Journal of Behavioral and Experimental Economics 117 (2025) 102377

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Economics

journal homepage: www.elsevier.com/locate/jbee

The impact of process automation on performance ☆

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ARTICLE INFO

JEL classification:
C91
D63
D80

Keywords:
Automation
Performance
Management process automation
Online experiment

ABSTRACT

This paper explores how process automation affects performance, particularly in bonus-related evaluations. Using a principal–agent framework, we study the impact of predefined criteria set during system design. Specifically, we examine two scenarios in which the performance threshold for bonus payments is set either ex-ante (before performance is known) or ex-post (after performance is known). Worker performance is measured using the chosen-effort method. Our design emphasizes the role of the decision-maker in the automation process, while also considering the influence of process fairness, trust in the process, and expectations. We find that performance is significantly lower when an automated process is used, but there is no difference in performance based on who makes the decision to automate. Furthermore, we observe no variation in perceived fairness or trust between the two processes, although expectations differ. Our results suggest that while automation impacts performance, the decision-maker's role and perceptions of fairness and trust do not significantly affect the performance, but expectations do.

1. Introduction

Automated processes are taking over more and more tasks from humans. This is not only the case in manufacturing, where robots are replacing assembly line workers, but also in management, where the level of process automation continues to increase (Aharoni & Fridlund, 2007; Brynjolfsson & McAfee, 2017; Lee, 2018). One management area in which automated processes are widespread is human resources (HR) (Kim-Schmid & Raveendhran, 2022). So-called gig economy companies, such as Uber (Fu & Soman, 2021) and Amazon (Shaima et al., 2024), already depend extensively on process automation, that is, the use of technology to execute tasks with minimal human intervention. Yen et al. (2017) provide an example for such a process by arguing that a semantic model can be used to guide data collection and facilitate data interpretation and integration to support big data analysis for job performance appraisal decisions. Companies like Nissan, Geico, and Mazars use software called AssessTEAM that can automatically assess employee performance.[1]

A key element of process automation is algorithmic decision-making, whether through predefined decision criteria or through robotic process automation (RPA) or intelligent process automation (IPA) (Chakraborti et al., 2020). However, according to Cheng and Hackett (2021), HR algorithmic applications are often not grounded in strong theoretical frameworks. Instead, they are better described as heuristics — problem-solving methods that offer practical and sufficient solutions, though not necessarily optimal or perfect ones (Tversky et al., 1982). The automation of processes in HR is thus often much less about the technology used than about the process applied.

The use of technology does not necessarily change who makes the decisions, but rather when a decision is made. Hence, what ultimately distinguishes automated processes from non-automated ones is that features for automated processes must be fixed in advance to calibrate or configure the automation.[2] Although people in a non-automated decision process possess spontaneity (i.e., the ability to make a decision under absolute freedom of choice at any time), this must be relinquished to a certain extent in order to make automation possible in the first place. This ultimately reduces the influence that a person has on a decision. Therefore, unlike in a non-automated process, an automated process is inherently more rigid and less adaptable.

Researchers have started exploring the impact of process automation on workplace dynamics.[3] Automated decision-making has already

☆ This document was created on April 28, 2025, with R version 4.2.2 (2022-10-31 ucrt), on x86_64-w64-mingw32. To maintain consistency throughout the paper, the pronoun "we" is employed instead of "I".

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[1] Other examples for HR software systems are IBM Kenexa, SuccessFactors, Oracle Taleo, BambooHR, Cornerstone Performance, Reviewsnap, Trakstar, and Halogen.

[2] With machine learning and neural network approaches, more and more of these features can be defined automatically by Artificial Intelligence (AI) in the process, but it is still necessary to provide certain parameters and (training) data to the algorithm in advance, which it uses for calibration.

[3] For a literature review see Chugunova and Sele (2022).

https://doi.org/10.1016/j.socec.2025.102377
Received 29 February 2024; Received in revised form 28 April 2025; Accepted 4 May 2025
Available online 19 May 2025

been researched in hiring (Avery et al., 2024; Dargnies et al., 2024) and dismissal decisions (Corgnet, 2023). Another key area in HR is performance management, performance evaluation, and bonus assessment. Previous research has shown that, in addition to monetary payments, the process itself has an impact on performance. Using data from the German Socio-Economic Panel, Kampkötter (2017) found that a performance appraisal process conducted by the supervisor increases the worker's job satisfaction and leads to higher performance.

A literature review of more than 300 management papers on performance appraisal research conducted by Levy and Williams (2004) also indicates that not only the monetary incentive but also the performance evaluation process itself matters. Along these lines, a literature review by Villeval (2020) on behavioral and experimental research papers shows that the process itself has a positive cognitive and motivational effect on performance. Although some work was conducted on the use of automated processes related to compensations and performance evaluation (Fisher, 2019; Greenfield, 2018; Kaur & Sood, 2017; Riberolles, 2020), we are not aware of any work investigating the effects of automated processes in bonus-relevant performance evaluation on performance itself or on the perception of the process.

With the introduction of process automation and algorithmic decision-making in the performance appraisal process, the process itself changes. During a non-automated bonus-relevant performance review, the manager reviews the performance of a worker ex-post, meaning reviewing the actual performance of work after it is performed, and then decides on the payment of a bonus. This is often based on some guideline or policy but still with some level of flexibility or freedom of the manager for the final determination. In an automated process, the criteria for the bonus payment are already set ex-ante to the performance, meaning before the actual work is performed. Based on these rigid criteria, the bonus is then paid or not once the work is performed, without the flexibility to take additional criteria into account that might not have been considered during the design or implementation of the algorithm in the process automation.[4]

We address two research questions. First, how does an automated bonus evaluation impact worker performance?[5] Second, does an automated bonus evaluation hinder or enhance workers' perceptions of procedural fairness, trust in the process, and alignment with expectations? Answering these questions allows us to assess whether algorithmic involvement in bonus evaluations can be successfully integrated into business processes. In fact, successful implementation will not be possible if automated bonus evaluations lead to reduced performance, diminished feelings of procedural fairness and trust, and mismatched or divergent expectations.

We mimic these differences by introducing a principal–agent game where the agent acts as a worker and the principal acts as a manager with two different roles, depending on the setup. In the non-automated process situation, the manager reviews the worker's performance and decides whether a bonus is paid. In the automated process situation, the manager determines the criteria that are to be used by the algorithm, before the actual performance of the worker is known to the manager. The bonus paid to the worker does not affect the manager (i.e., the bonus is paid by the experimenter). To exclude different levels of motivation or avoidance and fatigue effects that may arise from a real effort task and potentially impact performance, workers determine their performance with the help of the chosen-effort method. To enhance consistency and reliability and make efficient use of participant resources, we employed the strategy method. By gathering responses to various scenarios simultaneously, the strategy method reduces the variability that can come from contextual or temporal factors.

To determine the potential root cause of the performance disparity between an automated decision process and a non-automated decision process, we employ two different treatments. In the first treatment (treatment *SYSTEM*), the decision to utilize either the non-automated or automated process is made randomly, representing an impersonal and somewhat intangible decision maker, such as a company in a real-life scenario. In the second treatment (treatment *HUMAN*), the decision is made by a directly accountable being, the manager.

We expect performance to be lower in an automated decision process than in a non-automated decision process and that there will be a performance difference between the two treatments. This is because the manager's decision to actively choose an automated process may be perceived as a deliberate avoidance of information and an intentional relinquishment of direct control over the bonus decision. Such effect is much lower, if existing at all, if the decision is made outside of the influence of the manager. We also anticipate that automation will reduce procedural fairness and trust if the process is automated while the threshold expectation for receiving a bonus would remain unchanged by the (non-)automation of the process.

The study provides three main findings. First, we find a notably lower performance when employing an automated process. Second, we find no difference in performance based on who decides to use automation. This suggests that the performance remains the same regardless of whether the decision to use an automated process is made by the manager or randomly. Third, although workers' evaluations of procedural fairness and trust in the bonus process do not differ significantly between the two procedures, we find significant differences in their expectations regarding the bonus threshold. In other words, while workers rate both processes similarly in terms of fairness and trust, they expect a different minimum performance level for bonus eligibility depending on whether the process is automated or not. Thus, the drop in performance when employing an automated process cannot be predominantly linked to issues of fairness and trust in the process; instead, it seems to be more closely associated with divergent expectations.

2. Related literature

Our experiment connects to the literature on bonus incentives and control, and algorithmic engagement in personnel issues.

2.1. Bonus incentives and control

A body of experimental literature explores the influence of bonus incentives and control on performance and indicates that performance is sensitive to the level of control. Fehr et al. (2007), for example, find bonus contracts that rely on fairness and trust as an enforcement device to be more efficient and more profitable than incentive contracts enforced by the courts. In their experiment, the principal was able to choose a mechanism to enforce a specific performance from the

[4] One could also view this as policy, institution, or contract design. For instance, many companies establish guidelines wherein a worker is rewarded with a bonus upon achieving a performance target. Although drawing parallels among policies, laws, and algorithms can be intellectually stimulating and underscore their roles as rule-based systems designed to achieve specific outcomes, it is crucial to acknowledge the fundamental distinctions in their natures, purposes, and the processes involved in their creation and evolution. Policies, laws, and algorithms function by adhering to predefined rules. Although policies and laws form sets of rules governing behavior within a society, algorithms represent systematic procedures for automated reasoning tasks. Laws and policies are crafted to be interpreted, allowing for discretion and sometimes adaptability based on context and precedents. In contrast, algorithms, executed by computers, operate in a deterministic or probabilistic manner according to their design, without room for interpretation during execution. With machine learning and neural network approaches, more and more of these features can be defined automatically by AI without being hard coded into the system, but it is still necessary to provide certain parameters and (training) data to the system in advance, which the algorithm uses for calibration.

[5] In the context of this paper, we assume that effort is directly tied to performance.

agent with the support of a third party or to announce a non-binding, voluntary bonus payment instead, if the agent's performance was satisfactory. The results show that a non-binding, voluntary bonus payment leads to higher performance than an explicit incentive contract that fines the agent for unsatisfactory performance. Fehr and Rockenbach (2003) and Fehr and List (2004) show that the principal's decision to use a punitive device leads to a decrease in the agent's performance in Trust Games. Moreover, using a chosen-effort setup in a principal–agent experiment, Fehr and Schmidt (2007) find, that bonus payments increase performance and are more efficient than fixed-wage contracts and contracts that include the possibility of punishing the worker for poor performance. In a chosen-effort experiment conducted by Falk and Kosfeld (2006), the agent had to choose a costly performance that benefited the principal while the principal had the choice to either control (i.e., enforce a minimum performance) or trust the agent. The results show that the majority of the workers reduced their performance because most workers perceived control as a signal of distrust and low expectations by the principal. The performance of the agent was also higher if control was executed by a third party instead of directly by the principal. Kajackaite and Werner (2015) build upon the finding that control has a counterproductive effect on performance provision by showing that the principal's active decision to control affects the agent's kindness perception and triggers reciprocal responses. However, they find no significant change in the average output level in a real-effort experiment if the principal decides to implement a minimum performance requirement.

The effect of control on performance seems to also be influenced by who is exercising control. Schmelz and Ziegelmeyer (2015), for example, show that the effect of control depends on the closeness between the agent and the principal. By running a principal–agent game on the internet as well as in a laboratory, they find that exercising control is less likely to reduce work performance in a remote setting than in a laboratory setting. Control can be exerted not only by the principal but also by a third party. Burdin et al. (2018) found workers show higher performance if principals abstain from control than when a third party decides not to control. We are unaware of any prior studies that examine the impact of process automation, which limits control, on performance. Our study aims to fill this gap in the literature.

2.2. Algorithmic engagement in personnel issues

A range of experimental studies examine the effects of automation in personnel issues. One area of research focuses on the acceptance and impact of automation in the monitoring, hiring, and dismissal processes. Raveendhran and Fast (2021) explore computerized tracking tools in the workplace. Across five vignette studies conducted both online and in a laboratory, they found that participants were more likely to accept tracking managed by technology rather than by humans regardless of whether the tracked behaviors were job-related. Tracking operated by humans was seen as more controlling and diminished workers' motivation. Further, Avery et al. (2024) investigate through two field experiments whether using AI in recruitment significantly boosts diversity, impacting both the supply and demand sides. Specifically, they posted an actual job opening for a web designer and invited job seekers to apply. The then randomly varied whether the job seekers were informed that their application would be evaluated by AI software or a hiring team and found that AI recruitment tools increase the number of highly qualified female applicants. On the demand side, they find that evaluators scored women significantly lower than men when gender-revealing names are visible but equally when names are concealed. However, the introduction of AI scores eliminates this gap even when evaluators can infer gender from the names. Dargnies et al. (2024) consider in a series of online experiments the perspectives of both workers and managers on automated hiring decisions. Participants are allowed to choose whether the hiring decision between themselves and another worker is made by a participant acting as a manager or by an algorithm, utilizing three real-effort tasks. The researchers find that when the algorithm does not consider workers' gender to predict job-task performance, and workers are aware of this, they tend to prefer the algorithm more often than in the baseline treatment where gender is taken into account. In contrast, managers typically favor making hiring decisions themselves instead of relying on the algorithm. Furthermore, sharing information about how the algorithm operates does not increase the preference for it among either workers or managers. Fumagalli et al. (2022) investigate how information regarding workers' performance affects their choice of recruiter and whether the algorithmic recruiter is viewed as more or less gender-biased than the human recruiter. They assess the willingness to pay for either human or algorithmic evaluations in a real-effort task through two incentivized online experiments. The findings reveal that human and algorithmic recruiters received different ratings even when both used the exact same information for their hiring decisions. Human recruiters are seen as processing information in a more biased and error-prone way, placing greater emphasis on personal characteristics. In contrast, algorithmic recruiters are viewed as more transparent and more focused on task performance. However, workers do not exhibit a clear preference for one type of recruiter over the other. This suggests that workers have diverse preferences for recruiters, with those assigned to an algorithmic recruiter when they preferred a human experiencing greater welfare losses than those assigned to a human recruiter when they favored the algorithm. Additionally, Corgnet (2023) examine how workers react to dismissals made by algorithms compared to those made by humans. In a laboratory experiment varying the type of a real-effort task (measurable, non-measurable, bias, or handicap task), either a human or an algorithm decides which of two workers to dismiss. The algorithm automatically identifies and dismisses the least productive worker, while human managers have complete discretion in their choices. For instance, in the handicap task, human managers has the option to overlook performance metrics and reward the effort of the disabled worker, unlike algorithms. The results show that workers tend to respond more negatively to dismissals made by humans than by algorithms, depending on performance across different task types. Interestingly, non-fired workers generally performed better after being selected by a human manager than after being chosen by an algorithm; however, this difference was not significant for most tasks. This suggests that algorithms could help reduce negative reactions to dismissals, but it also raises concerns that they might undermine the positive impact of promotions on worker morale.

Another area of research specifically centers on algorithmic engagement in the performance appraisal process. Lee (2018) find in a vignette study, where the decision-maker (algorithmic or human) in four managerial tasks (work assignment, scheduling, hiring, and evaluation) was manipulated, that if an algorithm is used to conduct a performance review, the process is judged as less fair and trustworthy. The effect is moderated by the algorithms' perceived lack of intuition and subjective judgment capabilities. Although algorithmic decisions were perceived as less fair and trustworthy in tasks that need more subjective judgment and emotional capacities, they are perceived to be equally fair and trustworthy in mechanical tasks. Newman et al. (2020) confirm in a vignette study the finding that people judge an automated performance review process to be less fair, and document that this might be due to reductionism and procedural fairness concerns. The authors argue that automating the performance review process reduces the qualitative aspects of the performance to quantifiable metrics (i.e., quantification) and thus fails to evaluate performance in a broader context (i.e., decontextualization). Consequently, decisions by algorithms are perceived to be based on less accurate (i.e., incomplete) information than those made by humans and are thus perceived to be less fair.

Our experiment builds upon prior research that shows automated processes are perceived differently than non-automated ones, and it adds to the literature by utilizing an incentivized experimental design to explore the effects of algorithmic involvement in the performance appraisal process. Additionally, we analyze the decision-maker's role in implementing algorithmic engagement.

The remainder of the paper is organized as follows: Section 3 describes the experimental design. Section 4 then relates the experiment to the theoretical background and provides detailed research hypotheses. Section 5 reports our results, and Section 6 concludes. The Appendix contains several appendices with, among others, the experimental instructions and complementary statistical analyses.

3. Experimental design

We implemented an experimental design based on a multi-tiered principal–agent framework, an automated and a non-automated decision process, two treatments, and a questionnaire.

3.1. Automated and non-automated decision process

The design of the game is inspired by the principal–agent game with two stages by Falk and Kosfeld (2006). The agent represents the worker being evaluated, and the principal represents the manager. The worker engages in a productive activity that is costly to the worker but beneficial to the manager; the worker has an initial endowment of 120 points (1 point = \$0.01) while the manager's initial endowment is 0 points. The worker, in turn, chooses their performance x in the productive activity, and the cost of the performance for the worker is $c(x) = x$; the manager earns twice the worker's performance $p(x) = 2x$. We expand upon this framework by adding a bonus system. In the bonus system, the manager sets a performance threshold x_t that the worker must reach in order to receive a bonus $b^* \in \{0, 120\}$. We employ a binary mechanism because it simplifies the process for the worker to develop expectations about the bonus payment compared to a more complex mechanism. The bonus b^* is paid by the experimenter.[6] The worker receives the bonus if $x \geq x_t$. Thus, the payoff functions are $\prod_P = 2x$ for the manager and $\prod_A = 120 - x + b^*_{x_t}$ for the worker.

To replicate the automation element, the principal functions in one of the following roles depending on the setup. In the non-automated decision process, the principal acts as the superior assessing the performance and decides on the bonus threshold ex-post after knowing the worker's actual performance, similar to a classical, non-automated performance evaluation, wherein the actual performance of a worker is reviewed after it is performed. In the automated decision process, the principal defines the bonus-relevant performance threshold used in the algorithm.[7] Therefore, the principal in the automated decision process decides on the bonus-relevant performance threshold before (ex-ante) knowing the actual performance of the worker, akin to an algorithmic decision process where decision parameters must be predetermined for algorithm calibration ahead of the actual performance of the work. More formally speaking, the manager knows the worker's performance x before determining the threshold x_t for the worker to get the bonus b^* in the non-automated decision process but not in the automated decision process.

3.2. Treatments

Depending on the treatment, the choice to use either the non-automated or automated decision process system is made by either the manager (treatment *HUMAN*) or an automated third party (treatment *SYSTEM*). In treatment *HUMAN*, the manager freely chooses between using a non-automated and an automated decision process. In treatment *SYSTEM*, a random mechanism determines, with a 50% probability, whether to utilize either the automated or the non-automated decision process. The automation itself is not directly manipulated by the treatments. Instead, the occurrence of automated versus non-automated decisions processes differs between the treatments because the managers in treatment *HUMAN* might not decide with a 50% probability as the *SYSTEM* does. However, this only affects the number of observations per decision process because we apply a between-subject design for the treatments and a within-subject design for the performance.

Table 1
Procedure.

Stage 1	Human test, instructions, group matching, role assignment
Stage 2	Control questions
Stage 3	Worker decides about performance (chosen-effort method) Manager decides about decision process (treatment *HUMAN*)
Stage 4	Manager decides about bonus threshold
Stage 5	Questionnaire

3.3. Measurement of perceived fairness and trust

After the managers and workers made their choices for the effort and threshold, but before they were informed about the final performance and payoff, workers were asked about the perceived procedural fairness of the process as well as their trust in the process to receive a bonus. We use these questions as a proxy for the perceived fairness of and trust in the process. Because participants could refer to different concepts of fairness, we followed Konow (1996) and used a simplified dichotomous scale to measure the perceived overall subjective process fairness. Following debate over the length of the scale, we settled on a four-item scale to measure trust in the process for receiving a bonus (see Bauer & Freitag, 2018). To account for the possibility that trust in the process and fairness measurements are mainly driven by diverging expectations in an automated decision process versus a non-automated one, we also asked workers to state their expectations about receiving the bonus in both processes.[8] Workers also have the option of explaining in an open-ended question why they chose a specific performance. Finally, participants are asked about their general risk (Dohmen et al., 2011) and general trust preferences (Sturgis & Smith, 2010), their age, and their gender. All questions can be found in Appendix A.9.

3.4. Procedure

The experiment was conducted online via Amazon Mechanical Turk (MTurk), a website for crowdsourced labor, using oTree (Chen et al., 2016). The participants had to have completed at least 100 so-called human intelligence tasks (HITs) on MTurk and needed an approval rate of 99% for their completed HITs to take part in the experiment. The purpose of these requirements was to ensure the successful execution of the experiment because a premature departure from the study could potentially affect its feasibility. Furthermore, these requirements enabled a certain level of control over the pool of participants, which, in turn, influenced the quality of the generated data. All experimental stimuli and instructions were presented through a computer interface. The framing was done as neutrally as possible, avoiding any loaded terms. Participants received a participation fee of \$0.50 in addition to the money they earned during the experiment.

As Table 1 shows, participants went through five different stages. In Stage 1, all participants had to pass a human test to ensure that

[6] Should the manager grant a bonus in a way that involves some cost to themselves, this would resemble an employment relationship more in line with a trust game, as observed in Schniter et al. (2020).

[7] In a real-world scenario, this would happen during the design/implementation phase of the algorithm.

[8] Workers' expectations about the performance threshold are not incentivized to avoid hedging between the decision about the transfer amount and the expected payoff resulting from accurate expectations.

Table 2
Preferred performance (x) according to social preferences.

Social preference	Performance preference (x)
Selfishness	0
Efficiency	120
Fair split	~60
Equality	~80

only humans participated in the experiment and received the experiment instructions. In this test, the participants had to add two 2-digit numbers and write the correct answer in an input field. Participants who passed the human test were randomly assigned to a group of two as well as to a role and were provided with the experimental instructions.[9] Each group consisted of one worker (Participant A) and one manager (Participant B). In Stage 2, all participants had to answer a set of control questions and needed to pass them to confirm their comprehension of the instructions before proceeding. If the test was not passed on the first attempt, there was an opportunity to re-read the respective passage from the instructions and then retake the test. In Stage 3, depending on the treatment, managers had to make a decision about whether a non-automated or an automated decision process would be used. The order in which both systems were presented was randomly alternated for each participant in both treatments to control for potential order effects. The chosen-effort method was used to elicit the agent's performance as it provides a more streamlined, cost-effective, and controlled approach for studying economic decisions related to effort, particularly when the focus is on theoretical preference, choice behavior, or response to incentives rather than on physical or task-specific performance.[10] It also offers the opportunity to examine the effect on performance of both the non-automated and the automated decision process. Thus, using a strategy method, we asked workers to report their performance under both the non-automated and the automated decision process conditions.[11] In Stage 4, managers had to decide on the bonus threshold that had to be reached to get the bonus either before (automated decision process) or after (non-automated decision process) knowing the performance of the agent. In Stage 5, participants were questioned regarding their perceptions of the process's fairness as well as their general risk aversion and general trust level. Workers were asked about their threshold expectation and how trustworthy and fair they perceive the process after obtaining knowledge about the process relevant to their payoff but before the actual payoff was communicated. Additionally, demographic data was gathered.

4. Behavioral predictions

As predicted by standard economic theory, specific performances of workers are more likely to occur. Table 2 shows four social preferences, indicating that workers might prefer certain performances over others.

Assuming purely selfish preferences, the manager would not care whether the worker receives a bonus or not. Under this condition, workers maximize their payoff by choosing a transfer of $x = 0$. Assuming efficiency preferences, the worker and the manager strive to maximize overall social welfare. The worker would transfer $x = 120$ points, and the manager ensures a bonus payment of $b^* = 120$. Assuming that the worker expects the probability for receiving a bonus to depend on the transfer, a more detailed analysis is required.

If the manager attaches importance to a fair split, the manager might demand an equal split of the agent's initial endowment and therefore prefers the worker to choose a performance of $x \approx 60$.

If the manager's utility is negatively influenced by an unequal outcome (e.g., Bolton & Ockenfels, 2000; Fehr & Schmidt, 1999), the manager would want the worker to choose a performance roughly around $x \approx 80$, ensuring an overall equal outcome.

A utility-maximizing worker would therefore anticipate the preferences of the manager and choose a performance that matches the anticipated expectation set by the manager.[12]

Research shows that people seem to accept or even prefer automated decisions for analytical tasks (Bai et al., 2022; Cormier et al., 2013) but not for social tasks (Bigman & Gray, 2018; Castelo, 2019; Hertz & Wiese, 2019; Lee, 2018; Waytz & Norton, 2014).[13] This may be due to the fact that automated decisions on subjective issues are perceived differently than human decisions are.

If individuals perceive an automated decision process worse than a non-automated decision process, they might react by reducing their performance across all four social preference patterns. Hence, the agent's performance is expected to be lower in an automated decision process than that in a non-automated decision process (Hypothesis 1).

Hypothesis 1. In an automated decision process, workers demonstrate a reduced level of performance compared to that in a non-automated decision process.

Workers might also value the fact that the manager is directly controlling whether the bonus is paid or not and feel more appreciated if the decision is made knowing the actual performance. This enables direct adjustments, a factor found to influence procedural fairness (e.g., Colquitt, 2001). Research on intention-based reciprocity by Dufwenberg and Kirchsteiger (2004), Falk and Fischbacher (2006), and Rabin (1993), also shows that people tend to reward kind intentions and punish unkind ones. By actively choosing an automated decision process, the manager abstains from directly controlling whether a bonus is going to be paid because he or she decides not to know the worker's performance before determining the performance threshold to receive a bonus. The manager thus actively shows information-avoidance behavior. In this respect, the manager's decision to use an automated decision process could be perceived as a lack of interest in or appreciation for the worker's performance. Therefore, the worker might reciprocate by choosing a lower performance level if the manager decides to use an automated decision process. However, if a third party instead of the manager decides whether to use an automated or a non-automated decision process, the worker's reaction based on reciprocity can be expected to be less pronounced because of the lack of a direct counterpart to hold accountable for the decision.

Based on the considerations above, workers are expected to show a higher performance level if the manager decides to use a non-automated decision process compared to that when an automated third

[9] Instructions can be found in Appendix A.8.

[10] In a meta-study on performance measures in economic experiments (Charness et al., 2018) find qualitatively similar results for real-effort and stated-effort designs. Results from former experiments, for example by Brüggen and Strobel (2007), also confirm the alignment between the effort chosen and the actual effort expended in experiments.

[11] Theoretically, the strategy and direct-response methods are equivalent. However, the strategy method is sometimes seen as less emotionally intense, which could potentially influence observed behaviors. However, a survey on the literature on the strategy versus direct-response method by Brandts and Charness (2011) consistently finds that any treatment effect identified through the strategy method is also observed when employing the direct-response method.

[12] Models of social image concerns (e.g., Andreoni & Bernheim, 2009; Bénabou & Tirole, 2006) and concepts of self-perception maintenance (e.g., Beauvois & Joule, 1996; Rabin, 1995) suggest that individuals perceive an unpleasant tension or disutility if their actions cause harm to their social concept and/or self-concept of being a kind and fair individual. Thus, the performance of the worker may also be influenced by self- and social-image concerns, as well as risk preferences.

[13] For extensive literature reviews on the effects of decision automation in human resource management, see Langer and Landers (2021), Meijerink et al. (2021), and Vrontis et al. (2022).

party chooses the non-automated decision process. Correspondingly, workers' performance is expected to be lower if the manager decides to use an automated decision process compared to that when an automated third party chooses the automated decision process (Hypothesis 2).

Hypothesis 2. If the manager decides on the process, workers show a

(i) higher performance in a non-automated decision process, and
(ii) lower performance in an automated decision process

than if a third party decides on the process.

Previous research has demonstrated that factors such as personableness (Kaibel et al., 2019), process fairness (Lee, 2018; Nagtegaal, 2021; Newman et al., 2020; Wang et al., 2020), and trust (Castelo, 2019; Waytz & Norton, 2014) are perceived differently in automated decisions than in human decisions.[14]

Studies on procedural justice indicate that people view decision processes as fairer when they are consistent, based on accurate information, and free from bias (Levanthal, 1980; Thibaut & Walker, 1975). At the same time, experimental studies suggest that automated decisions are often seen as more rigid and decontextualized (e.g., Newman et al., 2020; Ötting & Maier, 2018) or overlooking the unique traits of individuals (Longoni et al., 2019). However, the results are mixed regarding procedural fairness. While some studies find algorithms to be procedurally fairer, others have found them to be perceived as less fair compared to human decisions. In this regard, the context of a task may influence fairness perceptions. In situations where human decisions could be perceived as biased, such as in hiring contexts (Avery et al., 2024) or work assignments (Bai et al., 2022), algorithms score higher on procedural fairness. A reason for this might be that they cannot change their decisions at will and are seen as inherently unbiased whereas humans may display favoritism. However, in contexts involving moral considerations or redistributive decisions (Chugunova & Luhan, 2024; Gogoll & Uhl, 2018; Lee, 2018; Newman et al., 2020), algorithms score lower on procedural fairness because their can be seen as reductionist, and failing to account for qualitative information and context. Thus, there seem to be different factors that come into play to determine the fairness of a process.

In the redistributive decision in our experiment, the agent has to send some of the initially owned points to the principal. When the principal is evaluating such a transfer, there is a possibility of "human flexibility". In the automated treatment, a worker will never receive a bonus if she or he transfers an amount slightly below the ex-ante determined threshold. However, in the non-automated treatment, the manager can change his or her decision at will by adjusting the threshold, based on his or her knowledge the actual transfer amount for the worker to receive a bonus, even if the initial intention of the manager was to set a slightly different bonus threshold. This is especially true because the manager has nothing to lose when changing the threshold compared to her or his initial intention. Although the task in the experiment and the transparency of the process remains the same, the decision-making process changes. Automated decisions are based on standardized processes and built upon predetermined rules that are programmed ex-ante to the occurrence. Non-automated decisions are more situation specific and can consider the actual effort of the worker. In the context of our experiment, two specific factors become particularly relevant. First, the decision is no longer an individual decision ex-post to the performance but rather a rigid ex-ante benchmark that was set before knowing the performance. Hence, the decision is disassociated from the real performance. Second, automation offers the chance to free managers from the immediate decision-making process by setting the thresholds in advance. Based on the factors discussed above, we anticipate that in an automated decision process the procedural fairness (Hypothesis 3) and trust in the process (Hypothesis 4) is lower than in a non-automated decision process.[15]

Hypothesis 3. In an automated decision process, workers perceive lower procedural fairness compared to that in a non-automated decision process.

Hypothesis 4. In an automated decision process, workers perceive a reduced level of trust in the process compared to that in a non-automated decision process.

Because automation does not necessarily change who decides but rather when a decision is made, the expectations regarding the performance threshold to receive a bonus should not change. This is also not impacted by the possibility that the manager adjusts the threshold based on the actual performance in the non-automated treatment, as such adjustments could go in both directions, meaning the threshold could be set below or above the actual performance. The perception of the worker for trust and fairness should also not influence the threshold that is set by the manager. As the action of the manager ('setting the threshold') is not influenced by the worker's perception, the expectation of the worker about the action should not be influenced by the perception of the overall process. Thus, we do not predict a difference in the expectation for the performance threshold between an automated and a non-automated process. Therefore, the expectation regarding the performance threshold to receive the bonus should remain the same (Hypothesis 5).

Hypothesis 5. In an automated decision process, workers maintain similar expectations regarding the performance threshold for receiving a bonus as in a non-automated decision process.

5. Results

Overall, 508 participants (43.3% female) contributed to the study. As Table 3 shows, 256 participants (41.7% female) were in treatment *HUMAN* and 252 participants (44.9% female) were in treatment *SYSTEM*. Half of the participants took on the role of workers (254 participants) while the other half assumed the role of managers.[16] There was an equal distribution between managers and workers for each of the numbers presented in Table 3. The participants were on average 37 years old.[17] The study took about 10 min to complete, and the participants earned on average \$1.73. The average threshold was set to 68.1 points, the average relevant performance of the workers was 58.23 points, and 57.1% of the workers received a bonus. Because we used a between-subjects design for the treatments and a within-subject design to elicit the workers' performance, the data for statistical tests is independent between but dependent within treatments.

In the following section, we compare the performance in the non-automated decision process with that in the automated decision process within and between treatments. We then analyze the workers' perceived fairness of and trust in the process as well as their expectations about the threshold.[18]

[14] For comprehensive reviews of the literature on factors influencing automation, see Chugunova and Sele (2022) and Langer and Landers (2021).

[15] Trust in the process might serve as a proxy for general trust.

[16] 14 workers left the experiment directly before answering the questions in stage 5. This is a well-known challenge for online experiments, as control over participants is limited. In the treatment *HUMAN*, 9 workers did not answer the questions (3 in automated, 6 in non-automated). In the treatment *SYSTEM*, 5 workers did not answer the questions (3 in automated, 2 in non-automated). If a worker departed before answering the questions, they are excluded from the analysis of the questions but included in the performance analysis.

[17] An analysis of the demographics can be found in Appendix A.1.

[18] An analysis of the managers' behavior can be found in Section 5.5 and Appendix A.6.

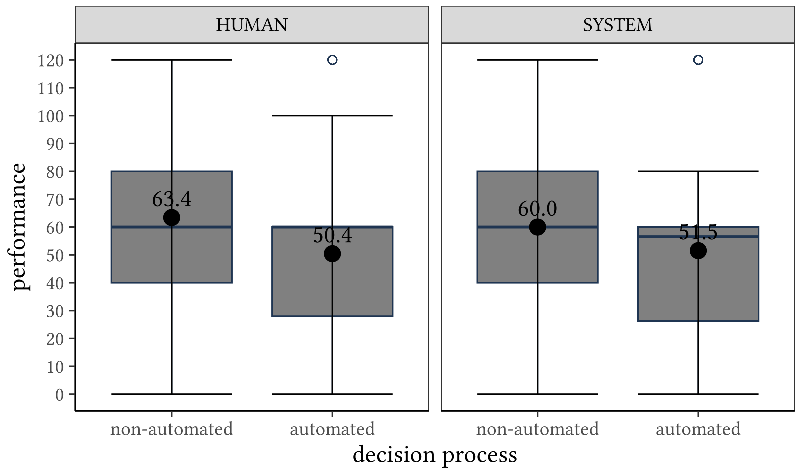

Fig. 1. Box-and-Whisker plots for workers' performance.
Note: For all Box-and-Whisker plots in this paper, the boxes indicate the interquartile range (IQR), the horizontal line indicates the median, the filled dot indicates the mean, the whiskers indicate 1.5 × IQR and unfilled dots indicate outliers.

Table 3
Number of participants per process type and treatment.

	Non-automated	Automated	Total
HUMAN	200	56	256
SYSTEM	124	128	252
Total	324	184	508

Table 4
Differences in the workers' performance between treatments.

	HUMAN	*SYSTEM*
Non-automated − automated	$\Delta = 12.98$ ($p = 0.0000$)	$\Delta = 8.47$ ($p = 0.0001$)
	$\Delta = 10.74$ ($p = 0.0005$)	

Note: The table shows p-values for a two-sided Wilcoxon signed-rank test/Wilcoxon rank-sum test.

5.1. Hypothesis 1: Performance depending on automation

As Fig. 1 shows, most workers selected a performance level close to half of the initial endowment of 120 points. However, workers' performance in the non-automated decision process is higher than that in the automated decision process in both treatments.[19] Table 4 shows the performance difference between the non-automated decision process and the automated decision process, and confirms that the workers' performance is significantly higher in the non-automated decision process than in the automated decision process in both treatments. Hence, Hypothesis 1, i.e., that the performance level is diminished in an automated decision process compared to a non-automated decision process can be confirmed.

5.2. Hypothesis 2: Performance depending on who decides to automate

According to Hypothesis 2(i) a worker's performance should be higher in the non-automated decision process and, according to 2(ii) lower in the automated decision process in treatment *HUMAN* compared to those in treatment *SYSTEM*. Indeed, this is what we see in Fig. 1. Workers' performance in treatment *HUMAN* in the non-automated (automated) decision is higher (lower) than that in treatment *SYSTEM*. However, as Table 5 shows, the difference is not statistically significant either in the non-automated or the automated decision. Thus, neither Hypothesis 2(i) nor 2(ii) cannot be confirmed.

[19] A detailed analysis of the workers' performance can be found in Table 21 in Appendix A.5.

Table 5
Performance differences between treatments.

	HUMAN − *SYSTEM*
Non-automated	$\Delta = 3.42$ ($p = 0.1194$)
Automated	$\Delta = -1.09$ ($p = 0.5028$)

Note: The table shows p-values for a one-sided Wilcoxon rank-sum test.

Table 6
Workers' answers to the question: "Do you consider the procedure to get the bonus to be fair?" (see Question 6 from Appendix A.9).

	Non-automated	Automated
	($p = 0.7725$)	
YES	83.77% (129)	81.40% (70)
NO	16.23% (25)	18.60% (16)

Note: The table shows p-values for a Chi-squared test.

5.3. Hypothesis 3 : Perceived fairness of the process

As Table 6 shows, the fairness assessments by workers do not differ significantly between the non-automated decision process and the automated decision process. Thus, workers do not perceive one process to be fairer than the other, so Hypothesis 3 (that workers perceive lower procedural fairness in an automated decision process than that in a non-automated decision process) cannot be confirmed.[20]

5.4. Hypothesis 4 : Perceived trust in the process

Table 7 shows that most workers expected to get a bonus, but workers' expectations about receiving a bonus did not differ significantly between the non-automated decision process and the automated decision process.[21] Hence, Hypothesis 4 (that workers perceive a reduced level of trust in an automated decision process compared to a non-automated decision process) cannot be confirmed.

5.5. Hypothesis 5 : Expectation about the performance threshold

As Fig. 2 shows and Table 8 confirms, workers in both treatments expect the threshold required to receive a bonus to be significantly

[20] The fairness assessment by the manager can be found in Table 23 in Appendix A.7. The fairness assessment by workers and managers by treatment can be found in Table 19 in Appendix A.3.

[21] The perceived trust in the process to receive a bonus by treatment can be found in Table 20 in Appendix A.4.

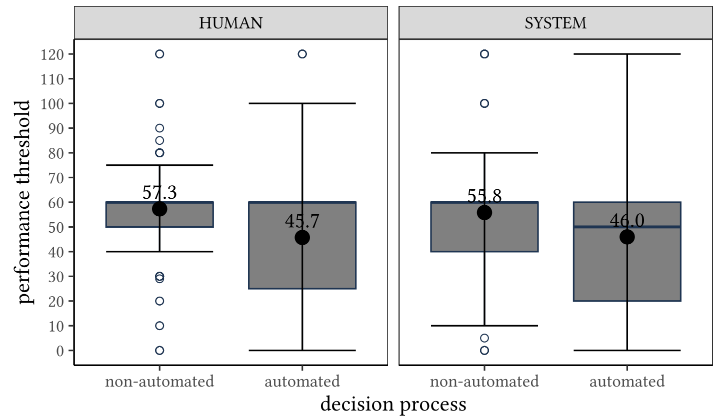

Fig. 2. Box-and-Whisker plots for workers' expectations about the performance threshold set by the manager (see Questions 3 and 4 from Appendix A.9).

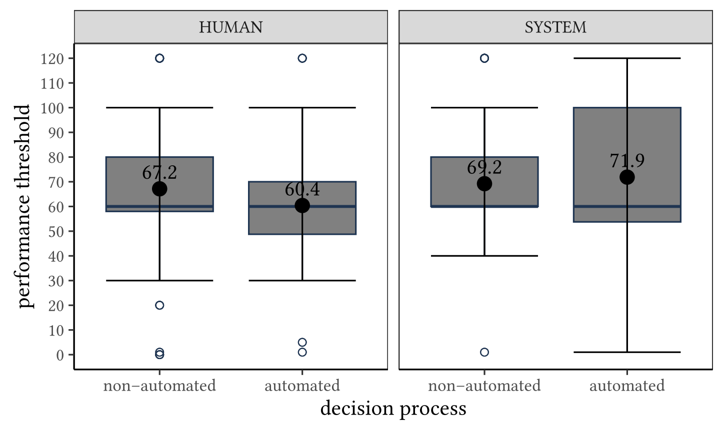

Fig. 3. Box-and-Whisker plots for performance thresholds set by managers.

Table 7
Workers' agreement with the statement: "I think that i will get a bonus" (see Question 5 from Appendix A.9).

	Non-automated	Automated
	(p = 0.6398)	
Strongly agree	14.3% (22)	11.6% (10)
Agree	71.4% (110)	70.9% (61)
Disagree	12.3% (19)	14% (12)
Strongly disagree	1.9% (3)	3.5% (3)

Note: The table shows p-value for a Cochran-Armitage test for trend.

Table 8
Differences in workers' expectations about the performance threshold (see Questions 3 and 4 from Appendix A.9).

	HUMAN	*SYSTEM*
Non-automated − automated	Δ = 11.57 (p = 0.0000)	Δ = 9.86 (p = 0.0001)
	Δ = 10.71 (p = 0.0000)	

Note: The table shows p-values for a two-sided Wilcoxon signed-rank test/Wilcoxon rank-sum test if the difference could be zero.

higher in the non-automated decision process than in the automated decision process. Hence, Hypothesis 5 (that workers will have the same expectation about the performance threshold in both processes) cannot be confirmed.

Interestingly, workers anticipate a different performance threshold in both processes, but the actual threshold set by the managers does not differ significantly. As Fig. 3 shows and Table 9 confirms, the performance threshold set by the managers in the automated decision process does not differ significantly from the performance threshold set in the non-automated decision process in both treatments.

Table 9
Differences in the managers' performance threshold set between the Non-automated and the Automated decision process.

	HUMAN	*SYSTEM*
Non-automated − automated	Δ = 6.76 (p = 0.1953)	Δ = −2.65 (p = 0.8511)
Non-automated	Δ = −2.08 (p = 0.9565)	
Automated	Δ = −11.49 (p = 0.2283)	

Note: The table shows p-values for a two-sided Wilcoxon signed-rank test/Wilcoxon rank-sum test if the difference could be zero.

The performance thresholds set in the automated decision process in treatment *SYSTEM*, however, are more dispersed than those in the other conditions. Managers in treatment *HUMAN*, who decide independently which approach to use, also do not set significantly different performance thresholds than managers in treatment *SYSTEM*, wherein an automated third party randomly decides which approach to use.

6. Conclusion

The number of automated management tasks has notably increased recently. Here, we report a first attempt to evaluate the impact of such process automation on performance. More specifically, we focus on the perceptions of individuals regarding automated processes in management tasks and whether these perceptions influence human performance. Our study design emphasizes the impact of process automation, with a focus on process rigidity. It centers on performance and whether performance is influenced by who decides to automate a process: the direct manager or a more remote third party. Additionally, we investigate procedural fairness, trust in the process for receiving a bonus, and expectations.

Earlier research has demonstrated that factors such as control, trust, and fairness play a significant role in influencing performance (Burdin et al., 2018; Falk & Kosfeld, 2006; Fehr et al., 2007; Fehr & Schmidt, 2007; Kajackaite & Werner, 2015; Schmelz & Ziegelmeyer, 2015). In our paper, we find that automation similarly influences performance.

First, our results show that performance is significantly lower under an automated than under a non-automated decision process. Furthermore, performance is higher in the non-automated decision process and lower in the automated decision process if a human rather than an automated third party decides to use the automated process. However, although the deviation aligns with the hypothesized direction, it lacks statistical significance. Nevertheless, the results could be seen as a preliminary step in exploring how the decision-maker's role influences performance in the context of automation.

Second, even though we did not find fairness and process trust issues to be decisive factors in this context, automation was found to influence performance, shaped by divergent expectations. Although the perceived fairness of both processes and trust in the process to receive a bonus do not differ significantly between the two processes, there is a significant difference in the expectations about the bonus threshold. Given that the decision-maker remains unchanged and only the decision-making process undergoes modification, one would expect that the expectations about the threshold would remain unchanged. This is, however, not the case, because the results reveal a significant disparity in expectations between the two processes.

Participants expect a significant difference in the threshold between the non-automated and automated processes, with a higher threshold in the non-automated scenario, regardless of who decides to use the automated process. The threshold expectation in the non-automated scenario is closer to a fair split and the actual threshold set by the managers. This could be an indication that the participants expect that a threshold will be lowered when automation is introduced. A potential reason for this expectation might be that in the non-automated scenario, a manager could grant a bonus even for a performance slightly under their initially intended threshold by lowering the actual threshold, after knowing the actual performance. In the automated scenario, the lack of human flexibility and hence the increased rigidity of the process might fuel the hope of the participants that the managers would account for this by setting a lower threshold in the automated scenario. Further analyses, however, show that this is not the case. The thresholds set by managers in both the non-automated and the automated decision process are essentially the same. In simple terms, the findings suggest that people hold differing expectations in an automated process than in a non-automated one, but these expectations are inaccurate. The subsequent change in willingness to perform could be linked to these altered expectations. Further research is needed to evaluate the reasons behind this difference in expectations.

Additionally, the results could be seen as indications of algorithm aversion, with managers expressing a greater preference for the non-automated process and a higher variance in setting the threshold. This may be due to managerial uncertainty regarding what constitutes a reasonable performance level. For future research, it would therefore be intriguing to investigate if difficulties in determining parameters for algorithms lead to algorithm aversion and whether such aversion undergoes any changes depending on the type of process automation.

In our experiment, we incorporate a subtle manipulation. The key factor distinguishing a non-automated process from an automated one is the actual decision-making authority concerning the bonus payment. This design's advantage lies in its ability to explicitly manipulate process rigidity while maintaining similarity in the decision about the bonus threshold between automated and non-automated processes. Notably, we intentionally refrained from modeling the unpredictability of a complex computerized decision, leaving this aspect for future research.

Certainly, this evidence represents only a first step into exploring the consequences of automation while also contributing to the existing economic literature on the impact of automation on performance by highlighting the significance of human involvement and control. We look forward to future experimental research to expand on our contributions in order to gain a deeper understanding of how process automation and algorithmic decision-making affect performance.

Statements and declarations

We thank Timo Heinrich, Oliver Kirchkamp, and Paul Gorny for their helpful suggestions and comments on early drafts of the paper. We thank seminar participants at the University of Jena and the Hamburg University of Technology as well as participants at the Interactions of Humans and Algorithms Workshop 2023, the 11th International Conference of the French Association of Experimental Economics 2022 (ASFEE), and the Verein für Socialpolitik (VfS) Annual Conference 2022 for their valuable feedback. We also thank two anonymous reviewers for their comments. This work was supported by the Max Planck Society through the International Max Planck Research School on Adapting Behavior in a Fundamentally Uncertain World and the Joachim Herz Add-on Fellowship through the Add-on Fellowships for Interdisciplinary Economics and Interdisciplinary Business Administration. The authors have no relevant financial or non-financial interests to disclose.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI GPT-3.5 (2022) in order to improve language and readability of individual sentences. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

This Section contains additional information on the interfaces and questions used in the treatments. We also present further analyses of the data we collected in addition to the data used to test our hypotheses. Data and methods are available upon request.

A.1. Descriptives

Tables 10 and 11 show an overview of the key demographics. There is no significant difference between the demographics.

Table 10
Means of age.

HUMAN	*SYSTEM*
p-value 0.126	
36.27 (10.72)	37.74 (10.58)

Note: Standard deviations in parentheses.

Table 11
Gender split [%].

	HUMAN	*SYSTEM*
	p-value 0.369	
Female	41.7	44.9
Male	58.3	54.7
Other	0	0.4

A.2. Regressions

In this section, we provide a correlation matrix for perceived trust in the process, general trust, and threshold expectation in the automated and non-automated decision situation (see Table 12). We also present different OLS regressions on the performance (for automated decision situation see Table 13, for non-automated decision situation see Table 14), threshold expectation (for automated decision situation see Table 15, for non-automated decision situation see Table 16), perceived trust in the process (see Table 17), and perceived fairness of the process (see Table 18).

As Tables 13 and 14 show, men appear to perform significantly higher than women in both decision situations. Other factors significantly influencing the performance are the trust in the process and the threshold expectation, as well as the general trust in other people and, in the non-automated decision situation, also the level of risk aversion of the participants. Among these, the trust in the process and the gender have the biggest influence on the performance.

Interestingly, as Tables 15 and 16 show, the threshold expectation is significantly influenced by age, with younger participants showing a lower threshold expectation, and in the non-automated decision situation the gender. Another factor that is significantly influenced by the gender is the perceived fairness of the process, as Table 18 shows, which is also significantly influenced by the trust in the process. As Table 17 shows, the trust in the process, in return is significantly influenced by the perceived fairness of the process, the general trust, and, in the automated decision situation, the performance.

A.3. Fairness assessment

Table 12
Spearman rank correlation.

	General trust	Th. expec. n.a.	Th. expec. a.
Trust in process	0.195 (0.002)	0.201 (0.002)	0.114 (0.078)
General trust		0.123 (0.058)	0.088 (0.173)
Th. expec. n.a.			0.533 (0)

Th. expec. n.a. = Threshold expectation non-automated.
Th. expec. a. = Threshold expectation automated.
p-values are displayed in parentheses.

A.4. Trust assessment

Table 13
OLS regression on the agent's performance in the automated decision situation.

	Dependent variable:			
	Performance automated decision situation			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	1.094	0.731	−0.511	−0.497
	(4.423)	(4.549)	(3.842)	(3.793)
Age		−0.033	0.138	0.054
		(0.225)	(0.190)	(0.190)
Gender [1 = male]		4.869	7.554*	8.679**
		(4.591)	(3.924)	(3.965)
Th. expec.			0.514***	0.500***
			(0.064)	(0.064)
Fairness			−4.860	−3.608
			(5.228)	(5.168)
Trust in process			15.634***	13.239***
			(3.247)	(3.290)
Risk aversion				1.238
				(0.762)
General Trust				1.882**
				(0.781)
Constant	50.430***	44.436***	−29.217*	−36.110**
	(3.115)	(10.441)	(14.933)	(15.040)
Observations	254	240	240	240
R^2	0.0002	0.005	0.303	0.330
Adjusted R^2	−0.004	−0.008	0.285	0.307

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Th. expec. = Threshold expectation.
Robust standard errors are displayed in parentheses.

Table 14
OLS regression on the agent's performance in the non-automated decision situation.

	Dependent variable:			
	Performance non-automated decision situation			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	−3.414	−4.747	−4.816	−4.950
	(4.270)	(4.372)	(3.674)	(3.587)
Age		0.111	0.246	0.146
		(0.216)	(0.182)	(0.180)
Gender [1 = male]		3.054	6.476*	7.837**
		(4.412)	(3.761)	(3.757)
Th. expec.			0.656***	0.610***
			(0.078)	(0.077)
Fairness			−0.788	0.940
			(5.014)	(4.912)
Trust in process			11.793***	9.269***
			(3.161)	(3.147)
Risk aversion				1.618**
				(0.720)
General Trust				2.136***
				(0.744)
Constant	63.406***	55.037***	−25.960*	−33.629**
	(3.008)	(10.034)	(14.293)	(14.192)
Observations	254	240	240	240
R^2	0.003	0.008	0.313	0.354
Adjusted R^2	−0.001	−0.005	0.295	0.332

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Th. expec. = Threshold expectation.
Robust standard errors are displayed in parentheses.

Table 15
OLS regression on agent's threshold expectations in the automated decision process.

	Dependent variable:			
	Threshold expectation automated decision situation			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	0.236	0.765	0.624	0.933
	(3.903)	(3.911)	(3.476)	(3.489)
Age		−0.296	−0.285*	−0.295*
		(0.193)	(0.171)	(0.174)
Gender [1 = male]		−1.885	−4.209	−5.265
		(3.946)	(3.568)	(3.669)
Performance			0.421***	0.423***
			(0.052)	(0.054)
Fairness			0.568	0.700
			(4.739)	(4.760)
Trust in process			−2.888	−2.649
			(3.075)	(3.126)
Risk aversion				−0.873
				(0.703)
General Trust				0.275
				(0.727)
Constant	45.731***	59.215***	48.810***	52.026***
	(2.771)	(8.976)	(13.242)	(13.584)
Observations	240	240	240	240
R^2	0.00002	0.012	0.233	0.238
Adjusted R^2	−0.004	−0.001	0.213	0.212

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Robust standard errors are displayed in parentheses.

Table 16
OLS regression on agent's threshold expectations in the non-automated decision process.

	Dependent variable:			
	Threshold expectation non-automated decision situation			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	−1.476	−1.005	0.398	0.561
	(3.141)	(3.143)	(2.720)	(2.734)
Age		−0.190	−0.233*	−0.253*
		(0.155)	(0.134)	(0.136)
Gender [1 = male]		−3.793	−5.299*	−5.733**
		(3.172)	(2.771)	(2.855)
Performance			0.357***	0.352***
			(0.042)	(0.044)

(*continued on next page*)

Table 16 (*continued*).

	Dependent variable: Threshold expectation non-automated decision situation			
	(1)	(2)	(3)	(4)
Fairness			4.625	4.943
			(3.687)	(3.716)
Trust in process			2.376	2.214
			(2.396)	(2.430)
Risk aversion				−0.333
				(0.552)
General Trust				0.509
				(0.574)
Constant	57.303***	69.634***	38.416***	39.100***
	(2.230)	(7.214)	(10.316)	(10.597)
Observations	240	240	240	240
R^2	0.001	0.015	0.281	0.285
Adjusted R^2	−0.003	0.002	0.263	0.260

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Robust standard errors are displayed in parentheses.

Table 17
OLS regression on agent's trust in the process.

	Dependent variable: Trust in the process			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	0.059	0.064	0.079	0.074
	(0.078)	(0.078)	(0.074)	(0.073)
Age		−0.001	−0.001	−0.002
		(0.004)	(0.004)	(0.004)
Gender [1 = male]		−0.071	−0.057	−0.038
		(0.079)	(0.076)	(0.077)
Performance automated			0.005**	0.004**
			(0.002)	(0.002)
Performance non-automated			0.001	0.001
			(0.002)	(0.002)
Th. expec. automated			−0.003	−0.002
			(0.002)	(0.002)
Th. expec. non-automated			0.004*	0.003
			(0.002)	(0.002)
Fairness			−0.235**	−0.208**
			(0.100)	(0.100)
Risk aversion				0.017
				(0.015)
General Trust				0.028*
				(0.015)
Constant	2.924***	3.054***	2.897***	2.728***
	(0.055)	(0.179)	(0.218)	(0.233)
Observations	240	240	240	240
R^2	0.002	0.006	0.151	0.170
Adjusted R^2	−0.002	−0.006	0.122	0.134

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Th. expec. = Threshold expectation.
Robust standard errors are displayed in parentheses.

Table 18
OLS regression on agent's perceived fairness.

	Dependent variable: Fairness			
	(1)	(2)	(3)	(4)
Treatment *SYSTEM*	0.039	0.031	0.045	0.043
	(0.049)	(0.048)	(0.048)	(0.048)
Age		0.001	0.001	0.002
		(0.002)	(0.002)	(0.002)
Gender [1 = male]		0.126***	0.129***	0.128**
		(0.049)	(0.049)	(0.050)
Performance automated			−0.002	−0.002
			(0.001)	(0.001)
Performance non-automated			0.001	0.001
			(0.001)	(0.001)
Th. expec. automated			−0.0004	−0.0004
			(0.001)	(0.001)

(*continued on next page*)

Table 18 (*continued*).

	Dependent variable:			
	Fairness			
	(1)	(2)	(3)	(4)
Th. expec. non-automated			0.002	0.002
			(0.001)	(0.001)
Trust in process			−0.100**	−0.090**
			(0.042)	(0.043)
Risk aversion				−0.001
				(0.010)
General Trust				−0.016
				(0.010)
Constant	1.151***	0.930***	1.159***	1.168***
	(0.035)	(0.111)	(0.173)	(0.178)
Observations	240	240	240	240
R^2	0.003	0.032	0.079	0.090
Adjusted R^2	−0.002	0.020	0.047	0.050

Note: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.
Th. expec. = Threshold expectation.
Robust standard errors are displayed in parentheses.

Table 19
Workers' and Managers' answer [%] to the following question: "Do you Consider the Procedure to Get the Bonus to Be Fair?" (see Question 6 from Appendix A.9).

		HUMAN		*SYSTEM*	
		Non-automated	Automated	Non-automated	Automated
Worker	YES	84.04	88.00	83.33	78.69
	NO	15.96	12.00	16.67	21.31
Manager	YES	85.00	78.57	87.10	79.69
	NO	15.00	21.43	12.90	20.31

Table 20
Workers' agreement [%] to the following statement: "I Think that I will get a Bonus" (see Question 5 from Appendix A.9).

	HUMAN	SYSTEM
Strongly agree	9.20	17.40
Agree	77.30	65.30
Disagree	10.10	15.70
Strongly disagree	3.40	1.70

Table 21
Workers' transfer decisions [%].

	HUMAN	SYSTEM
Less	42.20	30.20
More	7.00	7.10
Same	50.80	62.70

Table 22
Process choices by managers and the system [%].

	HUMAN	SYSTEM
Non-automated	78.10	49.20
Automated	21.90	50.80

Table 23
Managers' answer [%] to the question: "Do you Consider the Procedure to Get the Bonus to be Fair?" (see Question 6 from Appendix A.9).

	Non-automated	Automated
	($p = 0.2480$)	
YES	85.80	79.35
NO	14.20	20.65

The table shows *p*-values for a chi-square test.

Table 24
Means and standard deviations (in Parentheses) for levels of risk and trust.

	Worker	Manager
Risk	∅ = 4.36	∅ = 4.53
	(2.59)	(2.3)
Trust	∅ = 4.91	∅ = 5.04
	(2.55)	(2.41)

A.5. Relative frequency of the workers' transfer decision

Table 21 shows the relative frequency of workers who transferred less, more, or the same in an automated decision process than in a non-automated decision process. The table reveals that around half of the workers transferred the same in a non-automated decision process as in an automated decision process in both treatments. Nevertheless, around 40% of the workers transferred fewer points in an automated decision process than in a non-automated decision process in treatment *HUMAN*, and slightly less than one-third of the workers did so in treatment *SYSTEM*.

A.6. Analysis of the managers' behavior

As Table 22 shows, the vast majority of the managers decided to use a non-automated instead of an automated decision in treatment *HUMAN*, where the managers were able to choose.

A.7. Participants' propensity for procedural fairness, risk and trust in general

As Table 23 shows, the fairness assessments by managers do not differ significantly between a non-automated decision process and an automated decision process. Thus, managers do not perceive one process to be fairer than the other.

All participants were asked if they are a person who is willing to take risks or tries to avoid taking risks (see Question 7) and if they would say that most people can be trusted or that you cannot be too careful in dealing with other people (see Question 8). Willingness to take risks was measured by a continuous scale from "not at all willing to take risks" (0) to "very willing to take risks" (10). The level of general trust was measured by a continuous scale from "can't be too careful" (0) to "most people can be trusted" (10). As Table 24 shows, workers and managers were slightly risk- averse and somewhat concerned about the trustworthiness of other people.

A.8. Instructions and screens

Note: The following instructions are for treatment HUMAN. Differences for treatment SYSTEM are added in italic. Approach BLUE is the non-automated scenario and Approach GREEN is the automated scenario. Participant A is the worker, Participant B is the manager.

This HIT [Human Intelligence Task] is an economic experiment. Please read the following instructions carefully. The instructions provide you with all the information required for participating in the experiment. You will receive $0.50 USD for participating in the experiment (paid only if you finish the experiment). Your final payoff is the $0.50 USD for participating in the experiment plus the amount earned during the experiment. You will earn at least the $0.50 USD for participating in the experiment. In the experiment, the currency used is points. Your points will be converted to USD at the end of the experiment using a conversion rate of **1 point = $0.01 USD**.

General setup

In this experiment, you are matched with another human participant. You will play in a group of two. All decisions are made anonymously. No participant knows with whom (s)he is matched. During the experiment, the members of the group are called "participant A" and "participant B". The roles are randomly assigned.

The experiment

Participant A starts with 120 points at the beginning of the experiment. Participant B starts with no points. Each participant has to make a decision during the experiment. The decisions are explained below. Please read the explanations for both participants as both decisions will affect the number of points you will earn.

Participant A's decision:

Participant A has to decide how many points (s)he wants to transfer to participant B. The points transferred to participant B are doubled by the experimenter, meaning each point transferred to participant B reduces the points of participant A by one point but increases the points of participant B by two points.

Participant B's decision:

Before participant B knows what participant A transferred, participant B *[the system]* selects an approach. The two possible approaches (Approach BLUE or Approach GREEN) are explained below.

In each approach participant B has to decide if participant A should be given a **bonus of 120 points** for a **"very good transfer"**. The bonus is paid by the experimenter and does not reduce the points of participant B. The difference between the two approaches is how participant B determines the minimum amount (threshold) that participant A has to transfer to get a bonus.

In Approach BLUE, participant B **knows** the amount transferred by participant A when determining the threshold. The decision screen will look like this:

> You *[the system]* decided to use Approach BLUE.
>
> **Participant A has transferred X of 120 points to you.**
> If participant A has transferred at least the threshold amount (s)he gets a bonus of 120 points (paid by the experimenter).
> Please indicate your threshold here:
>
> ...... Points

In Approach GREEN, participant B **DOES NOT know** the amount transferred by participant A when determining the threshold. The decision screen will look like this:

> You *[the system]* decided to use Approach GREEN.
>
> If participant A has transferred at least the threshold amount (s)he gets a bonus of 120 points (paid by the experimenter).
> Please indicate your threshold here:
>
> ...... Points

Further note:

Participant A has different fields to enter amounts in case Approach BLUE or Approach GREEN is used.

Some examples:

- ***Example 1:*** Participant A transfers 0 points to participant B. Participant A will have 120 points (120-0) plus eventually a bonus of 120 points. Participant B will have 0 points (0×2). In addition, both participants receive $0.50 USD for participating.
- ***Example 2:*** Participant A transfers 40 points to participant B. Participant A will have 80 points (120-40) plus eventually a bonus of 120 points. Participant B will have 80 points (40×2). In addition, both participants receive $0.50 USD for participating.
- ***Example 3:*** Participant A transfers 80 points to participant B. Participant A will have 40 points (120-80) plus eventually a bonus of 120 points. Participant B will have 160 points (80×2). In addition, both participants receive $0.50 USD for participating.
- ***Example 4:*** Participant A transfers 120 points to participant B. Participant A will have 0 points (120-120) plus eventually a bonus of 120 points. Participant B will have 240 points (120×2). In addition, both participants receive $0.50 USD for participating.

Before clicking "Next" please make sure you have read and understood the instructions. After clicking "Next" we will match you with the next person starting the experiment. This might take some time.

Note: The following images (Figs. 4, 5 & 6) show examples of the experiment screens.

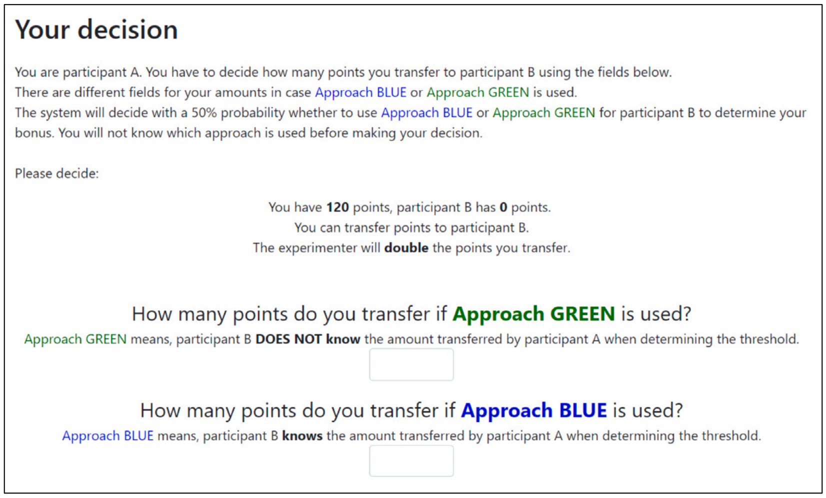

Fig. 4. Workers' performance decision screen.
Note: The figure shows the screen in treatment *SYSTEM*. In treatment *HUMAN* the third line begins with "Participant B will decide whether to use Approach BLUE (...)".

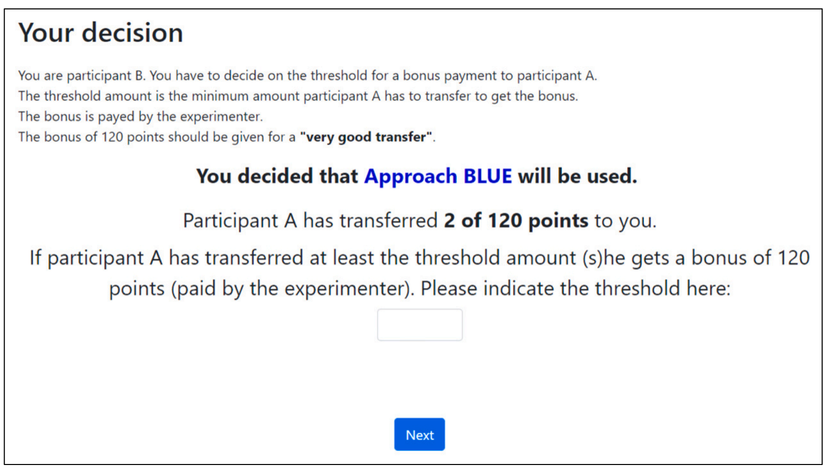

Fig. 5. Managers' threshold decision screen in treatment *HUMAN*.

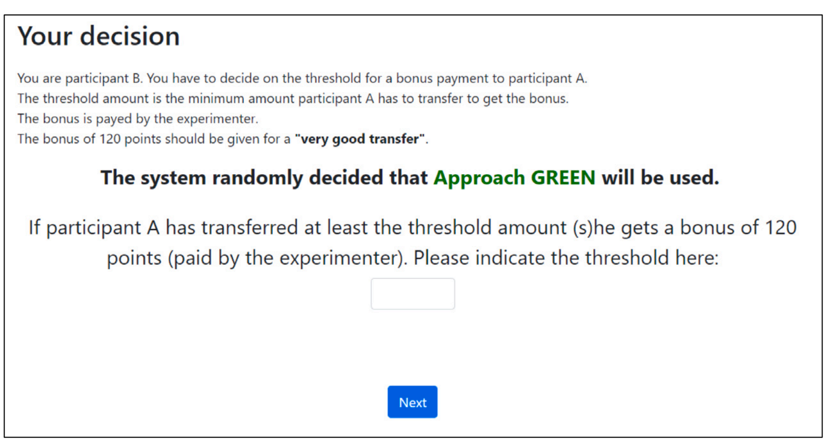

Fig. 6. Managers' threshold decision screen in treatment *SYSTEM*.

A.9. Questions

Note: All participants were asked to complete a questionnaire. The questions were asked right after the decision and before the final performance was announced. The answer method used is presented in brackets. Apart from the first five questions, which were only presented to workers, all questions were asked to workers and managers.

1. Why did you choose to transfer the amount you have chosen to participant B in Approach BLUE (participant B **knows** how

much you transferred)? [Open Question] *(For the answers given, see online data set.)*

2. Why did you choose to transfer the amount you have chosen to participant B in Approach GREEN (participant B **does not know** how much you transferred)? [Open Question] *(For the answers given, see online data set.)*
3. What do you think is the minimum amount you would have had to transfer to get the bonus if participant B decided to use Approach BLUE (participant B **knows** how much you transferred)? [Integer from 0 to 120 points] *(For an analysis of the answers given, see Section 5.1.)*
4. What do you think is the minimum amount you would have had to transfer to get the bonus if participant B decided to use Approach GREEN (participant B **does not know** how much you transferred)? [Integer from 0 to 120 points] *(For an analysis of the answers given, see Section 5.1.)*
5. How much do you agree with this statement: 'I think that I will get a bonus.'? *(For an analysis of the answers given, see Appendix A.4.)*
6. Do you consider the procedure to get the bonus to be fair? *(For an analysis of the answers given, see Appendix A.3.)*
7. How do you see yourself: Are you a person who is willing to take risks or do you try to avoid taking risks? Please select a number on a scale from 0 to 10. The value 0 means: "not at all willing to take risks" and the value 10 means: "very willing to take risks". [scale 0 to 10]. *(For an analysis of the answers given, see Appendix A.7.)*
8. Generally speaking, would you say that most people can be trusted or that you cannot be too careful in dealing with other people? Please select a number on a scale from 0 to 10. The value 0 means: "can't be too careful" and the value 10 means: "most people can be trusted". [Scale 0 to 10] *(For an analysis of the answers given, see Appendix A.7.)*
9. What is your gender? *(For a summary of the answers given, see Section 5.)*
10. What is your age [in years]? [*Integer*] *(For a summary of the answers given, see Section 5.)*

Data availability

Data will be made available on request.

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