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The adoption of algorithmic decision-making agents over time: algorithm aversion as a temporary effect?

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THE ADOPTION OF ALGORITHMIC DECISION-MAKING AGENTS OVER TIME: ALGORITHM AVERSION AS A TEMPORARY EFFECT?

Research Paper

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Abstract

Many individuals encounter algorithmic decision-making agents with algorithm aversion – the irrational discounting of superior algorithmic advice. So far, we know little about how algorithm adoption develops over time and how people may overcome algorithm aversion. In response, we explore the factors that foster the adoption of algorithmic decision-making agents – initially and over time. Based on an experiment with incentive-compatible awards over several rounds, we find that one's knowledge about peers successfully using the technology as well as low transaction costs serve as strong initial motivators to foster initial algorithm adoption. Further, by revealing that adoption rates increase and initial difference in adoption rates become smaller over time, we find evidence that despite the technology's particularities, algorithm aversion seems to have a temporary effect only.

Keywords: Algorithm aversion, Algorithm adoption, Decision-making.

1 Introduction

Algorithms play an increasingly important role, although they are not new to decision-making. A wide body of literature has analyzed their role in decision support systems and how decision-makers respond to these systems. However, the development of artificial intelligence (AI) has changed the potential agency of these systems fundamentally (Leyer and Schneider, 2021). Currently, AI technology is sufficiently advanced to outperform humans in highly specific tasks; however, we except the number and variety of such tasks to expand in the future (Hosny et al., 2018; Kellog et al., 2020). In contrast to human decision-making agents, algorithms do not show opportunistic behavior and motivation (Burton et al., 2020; Leyer and Schneider, 2021). Therefore, if we decide to adopt and use algorithms as decision-makers, these algorithms may freely create consequences for our private and business lives within the levels of autonomy that we are willing to grant to the technology. Many people tend to be averse to algorithmic decision-making agents (Bigman et al., 2021; Dietvorst, 2016); in some contexts they even reject to use them when knowing about their superiority – a phenomenon known as algorithm aversion (Dietvorst et al., 2015). Only in rare situations, studies have provided evidence for a preference for algorithmic over human agents – a behavior described as algorithm appreciation (Dijkstra et al., 1998; Logg et al., 2019). Fostering the adoption of AI-enabled algorithms is not desirable in all application contexts – due to ethical and accountability concerns (Martin, 2019b, 2019a) and the potential over- and underutilization that might lead to inferior decisions (Berger et al., 2021; Burton et al., 2020; Parasuraman and Riley, 1997). However, given the technology's potential to augment human decision-making, understanding how we can increase individuals' adoption behavior of algorithmic decision-making agents emerges as key challenge in many managerial contexts. Therefore, we need a deeper understanding of algorithm aversion in the adoption of technological decision-making agents. In recent years, algorithm aversion as a phenomenon has attracted interest within information systems research (Berger et al., 2021; Jussupow et al., 2020) as well as across various other disciplines, including organizational behavior and psychology (Dietvorst et al., 2015; Efendic et al., 2020; Filiz et al., 2021) or management and marketing science (Castelo et al., 2019; Dietvorst et al., 2018). So far, studies have identified several factors promoting resistance towards algorithmic decision-making agents, such as overconfidence (Grove and Meehl, 1996; Highhouse, 2008), the lack of an emotional connection with the algorithm (Broadbent, 2017; Gray, 2017), or the lack of vulnerability as the algorithm cannot be held responsible for decision outcomes (Broadbent, 2017; Gray, 2017). Likewise, recent research has identified factors enhancing adoption behaviors, e.g. the perceived improvement in decision-making speed and quality (Akinola et al., 2018), perceived control over the algorithm (Dietvorst et al., 2018), and low awareness of the decision making situation (Schneider and Leyer, 2019). However, this still leaves us with many blank spots, in particular concerning the conditions that foster one's adoption of algorithmic decision-making agents or how one's adoption behavior changes with more experience and exposure to the technology. In our study, we want to show that algorithm aversion is a phenomenon that can be overcome. With the current extensive knowledge about factors positively and negatively influencing algorithm aversion we want to equip decision-makers with tools to overcome initial and lasting aversion.

The objective of this study is therefore to explore under which conditions people adopt algorithmic decision-making agents. In particular, this study aims to find answers to the following two research questions*: (1) What increases the initial adoption of algorithmic decision-making agents? (2) How does one's adoption behavior change over time?* To explore these questions, we apply an experimental study with incentive-compatible awards to observe individuals' adoption behavior of algorithmic decision-making agents. In the experiment, we asked the participants to make investment decisions over several rounds and each time, we offered them the option to delegate the decision to an AI-enabled decision system. Each round consisted of a distinct manipulation. After seven rounds, the number of achieved experimental points collected by each participant was transferred to a monetary reward. Our findings show how the knowledge about others, i. e. peers, using the technology successfully, has a positive impact on the adoption of algorithms. We also show the initial influence of additional effort or reward as positive and negative influence on the adoption decision. Most interestingly, however, we reveal that over time, the impact of any of these factors on one's choice to adopt an algorithmic decision-making agent decreases. Here, we see that the adoption rates increase over time, regardless the particular contextual conditions. These findings thereby extend our understanding of the conditions that foster one's adoption of algorithmic decision-making agents. These results are in line with previous studies that have emphasized how the particular characteristics of algorithms make them stand out from traditional technology adoption processes. However, revealing that adoption rates increase over time indicates that despite the algorithms' particularities, initial aversion seems to be a temporary effect only. For practitioners, these insights provide useful indications on how to foster and accelerate algorithm adoption in decision-making contexts.

2 Conceptual Background

With advances in AI, algorithms have emerged as promising technological solutions to support, enhance and potentially even replace human decision-making in many fields (Seeber et al., 2020). For the purpose of this study, we understand AI as a bundle of algorithms designed to maximize efficiency as well as accuracy for a particular purpose and defined set of conditions (Hill, 2015; Seaver, 2017). Algorithms are typically elements of AI-enabled decision making systems that are capable of taking over decisions from humans, thereby eliminating the need for the decision maker to be involved (Buhmann et al., 2019; Martin, 2019b). By handing over decisions, we equip algorithms with agency, "the capacity to make a difference" (Giddens, 1984, p. 14). Actors equipped with agency possess the authority to make choices or to exercise control (Bandura, 1989; Giddens, 1984; Pickering et al., 2017) as well to refuse or to choose differently than suggested by another actor (Giddens, 1979; Orlikowski, 2000). While in pre-algorithmic times, agency was exclusively a human attribute, with the increasing technological capacities, machine agency has become reality (Leonardi, 2011). Nevertheless, algorithms as material agents are still manmade and brought into use by humans (Martin, 2019b). The degree of agency assigned to algorithms in decision-making varies. It may range from augmentation of human decision-making with the final choice to accept, refine or reject the algorithm's advice remaining with the human decision-maker to automation, implying the elimination of any human intervention in the decision-process and the full autonomy of the technological decision-agent (Garbuio and Lin, 2019; Raisch and Krakowski, 2020; Seeber et al., 2020). Decision augmentation and automation are poles of a continuum describing the potential roles and agencies of human and algorithmic agents in decision-making (Demetis and Lee, 2018; Martin, 2019a).

Prior research has shown that evidence-based algorithms can make more accurate decisions than humans (Dietvorst et al., 2018, p. 1155), e.g. in medical recommendations (Promberger and Baron, 2006) or predictions about employee performance (Highhouse, 2008). However, despite compelling evidence of the superiority of algorithmic judgment in particular contexts and the general progress in the diffusion of digital technologies, decision makers often remain reluctant to use algorithms (Dietvorst et al., 2018, p. 1155). The term "algorithm aversion" captures this behavior: the irrational discounting of imperfect, but superior algorithms (Dietvorst, 2016). Such irrational discounting of automated device is not an entirely new phenomenon. People tend to react differently towards statistical or mathematical problem-solving approaches than to more clinical or intuitive human approaches (Dawes, 1979; Dawes et al., 1989; Meehl, 1954). However, with rising availability, agency and autonomy of algorithmic decision-makers, understanding algorithm aversion becomes essential. The reasons for algorithm aversion are manifold and multifaceted. In their recent review, Muhad et al. (2022) propose a framework where they aggregate identified influencing factors of algorithm aversion, i.e., high-level factors (e.g., organizational, cultural, environmental, societal), individual factors (e.g., psychological, personality, familiarity, demography), task factors (e.g., morality, complexity), and algorithm-related factors (e.g., design, decision, delivery) – influencing positively or negatively algorithm aversion. Berger et al. (2021), for example, emphasized that studies so far have focused on algorithm aversion behaviors in two contexts: Before and after becoming familiar with the algorithm and its performance. Before getting to know the algorithm, Filiz et al. (2021) for example found that algorithm aversion increases with the seriousness of the decision's consequences. Castelo et al. (2019) showed that individuals do not believe algorithms to be capable of handling subjective tasks. Further studies have shown that human decision-makers struggle to connect emotionally with the algorithm (Broadbent, 2017; Gray, 2017) and are overconfident in their own abilities (Grove and Meehl, 1996; Highhouse, 2008). Other causes include false expectations, lack of decision control, lack of incentivization, combatting intuition, and conflicting concepts of rationality (Burton et al., 2020). However, there is also evidence for humans appreciating algorithms in their decision-making (Logg et al., 2019). Efendic et al. (2020), for example, have identified short response time as a positive influence factor on people's trust in algorithmic predictions. Additionally, Bigman et al. (2021) revealed that emphasizing inequality in triage situations leaders increases one's preference for algorithm decision-making. In line with that, Schneider and Leyer (2019) report a greater likelihood of humans advocating their decision towards algorithms when having a lower awareness of the situation.

In addition to knowing important factors that drive or mitigate aversion to algorithms, it is also important to know how to overcome current resistance to algorithmic decisions. Research has argued that 'loss of control' remains one of the biggest hurdles when adopting an algorithm (e.g., Burton et al., 2020). As a solution mechanism, research has argued that human decision-makers should be given a possibility to get involved, make suggestions and ultimately have the right to have the final say (Burton et al., 2020). First empirical evidence has shown that the reluctance dwindles when humans have some control over the algorithm (Dietvorst et al., 2018). Therebey it does not matter how much control remains with the human decision maker, as only the illusion of control is relevant for the adoption (Dietvorst et al., 2018). Therefore, we argue:

***H1**: Human-in-the-loop decision-making, i.e. giving humans control of the outcome of the algorithm, enhances the adoption of algorithmic decision-making agents.*

Another obstacle is the lack of suitable incentive mechanisms for the use of algorithms (Burton et al., 2020). People typically feel much more motivated when monetary or non-monetary incentives are given to use an algorithm in decision-making (Lim and O'Connor, 1996; van Esch et al., 2020). Research has shown that confidence of human decision-makers is boosted when accordingly incentivized (Kobis and Mossink, 2021). Dijkstra (1999) further noted that humans do not feel motivated to engage in mental effort to evaluate the algorithm's benefits when not incentivized to do so. However, when it comes to monetary incentivization, current research shows conflicting results. While in some cases incentives did not lead to algorithm aversion (e.g., Prahl and Van Swol, 2017), other experiments showed that algorithm aversion persisted in the absence of commercial economic incentives (e.g., Önkal et al., 2009). Yet, we argue that humans feel more motivated to adopt an algorithm when monetary rewards are present:

***H2**. Incentives, i.e. bonus output/ avoidance of additional effort, enhance the adoption of algorithmic decision-making agents.*

Besides monetary incentives, however, there are also social incentives that play an important role (Burton et al., 2020). Social incentives are typically the wish to adhere to social norms and / or maintaining the 'right' reputation among peers and colleagues (Burton et al., 2020). Research acknowledges that decision-making is inextricably linked to the social environment where the decision-making situation takes place (Burton et al., 2020). Decision-makers are typically motivated to conform to social norms (e.g., Arkes et al., 2007; Eastwood et al., 2012; Sanders and Courtney, 1985) and information about peers' adoption behavior sets the frame for it (e.g., Alexander et al., 2018). The view of peers on algorithms heavily shapes how humans perceive algorithms itself (Langer and Landers, 2021). Furthermore, empirical evidence has shown that receiving feedback about the decision-making performance of previous users positively impacts the perception of the algorithm (Alexander et al., 2018; Zhang et al., 2021). Therefore, we propose 'peer information' as a useful tool in tackling algorithm aversion:

***H3**. Peer information, i.e. learning about others' success when using the algorithm, enhances the adoption of algorithmic decision-making agents.*

In addition to these instruments, we propose another influential factor that has received mixed support in both directions, i.e. paying for the usage. Research has pointed out that humans do follow paid or costly decision typically more than those which are free of charge (Gino, 2008). Hence, a reason for aversion might be the perceived cheapness of the algorithm that drives human decision-makers away. A potential countermeasure might therefore to introduce an algorithm for which one has to pay. However, on the other side a typical reaction of users to perceived high up-front costs is rejection (Claudy et al., 2015), when users perceive the financial investment as a squandering of resources (Kleijnen et al., 2009; Szmigin and Foxall, 1998). Therefore, we assume:

***H4**. Costs, i.e. paying a fee when using the algorithm, decreases the adoption of algorithmic decision-making agents.*

Familiarity with algorithms is a double-edged sword and can go in both directions (Mahud et al., 2021). Learning about the algorithm over time means also learning that an algorithm makes errors. Negative experiences with erring algorithms lead to a negative attitude toward algorithms due to affect heuristics (Liu et al., 2019). Yet, it makes a difference at which point the error of the algorithm occurs (Mahud et al., 2021). Typically, erring algorithms in earlier stages have a greater impact on aversion than in later stages (Manzey et al., 2012). In opposite to that, Berger et al. (2021), for example, found decision-makers to make no difference in their confidence in unfamiliar human and algorithmic advisors, but to have varying levels of confidence in familiar human and algorithmic advisors. Research has also indicated that people tend to lose trust in poorly performing algorithms more quickly than in individuals (Dietvorst et al., 2015), but that trust can be recovered if an algorithm learns from its mistakes over time (Berger et al., 2021). Additionally, Filiz et al. (2021) show that over time, when individuals compare a superior, but imperfect algorithm's performance with their own, their algorithm aversion decreases. In light of this, we argue that over time, as previous studies have indicated, individuals are likely to realize the performance gap between their own, and the algorithm's superior performance and algorithm is likely to fade. We therefore argue that over time, the initial aversion towards algorithms decreases:

***H5**. Algorithm aversion, i.e. the irrational discounting of superior but imperfect algorithmic advice, decreases over time.*

3 Method

Even though algorithmic decision-making becomes increasingly available, so far, people have been reluctant to engage with algorithms (e.g., Dietvorst and Bartels, 2021). This motivated us to apply an experimental research design to analyze the impact of several influence factors in isolation in a fictitious, however realistic decision scenario. We developed an experimental paradigm to measure the adoption rate of algorithms in decision-making situations to test the hypotheses above. Further, we used incentive-compatible rewards to ensure the participants' motivation to make the best decisions possible.

3.1 Sample and Procedure

In total, 537 participants recruited using Clickworker completed the study. We excluded participants who completed the survey in less than 5 minutes or took longer than 30 minutes. Thus, 474 participants remained after data cleaning. The number of participants per treatment ranged between 93 and 97. The respondents' average age was 30.19 (SD = 5.98). About 47 % of the participants identified themselves as male and 53 % as female. One participant answered "non-binary" and one participant preferred not to answer this question. Furthermore, the distribution of age and gender did not differ significantly between treatments. Respondents received a show-up fee of again € 2.00 and, in addition, were monetarily incentivized with the amount the earned by the investments. On average, the additional payoff was € 2.82 (SD = 0.51), and it took them 14.57 minutes to complete the survey. Participants were told to predict the success or failure of crowdfunding projects, i.e., the achievement of the fundraising goal, by placing experimental money on the indicated projects. We first made sure that everyone has the same understanding of crowdfunding projects and success by providing supporting information. On a next page, we asked the participants a couple of questions on this topic, thereby ensuring that everyone has understood the matter of crowdfunding. Afterwards we proceeded with our experiment, where we presented 21 crowdfunding projects in 7 rounds to our participants. On each page, our participants have been presented with three projects in tabular form (see Table 1 for an example presentation). The information about the projects included the name of the project, a short description of the project, the funding goal (funding target) of the project, the different ways of contributing (e.g. 10 €, 40 €, 100 €, 250 €), the amount of media presented (i.e. how many videos and photos a campaign presents), as well as the duration of the project (i.e. how long the project will be active). On the same page, participants were asked whether they want to use the AI-enabled decision system or whether they want to predict the success of the projects by themselves. In addition, after each round the participants received feedback on how much money they won and how the algorithm would have performed. In each round, all participants received 120 experimental points that they had to distribute among the three different crowdfunding projects across seven rounds (in total 840 experimental points). 120 experimental points equaled 0.50 €. In case the participants predicted the success of a crowdfunding project correctly, they won the invested amount of experimental points for this round. In case, they made a wrong prediction, participants lost the invested experimental points in this project for this round. We informed the participants that the total amount of the experimental points achieved after seven rounds would be calculated and transferred into real money based on individual performance. Table 1 shows an example about the described projects.

	Project 1	**Project 2**	**Project 3**
Name	Powerful, Convertible portable PRIVATE screen	EZ E-Commerce	Mibudi - pet adopt or lost?

Picture			
Description	Portable and convertible touchscreen PRIVATE MONITOR for your privacy and productivity!	The online market has revolutionized the way we shop... but how can we be sure we are receiving the best price?	Hello! My brother and I are creating an app to help find animals homes as well as help find them if they are lost.
Funding Goal (€)	500	25.000	70.000
Ways to contribute (€)	229; 298; 399; 439	50; 100; 250	5; 10; 20; 50; 100
Amount of media	> 20	1	1
Duration of the project	3 days	60 days	35 days

Table 1 Exemplary decision task.

3.2 Variables

Dependent Variable In each round, participants could choose between making the investment decision by themselves or delegating it to an algorithm, resulting in a binary dependent variable. Overall adoption behavior was then assessed by using the number of times, the algorithmic decision-maker was chosen. Across all rounds, this variable ranges from zero to seven. In later analysis we use the adoption rate in round one/two and six/seven. In this case the adoption rate ranges from zero to two.

Algorithm We obtained the data on the crowdsourcing projects from the platform "Kickstarter" for December 2020 and January 2021 for the category "Technology" and subcategories "Apps", "Categories", and "Gadgets". Ultimately, 74 projects met our criteria, of which 14 were successful and 60 failed. We have selected 21 projects – 10 successful and 11 unsuccessful projects randomly – to show to the participants in groups of three over seven rounds. We trained a classification model based on a logistic regression that predicts the success of a project based on almost the same variables as the participants received. These variables include the funding goal, the project duration, the number of contribution options, the number of words in the project title and description, and the number of different medias used to describe the project. The included variables match the information the participants received during the experiment and are displayed in Table 2.

Variable	**Explanation**
Financial Goal in US-Dollar	Funding goal of the crowdfunding project
Duration of the project in days	The duration of the project measured, i.e., how long the project will be active and open to contribute
Number of different levels to contribute	The number of possibilities someone can contribute (e.g., 10 $, 20 $, 30 $ = 3 levels of contribution)
Length of the project's title in words	The number of words a projects' title is written in
Number of media	The number of media, that is provided to describe the project
Length of project description	The amount of word a projects' description is written in

Table 2. Variables for the prediction of a project's success

The results from the logistic regression are shown in Table 3. From the set of financial variables, the financial target and the number of different contribution levels have a positive and significant influence on the probability of success. Furthermore, the project descriptive variables, number of different media and length of the project description have an influence on the probability of success.

	Coef.	p-value	
(Intercept)	-6.304	0.015	*

Financial goal	0.0003	0.007 **
Duration	0.050	0.293
No. of contribution levels	0.515	0.040 *
Length project name	-0.054	0.112
No. of media	0.173	0.035 *
Length of project description	0.038	0.037 *
N	74	
AIC	43.322	
*** p<0.001, ** p<0.01, * p<0.05, p< 0.1		

Table 3. Results from the logistic regression

After training the model, we evaluated the predictive accuracy of the model. To this end, the overall accuracy, the precision as well as the recall have been computed. From 58 failed projects, the algorithm wrongly predicted three projects as successful and from 16 successful projects, the algorithm falsely predicted five projects as failures. According to the accuracy measures, the simple logistic regression worked sufficiently well for serving as superior, but imperfect algorithm. Based on all projects, the algorithms predicted 90 percent correctly (accuracy). From all projects predicted as success, 80 percent succeeded (precision) and of all true successful projects, the algorithm detected 70 percent (recall).

Manipulation We draw on a between-subjects design with one control group and five experimental groups. While there was no treatment in the first group ("control"), participants in the second treatment group were asked to pay ten experimental points for using the algorithm ("transaction costs"). In contrast, participants in our third experimental group received an additional amount of ten trial points ("benefit") each time they chose to use the algorithm. In the fourth treatment group, participants remained at least partly in control by having the chance to make minor changes to the suggested allocations ("human-in-the-loop"). Finally, in our fifth experimental group, we informed the participants about the better performance in terms of money won by the participants who predominantly used the algorithm ("peer information").[1] The following Table 4 describes our experimental groups.

Group	Information for Participants
1 – Control	No further information
2 – Costs	Each time you choose to use the algorithm-based decision system, you will have to pay 10 NIM coins. The 10 NIM coins will be deducted from your total winnings in that round.[2]
3 – Benefits	Each time you choose the algorithm-based decision system, you will get an additional amount of 10 NIM coins as a reward. The 10 NIM coins will be added to your total winnings.
4 – Human-in-the-loop	In case you decide to follow the advice of the algorithm, you will be able to slightly change the amount of the assigned NIM Coins to each project by 10 points.
5 – Peer Information	In previous studies with a total of 160 participants, 113 participants opted predominantly for the algorithm and achieved an average payoff of € 3.11. In contrast, 47 participants chose to predominantly refrain from using the algorithm and achieved an average payoff of € 2.40.

Table 4. Experimental Group Description

4 Results

4.1 Manipulation effect on the initial adoption behavior

With regards to the overall adoption behavior across all rounds, independent samples t-tests shows that compared to our control group ($M_{control}$ = 4.13, $SD_{control}$ = 2.47), participants who received peer information (M_{peer} = 5.3, SD_{peer} = 2.08) adopted the algorithm on average significantly more (t(183) = -

[1] The experiment included an additional treatment group ("literacy") which was not considered in the present analysis.
[2] The experiment used the fictive currency NIM coins as experimental money.

3.55, $p < 0.001$) and participants who had to pay for the algorithm significantly less ($M_{costs} = 3.03$, $SD_{costs} = 2.37$, $t(187) = 3.11$, $p = 0.002$). Further, there was no significant difference between the control group and participants who received monetary benefits ($M_{benefits} = 4.5$, $SD_{benefits} = 2.3$) or participants who had the chance to adjust the algorithms outcome ($M_{HITL} = 4.65$, $SD_{HITL} = 2.34$). Hypothesis 1-4 posited that human-in-the-loop decision-making, peer information, transaction costs, and benefits influence the initial adoption behavior. Therefore, we conducted independent samples t-tests for the rounds 1-2. Again, the group peer information ($M_{peer} = 1.45$, $SD_{peer} = 0.75$) adopted significantly more the algorithm than the control group ($M_{control} = 1$; $SD_{control} = 2.47$, $t(188) = -4.05$, $p < 0.001$) and the cost group ($M_{costs} = 0.66$, $SD_{costs} = 0.78$) significantly less ($t(188) = 2.94$, $p = 0.004$). In addition, the group that received monetary benefits ($M_{benefits} = 1.2$, $SD_{benefits} = 0.77$) adopted the algorithm weakly significantly more often than the control group ($t(186) = -1.77$, $p = 0.078$). However, there was again no significant difference between the human-in-the-loop group ($M_{HITL} = 1.16$, $SD_{HITL} = 0.84$, $t(185) = -1.35$, $p = 0.179$). Thereby, hypotheses 2-4 is supported by our data, while hypothesis 1 finds no support.

4.2 Development of the adoption behavior over time

Hypothesis 5 stated that algorithm aversion, i.e., the irrational discounting of superior but imperfect algorithmic advice, decreases over time. Figure 1 depicts the average adoption rate for each round per treatment. It already implicates increasing adoption rates over time for all groups. Noteworthy is that in round 4 the adoption behavior of all groups decreases. This is due to the fact that the participants realized the imperfection of the algorithm for the first time, as the algorithm had made mistakes in the rounds before.

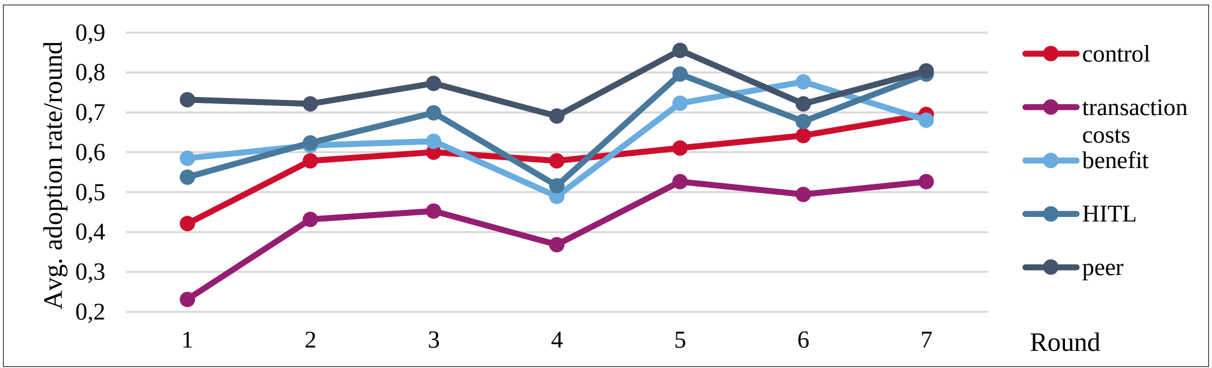

Figure 1. *Individual adoption decisions over time*

In order to test for our hypothesis 5, we again drew on paired sample t-tests and compared the adoption behavior in the first two rounds with the adoption behavior in the last two rounds. In all groups – except for the group that received information about the peers – we found significant differences in the adoption behavior, in such that the adoption is significantly higher in late phases than in early phases indicating that algorithm aversion fades. Table 5 shows the individual results. Furthermore, we also compared the adoption behavior of our manipulation groups to our control group by calculating another set of independent samples t-tests for the late phases (round 6 and 7). Only participants who had to pay for the algorithm ($M_{costs} = 1.02$, $SD_{costs} = 0.86$) adopted the algorithm significantly less than the control group ($M_{control} = 1.34$, $SD_{control} = 0.87$, $t(187) = 2.51$, $p = 0.013$).

Treatment	**Round 1 and 2**			**t-value**	**p**	**Round 6 and 7**	
	M	**SD**				**M**	**SD**
control	1	0.8	<	t(187) = 2.78	0.006	1.34	0.87
transaction	0.66	0.78	<	t(186) = -3.00	0.003	1.02	0.86
benefits	1.2	0.77	<	t(186) = -2.29	0.023	1.46	0.76
HITL	1.16	0.84	<	t(184) = -2.59	0.01	1.47	0.8
peer	1.45	0.75	<	t(192) = -0.67	0.504	1.53	0.75

Table 5. *Independent sample t-tests for the adoption behavior over time.*

A more detailed analysis of time effects including all rounds and controlling for other influencing variables is done using a regression analysis including the round as regressor. Since the adoption decision is a dichotomous variable, we compute a logistic regression with the respondents as random effects controlling for unobserved heterogeneity in the repeated measurement. Furthermore, we added additional variables potentially influencing the individual's decision, i.e., the individual's adoption decision in the previous round, the monetary outcome of the previous round, an indicator variable whether the algorithm erred in the previous round as well as sociodemographic information. Table 6 reports the regression results, which confirm the findings of the t-tests. Even when controlling for respondents' experience, i.e., previous decisions, outcome, and the algorithm's performance, the regression results show a positive and highly significant time effect.

	Coef.	p-value
(Intercept)	-0.549	0.461
Transaction Costs	-1.127	0.003 **
Benefits	0.320	0.393
HITL	0.477	0.207
Peer Information	1.133	0.003 **
Round	0.270	<0.001 ***
Adoption choice in t-1	0.833	<0.001 ***
Monetary payoff in t-1	-0.010	<0.001 ***
Algorithm erred in t-1	-0.445	<0.001 ***
Age	-0.004	0.833
Gender	0.657	0.005 **
AIC	2804	
Observations	3318	
Individuals	474	
Rounds	7	
*** p<0.001, ** p<0.01, * p<0.05, . p< 0.1		

Table 6. Logistic regression for the adoption behavior over time

5 Discussion and Conclusion

This study aimed at replicating and identifying factors that facilitate the adoption of algorithmic decision-making agents and at exploring how one's adoption behavior changes over time. Based on an experiment with incentive-compatible awards, we analyzed how various manipulations influence one's adoption choices when confronted with algorithmic decision-making agents. We see that initially, when first confronted with algorithmic decision-making agents, individuals are more likely to adopt the algorithm when they have any form of additional incentive to try the technology rather than additional hurdles, and when individuals learn about others using the technology successfully. In contrast, they are less likely to adopt the algorithm when they must pay for it. Furthermore, we reveal that the adoption of superior, however imperfect algorithms increases over time.

5.1 Theoretical Implications

While the perceived usefulness of a novel technology is generally a strong predictor of technology adoption, algorithm aversion – defined as the irrational discounting of superior advice provided by algorithms (Dietvorst et al., 2015) – indicates that the adoption of algorithmic decision-making agents works differently. Given the nature of algorithms (limited transparency; highly skilled at specific tasks, however, incapable of performing other tasks; enabled to act and learn autonomously; difficult to motivate or incentivize) paired with the potentially high degree of agency granted to the technology, the adoption resistance stands to reason. So far, the literature has differentiated between factors that shape one's initial attitude towards the algorithm and the adoption behavior once one has become familiar with the technology (Berger et al., 2021). Our findings reveal that people's initial adoption behavior differs from how they use the technology over time.

With regard to the *overall adoption behavior*, our findings show that peer information significantly increased, while transaction costs significantly decreased adoption behavior. Thereby, we identify one previously not discussed influence that support the adoption of algorithmic decision agents: The information about others using the technology successfully. This manipulation had the strongest impact on people's adoption of the technology in our study. Here, learning about success stories and potentially the arising fear of missing out on something served as a strong motivator for technology adoption. This finding does confirm that this mechanism also works in the context of "intelligent" technological decision-agents. The implications of this finding - the positive experiences, even made by others, - tend to outweigh some of the sources of resistance that we are facing in regard to the technological decision-making agents. The results do not allow us to include what these sources of resistance are, but trust (in experience vs. in the technological agent) emerges throughout the discussion as a potential explanation – which offers an interesting avenue for future research. With regard to the *initial adoption behavior*, our findings confirm that incentives as well as low transaction costs increase the initial adoption of algorithm decision agents (Burton et al., 2020): While incentives in form of a bonus or the avoidance of additional transaction cost appear rather simple mechanisms, our results support their effectiveness in motivating initial technology adoption behavior in the context of algorithmic decision agents. Furthermore, in our setting, we do not find support for the previously identified significant initial impact of allowing users to adjust the outcome marginally (Dietvorst et al., 2018). With regard to the *adoption behavior over time*, our findings show that the adoption of algorithms increases naturally. Interestingly, the initial impact of particular influences such as peer information with the exception of transaction costs vanish as adoption rates tend to converge. Furthermore, the initial positive effect of incentivization fades over time. This indicates a temporary nature of the impact of people's algorithm aversion on their behavior. Furthermore, this research explores people's adoption behavior of AI-enabled decision-making systems. One may use the results to foster the adoption of AI-enabled algorithms in decision-making, implying a rising level of agency granted to intelligent technologies. Thereby, this research leads us to an important debate, which deserves a conscious debate within all participating academic disciplines, including information systems: To what extent is it desirable to foster AI-enabled decision making? To answer this question, we need to take many variables, including the decision-context, the level of technological agency, characteristics of the technological agent, and considerations of ethics and accountabilities into account. Based on our research, we are not in the position to provide an answer to this question. However, we consider it as our responsibility to raise this question and to encourage a more intense debate building on recent works on agency of AI (e.g., Demetis and Lee 2018), their role in human augmentation/ automation (Langer and Landers 2021; Leyer and Schneider 2021; Raisch and Krakowski 2021), and algorithmic accountability (e.g., Martin 2019a, 2019b)

5.2 Managerial Implications

Even though we acknowledge and support that blindly pushing the adoption of algorithmic decision-making agents is not desirable, we emphasize the need to understand the factors that can help us to foster algorithm adoption in managerial decision-making contexts. Our results reveal two interesting aspects that managers designing the implementation of algorithmic decision-making agents need to consider: First, to foster the initial adoption of algorithms, managers should focus on reducing transaction costs, informing about successful usage of the technology by others or make use of monetary incentives. These results may even be more interesting the design of pricing, rather than in the work context. Second, managers should provide their employees with opportunities to get to know the technology as our results reveal how algorithm adoption increases over time.

6 Limitations and Avenues for Future Research

Even though many of the technologies underlying algorithmic decision-making agents are neither path breaking nor novel, we are still exploring how users adopt these agents. This study's experimental results provide first insights into how individuals' behavior develops over time after one's initial contact with the technology. However, despite the incentive-compatible awards for the experiment's participants, these results are limited to one fictitious application context only. Our data builds on a specific investment scenario. The specific context might have caused decision biases related to the role of algorithms in financial investment decision-making. Further, before claiming the transferability of the results to decision-making in general, we would need more research on participant behavior in other decision contests. This provides an interesting avenue for future, longitudinal observations of algorithmic decision-making agents over time and in multiple decision-contexts in real-life situations. Moreover, in our best-performing instrument 'peer information' we integrated information about the number of others successfully using the algorithm, but have also given performance information of the other. Future research should measure both factors independently in order to single out each effect. Furthermore, even though many decisions are made by groups of decision-makers (e.g. committees), in this study, we limit our focus on single decision-makers only. Exploring the impact of the composition of mixed human and algorithmic decision-making groups provides additional opportunities for future research. Additionally, diving further into the underlying reasons of the strong impact of peer information displayed to potential users emerges as a promising research opportunity: Does this strengthen people's trust in the technologies' capabilities or is the behavioral reaction tied to a fear of missing out?

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