out of 10 cases.

Procedure

After reading the instructions and answering the test questions, you initially choose whether your own share price forecasts or the forecasts of the forecasting computer (algorithm) are used to determine your payment.

Following this, you will see the price history of share Z, the trend of the influencing factors and the trend of the random influence Ɛ in the last ten periods. In addition, you will receive the influencing factors for the next period. You will be asked to forecast the trend of the share price in the next period.

After making your share price forecast you will see the actual price of share Z. Following this, you will hand in your share price forecasts for the next period. A total of ten rounds are played.

You have a time limit of two minutes available for handing in each share price forecast.

Information

- Please remain quiet during the experiment!
- Please do not look at your neighbor's screen!
- Apart from a pen/pencil and a pocket calculator, **no** other aids are permitted (smartphones, smart watches etc.).
- Only use the sheet of white paper issued to you for your notes.

Appendix A-2: Instructions for the game in Treatment 2 (opportunity to influence the algorithmic output)

The game

In this game you are requested to make forecasts on the future trend of a share price. You will forecast the price movements of a share (share Z) in 10 periods.

The price of share Z is always the result of four influencing factors (**A**, **B**, **C** and **D**) and a random influence (**Ɛ**). The influencing factors are announced before every round of forecasting. In addition, you receive an insight into the past development of the share price, the influencing factors and the random influence in the last ten periods.

The influencing factors **A**, **C** and **D** have a positive effect on the share price. This means that when these influencing factors rise, the share price will also tend to rise (Table 1).

The influencing factor **B** has a negative effect on the share price. This means that when the influencing factor **B** rises, the share price will tend to fall (Table 1).

Table 1: Influencing factors in the formation of the share price

Influencing factor	Influence	Strength of the influence
A	Positive	Strong
B	Negative	Strong
C	Positive	Strong
D	Positive	Medium

The random influence **Ɛ** has an expected value of 0, but it can lead to smaller or larger deviations of the share price from the level which the influencing factors would suggest.

You can choose the basis which is used to determine your payment:

- Either you can forecast the future share price yourself and forego the use of a forecasting computer (algorithm)
- Or you can use the forecasts of the forecasting computer. <u>If you decide to use the forecasting computer's forecasts (algorithm), you are not bound to the exact forecast provided by the computer. You can change the computer's proposal by up to +/- €5.</u>

You will receive a show-up fee of €4 for participating. In addition, you receive a performance-related payment: the more precise your share price forecasts are, the higher your payment. For each forecast made, you receive…

- €1.20 in the case of a deviation of a maximum of €5 of the forecast from the actual share price;
- €0.90 in the case of a deviation of a maximum of €10 of the forecast from the actual share price;
- €0.60 in the case of a deviation of a maximum of €15 of the forecast from the actual share price;
- €0.30 in the case of a deviation of a maximum of €20 of the forecast from the actual share price.

In the past, the share price forecasts of the algorithm have achieved a payment of at least €0.60 per forecast in 7 out of 10 cases.

Procedure

After reading the instructions and answering the test questions, you initially choose which basis is used to determine your payment. You can forecast the future share prices without the help of the forecasting computer (algorithm). Or you can use the forecasts of the forecasting computer and change them by up to +/- €5.

Following this, you will see the price history of share Z, the trend of the influencing factors and the trend of the random influence Ɛ in the last ten periods. In addition, you will receive the influencing factors for the next period. You will be asked to forecast the trend of the share price in the next period.

After making your share price forecast you will see the actual price of share Z. Following this, you will hand in your share price forecasts for the next period. A total of ten rounds are played.

You have a time limit of two minutes available for handing in each share price forecast.

Information

- Please remain quiet during the experiment!
- Please do not look at your neighbor's screen!
- Apart from a pen/pencil and a pocket calculator, **no** other aids are permitted (smartphones, smart watches etc.).
- Only use the sheet of white paper issued to you for your notes.

Appendix A-3: Instructions for the game in Treatment 3 (opportunity to influence the algorithmic input)

The game

In this game you are requested to make forecasts on the future trend of a share price. You will forecast the price movements of a share (share Z) in 10 periods.

The price of share Z is always the result of four influencing factors (**A**, **B**, **C** and **D**) and a random influence (**Ɛ**). The influencing factors are announced before every round of forecasting. In addition, you receive an insight into the past development of the share price, the influencing factors and the random influence in the last ten periods.

The influencing factors **A**, **C** and **D** have a positive effect on the share price. This means that when these influencing factors rise, the share price will also tend to rise (Table 1).

The influencing factor **B** has a negative effect on the share price. This means that when the influencing factor **B** rises, the share price will tend to fall (Table 1).

Table 1: Influencing factors in the formation of the share price

Influencing factor	Influence	Strength of the influence
A	Positive	Strong
B	Negative	Strong
C	Positive	Strong
D	Positive	Medium

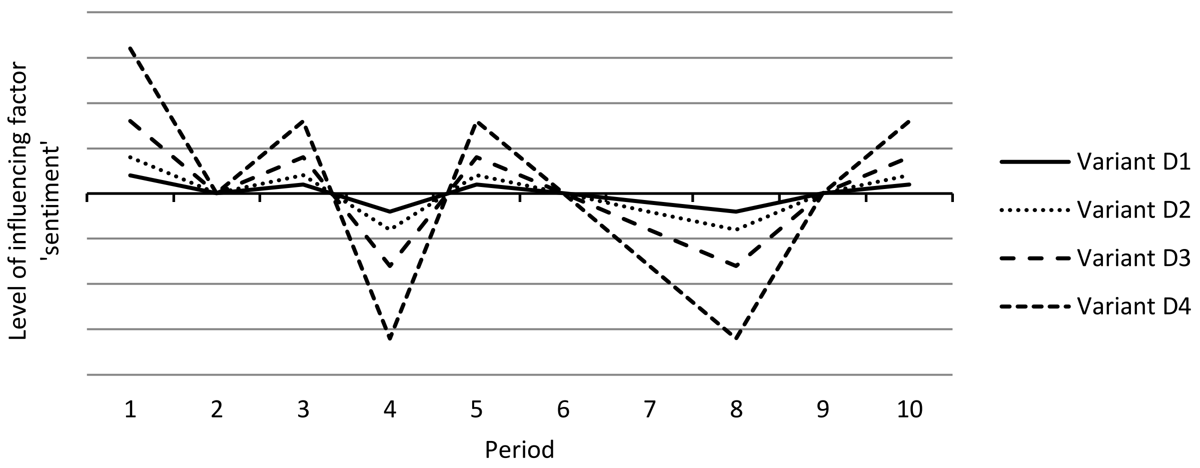
The random influence **Ɛ** has an expected value of 0, but it can lead to smaller or larger deviations of the share price from the level which the influencing factors would suggest.

You can choose whether your own share price forecasts or the share price forecasts of a forecasting computer (algorithm) are used to determine your payment. Regardless of your choice, you will make your own share price forecasts.

<u>If you decide to use the forecasting computer's forecasts (algorithm), you have the opportunity to influence the design of the algorithm.</u>

As mentioned above, the influencing factor **D** also has an effect on the formation of the price alongside the influencing factors **A**, **B** and **C**. The influencing factor **D** is the sentiment of capital market participants. The influencing factor **D** can be taken into account to differing extents (D1, D2, D3 or D4) (Figure 1). You decide which of these four variants should be taken into account by the forecasting computer (algorithm).

Figure 2: Variants of the influencing factor D (sentiment)



You will receive a show-up fee of €4 for participating. In addition, you receive a performance-related payment: the more precise your share price forecasts are, the higher your payment. For each forecast made, you receive…

- €1.20 in the case of a deviation of a maximum of €5 of the forecast from the actual share price;
- €0.90 in the case of a deviation of a maximum of €10 of the forecast from the actual share price;
- €0.60 in the case of a deviation of a maximum of €15 of the forecast from the actual share price;
- €0.30 in the case of a deviation of a maximum of €20 of the forecast from the actual share price.

In the past, the share price forecasts of the algorithm have achieved a payment of at least €0.60 per forecast in 7 out of 10 cases.

<u>Procedure</u>

After reading the instructions and answering the test questions, you initially choose whether your own share price forecasts or the forecasts of the forecasting computer (algorithm) are used to determine your payment.

Following this, you will see the price history of share Z, the trend of the influencing factors and the trend of the random influence Ɛ in the last ten periods. In addition, you will receive the influencing factors for the next period. You will be asked to forecast the trend of the share price in the next period.

After making your share price forecast you will see the actual price of share Z. Following this, you will hand in your share price forecasts for the next period. A total of ten rounds are played.

You have a time limit of two minutes available for handing in each share price forecast.

<u>Information</u>

- Please remain quiet during the experiment!
- Please do not look at your neighbor's screen!
- Apart from a pen/pencil and a pocket calculator, **<u>no</u>** other aids are permitted (smartphones, smart watches etc.).
- Only use the sheet of white paper issued to you for your notes.

Appendix B: Test questions

Test question 1: For how many periods should a share price forecast be made?

a) 5.
b) 10. *(correct)*
c) 15.

Test question 2: On which influences is the share price dependent?

a) Influencing factors A and B as well as the random influence.
b) Influencing factors A, B and C as well as the random influence.
c) Influencing factors A, B, C and D as well as the random influence. *(correct)*

Test question 3: Which alternatives do you have when submitting your forecast?

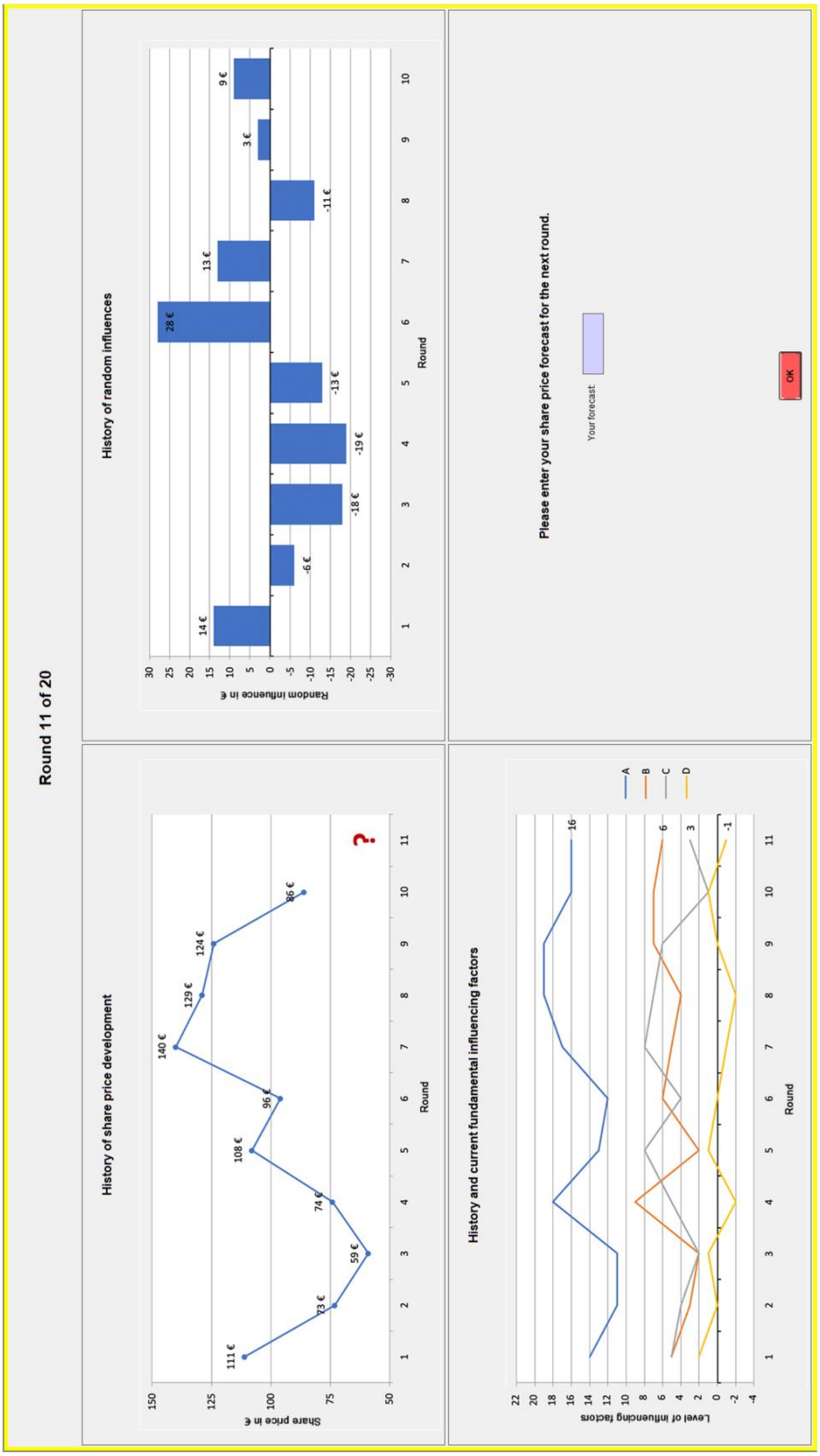
a) I can only submit my own forecasts.
b) I can either submit my own forecasts or use a forecasting computer (algorithm). *(correct)*
c) I can either submit my own forecasts, use a forecasting computer or consult a financial expert.

Test question 4: How much is the payment for a forecast which deviates no more than €15 from the actual price?

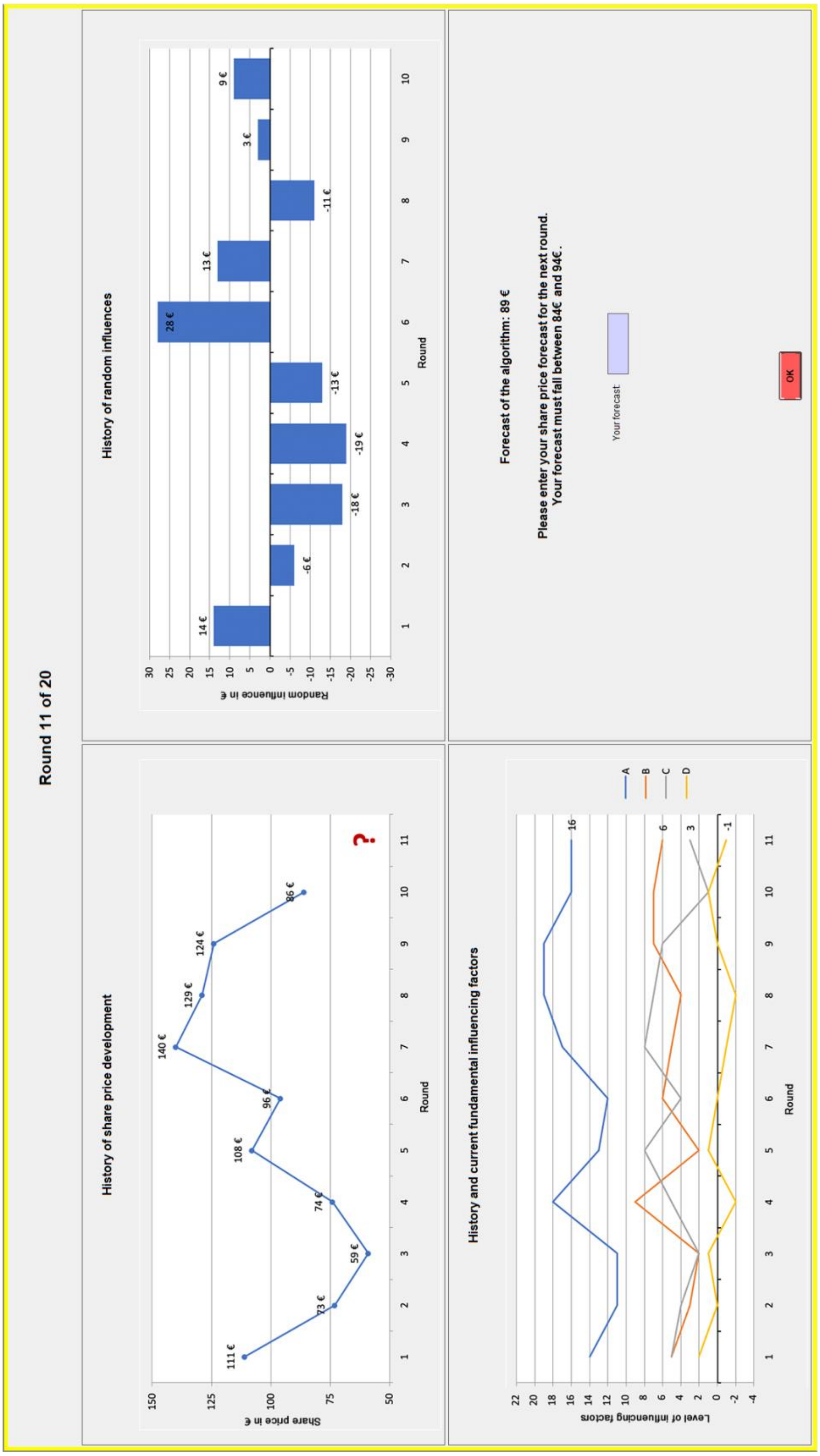
a) €1.20
b) €0.90
c) €0.60 *(correct)*

Appendix C: Screens

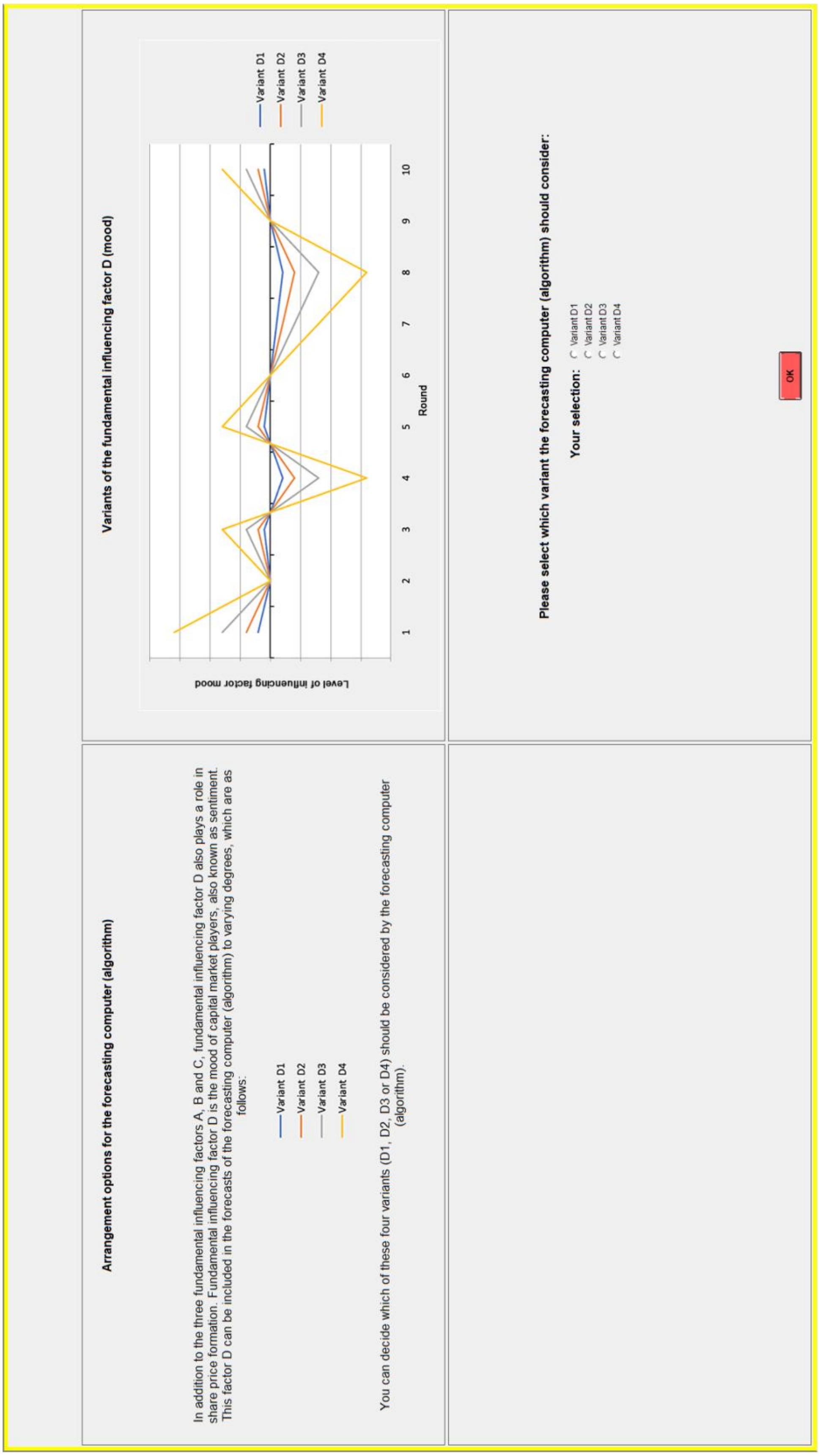
Appendix C-1: Screen when submitting one's own forecasts (Treatments 1, 2 and 3)



Appendix C-2: Screen when influencing the algorithmic forecast (Treatment 2)



Appendix C-3: Screen during the configuration of the algorithm (Treatment 3)



Appendix D: The functioning of the algorithm

The mechanism with which the share price is formed functions as follows:

$$K_t = 7A - 6B + 5C + 2D + \mathcal{E}$$

The level of the influencing factors A, B, C and D are announced before every round of forecasting. The level of the random influence is not announced. What is known, however, is that the random influence has an expected value of 0. In every round, the algorithm inserts the values of the four influencing factors A, B, C and D into the formula for the formation of the price. Due to the fact that the subjects can influence the algorithmic input, the weighting of the influencing factor D can diverge somewhat in Treatment 3. For the random influence, the algorithm sets the expected value at €0. The result of this equation is the forecast of the algorithm P_t (see Table A1). In period 1, the algorithm calculates as follows:

$$P_1 = 7 * 14 - 6 * 5 + 5 * 5 + 2 * 2 + 0 = 97$$

For the calculation of the actual price, the random influence also has an effect. In period 1 it has a value of €+14. The actual price is thus calculated as follows:

$$K_1 = 7 * 14 - 6 * 5 + 5 * 5 + 2 * 2 + 14 = 111$$

The difference between the actual share price K and the forecast of the algorithm P is the forecast error. This determines the amount of the bonus of the current forecasting round as described in accordance with the formula described in Table 2. For a forecast whose forecast error lies within the interval $10 < |K_t - P_t| \leq 15$ for example, there is a bonus of €0.60.

Table A1: Illustration of the modus operandi of the algorithm, how the share price is formed, and the calculation of the bonus

Period	**Influencing factors**				**Forecast of the algorithm P_t**	**Random influence**	**Actual price K_t**	**Forecast error**	**Bonus**
	A	B	C	D					
1	14	5	5	2	€97	+€14	€111	€14	€0.60

In practice one can see that perfect share price forecasts are not possible, even with knowledge of the most important influencing factors. On the contrary: share price trends have a number of similarities with random processes. This circumstance is taken into account by introducing the random influence. The random influence has the effect that the algorithm cannot make perfect forecasts. The forecast error of the algorithm thus corresponds to the random influence.

In this economic experiment, the random influence consistently lies within the interval $-€30 \leq Ɛ \leq €30$. It is always a whole number without decimal places. The exact distribution is described in Table A2. The area $-€15 \leq Ɛ \leq €15$ (grey background) has a cumulative probability of 70%. For a forecast with a maximum forecasting error of €15 there is a payment of €0.60. In this way it can be ensured – as stated in the instructions – that the forecasts of the algorithm lead to a payment of at least €0.60 in 70% of cases.

Table A2: Distribution of the random influence, which has an effect on the share price

Level of the random influence	Probability
$-€30 \leq Ɛ \leq -€21$ and $€21 \leq Ɛ \leq €30$	5% each (10%)
$-€20 \leq Ɛ \leq -€16$ and $€16 \leq Ɛ \leq €20$	10% each (20%)
$-€15 \leq Ɛ \leq -€11$ and $€11 \leq Ɛ \leq €15$	20% each (40%)
$-€10 \leq Ɛ \leq -€6$ and $€6 \leq Ɛ \leq €10$	10% each (20%)
$-€5 \leq Ɛ < €0$ and $€0 \leq Ɛ \leq €5$	5% each (10%)

As the level of the random influence is not known when handing in a forecast, the optimal strategy is to insert the values of the influencing factors A, B, C and D into the formula for the price formation mechanism and to assume an expected value of 0 for the random influence. This is precisely what the algorithm does. With the information available, it is thus not possible to make better forecasts than the algorithm.

When they make their own forecasts, the subjects also have the additional disadvantage that they do not know the exact formula for the price formation mechanism. They can only create an approximate picture of the price formation mechanism on the basis of examples of rounds of the game for which no payments were made (price history). For this purpose they are provided with the exact level of the share price, the influencing factors A, B, C and D as well as the random influence from ten previous rounds. From this information it is also already clear that making naïve forecasts – i.e., using the current price K_t without adaptation as a forecast for the following period P_{t+1} – and continuously forecasting the average price of the last ten rounds are not promising approaches.

Given the advantage which the algorithm has in terms of information, there is thus no reason to presume that the subjects could succeed in making better forecasts. In effect they achieve an average total payment of €8.94 with their approach. They are thus clearly behind the payment of €10.03 obtained with the algorithm (p-value Wilcoxon rank-sum test = 0.000). Decisions against using the algorithm can thus be considered to be algorithm aversion.