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AI Resource Allocation: On the Contribution of Distributive and Procedural Fairness

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Abstract

This study investigates how users perceive AI-driven decision-making systems in resource allocation contexts based on three key factors: outcome favorability, transparency, and task type. We conducted an online experiment with a 2 (outcome: favorable vs. unfavorable) x 3 (transparency: low vs. balanced vs. high) mixed design across four different resource allocation scenarios that reflected tasks perceived as more mechanical versus more human (N = 929). Our Bayesian linear mixed-effects models revealed that outcome favorability was the strongest single predictor of perceived fairness, trust, acceptance, and behavioral intention to use the respective AI. Task type (perceived "humanness") further influenced user perceptions and additionally interacted with outcome favorability and transparency. Surprisingly and in contrast to prior studies, we found evidence against a main effect of transparency. Our findings highlight the critical importance of AI-based resource allocation performance, that is, outcome optimization, for users' perception of corresponding AI systems. Conversely, the impact of transparency on user perceptions appears to be even more nuanced than previously thought.

CCS Concepts

• **Human-centered computing** → Human computer interaction (HCI); Empirical studies in HCI.

Keywords

AI decision-making, outcome favorability, task type, transparency

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1 Introduction

Artificial Intelligence (AI) is increasingly becoming integrated into modern society, influencing critical aspects of human life across diverse sectors such as healthcare, finance, or employment, especially in the context of resource allocation [3, 46]. AI systems are not only tools for automation but also active agents in processes with tangible social consequences, making pivotal decisions or significantly assisting humans in doing so [29]. As AI's societal footprint expands, understanding the factors that drive users' acceptance and adoption of AI technologies becomes paramount [3]. Ensuring that AI systems are designed and deployed in a manner that fosters positive user perceptions and their willingness to use corresponding AI systems is essential to realize their benefits effectively and equitably.

Central to the acceptance and effective integration of AI systems are user perceptions of fairness [51]. Parallel to the spreading use of AI systems, concerns about their risk for bias and unfairness have grown, spurring a surge in research on how humans perceive algorithmic fairness [28]. Developing more human-centered AI necessitates more insights into when and why individuals perceive algorithmic decisions as fair or unfair [62], a challenge that extends beyond mere technological fixes to encompass the psychological and social dimensions of human-AI interaction.

This paper investigates the interplay of three critical factors influencing the perception of AI resource allocation systems that have previously not been considered jointly: The favorability of the outcome, the level of transparency provided, and the perceived nature of the decision-making task (task type). Specifically, we assessed users' judgments of fairness, their trust in the AI, their acceptance of its decisions, and their behavioral intention to use the respective AI system. Drawing upon established theories of organizational justice, trust, and technology acceptance, we aimed to provide a nuanced understanding of how these variables combine, to shape users' experiences with AI decision-makers.

1.1 Organizational Justice Theory: A Framework for Fairness

To understand how individuals form fairness perceptions in the context of AI-driven decision-making, we draw on organizational justice theory, a well-established framework for analyzing individuals' subjective evaluations of fairness in relation to decisions and procedures enacted by organizations, authorities, or systems [2].This theory conceptualizes fairness as multidimensional construct [23], a perspective particularly suited to the complex evaluations of AI systems. Contemporary research often distinguishes at least three or four dimensions of justice [13]: Distributive and procedural justice (focus of this study; core dimensions in all models: e.g., [13]) as well as interpersonal and informational justice. Our focus on distributive and procedural justice is particularly suited to the context of AI-based resource allocation, where outcome-related (distributive justice) and process-related (procedural justice) fairness concerns are especially salient [5, 13] and allows for a theoretically robust yet empirically manageable operationalization of fairness perceptions in our study.

Distributive justice concerns individuals' perceptions of the fairness of outcomes or allocations resulting from decision-making processes [13, 22]. This dimension is often associated with equity theory, which posits that people evaluate fairness by comparing their input-to-output ratios to those of relevant others [60]. Equity is one of the most dominant distribution principles and plays a central role in understanding fairness perceptions in algorithmic contexts. For instance, when AI systems allocate resources or opportunities (such as university admissions; see [39], for AI in higher education), users tend to evaluate the fairness of these outcomes in distributive terms, that is, whether the allocation of outcomes to themselves and others (i.e., the end result) was fair. For instance, using equity as a judgement principle for the distribution, university applicants might evaluate a university admission process as fair if they perceive admission to be based on a person's prior grades and performance, irrespective of the process used to arrive at this decision.

Procedural justice, by contrast, refers to the perceived fairness of the processes and procedures used to reach a decision [53]. It is analytically distinct from the fairness of the outcome itself and instead focuses on how the decision was made. Continuing with the university admission example, procedural justice concerns whether a (AI) university admission system's evaluation criteria were (among others) transparent and consistent, irrespective of the decision outcome. This dimension is particularly relevant in algorithmic settings where transparency, consistency, and perceived neutrality of the procedure play a central role in shaping users' fairness perceptions [32]. It significantly influences individuals' reactions to outcomes, their trust in the decision-making authority, and their overall satisfaction with the decision [10, 24, 31]. Key facets contributing to procedural justice include (but are not limited to) consistency in application, decision-making transparency, accuracy of information, opportunities for voice or correction (correctability), ethicality of standards, and lack of bias [17, 33, 43].

Although distributive concerns are undeniably important, a vast body of research additionally underscores the profound impact of procedural justice in shaping overall fairness perceptions, influencing the acceptance of decisions (even unfavorable ones), and fostering trust [24, 51]. Thus, it is essential to consider both distributional and procedural fairness perceptions when assessing AI-based resource allocation. Extending prior work on AI fairness perception (see [51] for an overview), here, we therefore directly investigated participants assessments of both distributive and procedural fairness in an AI decision-making setting.

1.2 Trust in AI Systems

The concept of trust is closely linked to fairness perceptions [9]. In the context of human-AI interaction, trust can be understood as a psychological state involving the intention to accept personal vulnerability due to positive expectations of an AI system's intentions or behavior [41]. This conceptualization draws from foundational models of trust, such as Mayer et al.'s [41] model of organizational trust, which was later adapted by Lee and See [29] to the specific domain of trust in automation. Building on this research, Körber et al. [26] further refined a model of trust in automated systems, distinguishing between a more general and interaction-moderating propensity to trust automation (a trait-like trust which individuals bring to an interaction) and a more state-like trust in a specific automated system (which develops through interaction with the respective system). The latter is especially important when shaping perceptions of specific novel AI systems, albeit being influenced by the propensity to trust.

The development of trust in a specific AI system is significantly influenced by perceptions of its fairness [24]. As discussed in the preceding section on organizational justice, when users perceive an AI system as operating according to fair procedures (procedural fairness) and delivering fair outcomes (distributive fairness), they are more likely to develop trust in that system. Transparency, as a key component of procedural justice, is often highlighted as a foundation for fostering this trust [3]. By providing insight into the AI's operations, appropriate levels of transparency can demystify its processes, reduce perceived arbitrariness, and offer assurance of its intended behavior, thereby strengthening trust [27]. This is why we regarded it as essential to conduct this study which first jointly assessed both distributive and procedural fairness as well as trust while systematically manipulating transparency (see 1.4.2).

Once formed, trust (or its absence) plays a critical role in shaping how users engage with AI systems and is a crucial determinant of their subsequent adoption intention and effective use. Although trust is a critical intermediate step [58], the ultimate goal is technology acceptance and adoption. If users do not trust an AI, they are less likely to rely on its decisions, accept its outputs, or integrate it into their activities, irrespective of its objective capabilities [29, 49, 50]. For instance, recent versions of the Technology Acceptance Model [14], such as the Intelligent Systems Technology Acceptance Model (ISTAM) argue, that trust acts as a central link between users' initial perceptions of an AI (influenced by its design, transparency, perceived fairness, and the user's own propensity to trust) and their ultimate willingness to depend on it and form positive behavioral intentions towards it [24, 58]. Therefore, understanding how factors like outcome favorability, transparency, and task type impact trust is essential for predicting and facilitating this chain towards more widespread user acceptance, willingness to use, and actual use of AI systems.

1.3 Acceptance and Behavioral Intentions in Response to AI Systems

Understanding user perceptions of fairness and trust is vital as these evaluations can significantly influence further responses, such as the acceptance of AI systems and users' behavioral intentions towards them [1, 7, 24].

Acceptance of an AI system can be defined as a user's willingness to assent to, receive, or agree with the decisions or outputs generated by the AI [24, 61]. It reflects a general positive disposition towards the AI system's role in the decision-making process. Perceived fairness is a strong driver of acceptance. When individuals believe a decision-making system (such as an AI) operates fair (both in its procedures and outcomes), they are more inclined to accept its decisions, even if those decisions are not personally favorable [34]. Trust additionally impacts on acceptance, as higher trust in an AI system often leads to greater acceptance of its outputs [59]. Behavioral Intention to use refers to the subjective likelihood of engaging with or utilizing a particular technology [7, 14]. Within the context of AI, this is a further intermediary and critical indicator of the actual adoption and sustained use of AI systems (see e.g., TAM and UTAUT; [14, 56, 57]).

Again, perceived fairness and trust act as significant antecedents that can influence behavioral intentions towards AI systems. The FATE [Fairness, Accountability, Transparency, and Explainability/Ethics] framework suggests that fairness and transparency influence trust, which then mediates the relationship with usage intentions [48, 59]. Thus, fostering an appropriate amount of fairness and trust is not just an ethical concern but also of practical importance for ensuring the successful adoption and use of AI technologies. These complex relationships, however, are also subject to contextual factors, including, among others, task type [27, 31, 51].

1.4 Factors Influencing User Perceptions of AI Decision-Making

Building on prior research and theories [58], we assumed a causal sequence connecting the dependent variables: That is, we expected fairness to be a precursor of trust, which in turn is essential for fostering acceptance and positive use intentions. We thus expected our manipulations targeted at affecting perceived fairness and trust to correspondingly also impact on the main determinants of AI implementation success: Acceptance and positive use intentions. Assessing perceived fairness, trust, acceptance, and behavioral intention as crucial foundations of the adoption and use of AI systems, this study builds on prior work [27, 51] to investigate three factors we anticipated to essentially influence how users perceive AI decision-making systems in the context of resource allocation: outcome favorability, transparency, and perceived task type. Singularily, the influence of each of these factors on at least some relevant outcome measures (e.g., trust or acceptance) has been investigated previously. However, we assumed crucial interactions between these factors and furthermore aimed to ascertain their impact on trust, acceptance, and behavioral intention as well as the measures of perceived fairness (distributive and procedural) we newly introduced in this context to assess all relevant variables along the causal sequence we assumed.

1.4.1 Outcome Favorability. The outcome of a decision, whether made by a human or an AI, has a strong influence on how it is perceived [51]. Outcome favorability refers to whether the result of a decision is positive or negative for the individual concerned. Extensive research shows that those affected by decisions tend to perceive these decisions as fairer, more trustworthy, and more acceptable when the decision outcome is personally beneficial [54]. This also holds true in the context of AI decision-making [5, 60]. The outcome-based decision evaluation (known as outcome bias) can even lead to positive evaluations of a decision-making (e.g., AI) system in cases where the underlying decision process is known to be biased [35, 60]. In essence, outcome favorability serves as a strong predictor for user evaluations of the AI's ability to achieve outcome optimization, that is, its capacity to deliver the best possible or at least a very beneficial result for the individual.

This bias towards favorable outcomes can be understood through the lens of self-interest. Individuals are naturally inclined to prefer and positively evaluate systems that serve their interests [10, 60]. When a decision-maker (such as an AI) delivers a positive result, it aligns with this self-interest, leading to more positive appraisals of the system's fairness and overall quality [5, 19, 35]; see also attribution theory e.g., [10]. For AI systems, it has been found that positive outcomes generally lead to more positive perceptions of the AI itself [5, 19, 51]. The favorability of the decision often appears more critical than the nature of the decision-maker in shaping fairness-related responses in particular [59]. It is therefore of outmost interest to additionally consider both distributive and procedural fairness perceptions in the contexts of outcome bias. This is particularly relevant, as fairness perceptions, influenced by outcome favorability, subsequently impact trust, acceptance and behavioral intentions [27, 47]. Given the previously confirmed strong effects of decision outcomes in other (AI) decision contexts, here, we systematically manipulated and assessed outcome favorability under the hypotheses that:

H1: A decision-making process that leads to a favorable outcome is perceived as a) fairer (especially in terms of distributive fairness, but also procedural fairness), b) more trustworthy, and c) more acceptable, and leads to a d) higher behavioral intention to use an AI than one that leads to an unfavorable outcome (outcome favorability hypotheses).

1.4.2 Transparency. Transparency in algorithmic decision-making refers to the extent to which the decision-making process of an AI system is visible and understandable to those affected by it [3]. It involves understanding the "how" and "why" behind an AI's decision, often facilitated through explanations of its workings or the rationale for specific outputs [8, 49]. As a key component of procedural justice, transparency is widely advocated to enhance perceived fairness, accountability, and trust in AI systems [3, 27].

By illuminating the process, transparency can help users assess whether an AI operates according to fair principles [32].

However, the relationship between transparency and user perceptions is rather complex and possibly nonlinear. While an intermediate degree of transparency can indeed foster trust and positive attitudes, providing too much, or overly detailed information can sometimes confuse users, diminish perceived fairness, and even erode trust [6, 25, 32]. This inverted U-shaped effect can be explained by Cognitive Load Theory [52], which argues that excessive or overly complex information imposes a cognitive burden that may overwhelm users and lead to decision fatigue [36], while moderate transparency fosters more trust [42]. Similarly, Trust Calibration Theory [21] posits that the goal is not to maximize transparency, but to provide an optimal amount of information that allows users to appropriately calibrate their trust in a system. While some studies have found support for this inverted U-shaped effect [25, 44], at present, the exact constituents of a positive impact of transparency on perceived fairness and trust are yet to be determined. Here, we aimed to further elucidate the optimal conditions of transparency in AI resource allocation by constructing a balanced transparency condition to contrast with a low and (excessively) high transparency condition. The FATE characteristics are often seen as heuristic cues that users employ to build trust [49]. We presumed that a balanced degree of transparency provides sufficient insight without overwhelming users with overly complex information [25] and therefore has the most positive impact:

H2: A decision-making process with a balanced level of transparency is perceived as a) fairer (especially in terms of procedural fairness, but also distributive fairness), b) more trustworthy, and c) more acceptable, and leads to a d) higher behavioral intention to use than processes with either low or (excessively) high levels of transparency (transparency hypotheses).

Building on prior findings in non-AI decision contexts [10], we further presumed that transparency, linked to procedural fairness, and outcome favorability, connected to distributive fairness, interact. That is, when the outcome is favorable, transparency plays a secondary role, but when the outcome is negative, transparency has a stronger influence on the perception of a decision process:

H3: Transparency and outcome favorability interact. When the outcome is unfavorable, a) fairness perception (both in terms of distributive as well as procedural fairness), b) trust, c) acceptance, and d) behavioral intention to use are substantially lower under low or high transparency, as compared to under balanced transparency. When the outcome is favorable, no (or less pronounced) differences are expected between transparency levels.

1.4.3 Task Type. As previously mentioned, the (perceived) task type of an AI-based decision is another critical contextual factor shaping user reactions [31, 51]. This is presumed to be the case, as individuals do not consider every type of task as equally suitable for AI decision-making. AI decision-makers are viewed as more appropriate, fair, and trustworthy when applied to mechanical tasks (e.g., tasks involving objective data processing, scheduling, or quantitative calculations), where their perceived consistency, objectivity, and reliability are valued [16, 31]. Conversely, for tasks perceived as demanding human-like skills (e.g., tasks involving subjective judgment, empathy, intuition, or nuanced social understanding, such as in hiring or complex social evaluations), AI systems may be perceived as less fair, less trustworthy, and potentially dehumanizing, as they are perceived to lack the required nuanced understanding or empathic capacity [31]. The perceived relevance of the decision [4] and the specific domain of application further explain the influence of task type on the evaluation of AI decision-making [51]. The perception of what constitutes a task that can be suitably handled by AI may also evolve as AI capabilities advance. Here, we further systematically manipulated task type across four decision scenarios and assessed participants' perceptions of task type and task relevance. We hypothesized:

H4: An AI decision-making process is perceived as a) less fair (especially in terms of procedural fairness, but also distributive fairness), b) less trustworthy, c) less acceptable and leads to a d) lower behavioral intention to use, when the task is perceived as more human compared to when the task is regarded as more mechanical (task type hypotheses).

Given the dominant role of outcome favorability for the evaluation of AI decision-making, we expect that the impact of task type, similar to transparency, is more pronounced for unfavorable, as compared to favorable outcomes:

H5: Outcome favorability and task type interact. When the outcome is unfavorable, the difference in a) fairness perception (both in terms of distributive as well as procedural fairness), b) trust, c) acceptance, and d) behavioral intention to use between more mechanical and more human tasks is larger compared to when the outcome is favorable.

We further expected task type to yield a stronger influence on the perception of AI decision-making under suboptimal transparency conditions, that is, too low or excessively high transparency, as this may focus the importance of the underlying decision context:

H6: Transparency and task type interact. When transparency is low or high, the difference in a) fairness perception (both in terms of distributive as well as procedural fairness), b) trust, c) acceptance, and d) behavioral intention to use between tasks perceived as more mechanical or human is larger compared to when transparency is balanced.

1.5 Current Study

In the present study, we set out to address the previously outlined research gaps (section 1.4) as well as to reconfirm well-known and established prior findings when accounting for such potential additional sources of influence on the perception of AI decision-making in resource allocation settings. To do so, we had our participants evaluate four AI resource allocation scenarios (task allocation at work, allocation of work time models, allotment garden plot allocation, kindergarten spot allocation) introduced to them in a (hypothetical) vignette design. That is, the demonstrated AI allocation was openly introduced as a system to be tested for a planned future implementation and usage. Prior research has established the individual importance of outcome favorability, transparency characteristics, and task type in shaping perceptions of and responses to AI. Yet, at present, what exactly constitutes "optimal" transparency conditions and how specific features of a task that contribute to the task's perception as a certain task type influence the perception of AI remains largely unanswered. Furthermore, how outcome favorability, transparency, and task type interact to differentially shape each stage of the presumed cascade from fairness perception (differentiating distributive and procedural fairness) towards trust, the acceptance and use of AI systems requires further systematic investigation. Whereas prior work has examined these factors individually, this study addresses this gap. To do so, we systematically manipulated the distribution-focused outcome favorability (favorable vs. unfavorable), the procedural transparency level (low vs. balanced vs. high), and perceived task type (more mechanical to more human; manipulated via the scenarios) and assessed their impact on a comprehensive set of user evaluations: perceived procedural and distributive fairness, trust, acceptance, and behavioral intention to use AI systems. Crucially, our design moves beyond simplified classifications based on experimenters objective criteria for outcome favorability, task type, and decision relevance by directly assessing participants' corresponding individual subjective perceptions and incorporating them in our analysis models. Doing so, we aimed to further unravel complex interdependencies observed or assumed in prior studies to offer empirical guidance for designing AI systems that resonate more adequately with human users, fostering trust and more responsible adoption.

2 Methodology

The experiment followed a 2 (outcome favorability: favorable vs. unfavorable; within) x 3 (transparency: low vs. balanced vs. high; between) mixed design. We manipulated task type across four decision scenarios and used participants' individual task type perceptions as a continuous predictor for our analysis. The study was conducted online with German-speaking participants and was preregistered at the Open Science Framework (OSF; https://osf.io/k8ftn). Detailed information on the scales used in this study is provided in an overview at the end of the methodology section. The data, analysis scripts and study materials (e.g., scenario descriptions and questions, transparency manipulation texts) are also available in OSF (https://osf.io/jkf4u/).

2.1 Participants

A total of 1202 participants were recruited through an online panel service, and participants were financially compensated for their time. Eligibility criteria included being at least 18 years old, possessing native-level proficiency in German, and residing in Germany. Due to technical issues, the first 82 participants were not considered in the analysis. Another 191 participants were excluded due to failing at least one of the three attention checks. The final sample consisted of 488 males (52.5%), 440 females (47.4%), and 1 participant (0.1%) who identified as "non-binary/third gender" (N = 929). The mean age of participants was 46.27 years (SD = 13.44, Min = 18, Max = 70). Participants' highest educational qualifications were categorized as low (e.g., no degree or basic schooling degree with or without apprenticeship; n = 282, 30.4%), middle (e.g., secondary school degree; n = 244, 26.3%), and high (e.g., university entrance qualification, university degree; n = 403, 43.4%). The achieved sample was close to representative for the German population in terms of age, gender and education.

2.2 Procedure

Participants were invited to take part in an online vignette-like study about their opinions on AI systems. After providing informed consent, participants completed a pre-experimental questionnaire assessing demographic information (gender, age, education, net monthly income) and their general trust in automation using the Trust in Automation (TiA) scale. An initial attention check was administered within the demographic questions, instructing participants to select a specific response option (e.g., "fully agree") while ignoring any other. While this study was conducted in German, we present the English equivalents for easier reading.

Participants were then informed that they would be grouped with 40 other participants to test an AI decision-making system across four different scenarios. To simulate a collective, real-time AI allocation process with multiple participants, a dynamic countdown timer was displayed before each scenario. This visually simulated other participants joining the session, indicating that the system was waiting for the full group to convene before proceeding. The duration of this waiting period was randomized for each scenario.

Participants were asked to choose a username and were then assigned a random user profile (including a fictional place of residence and place of work) to enhance the realism of the experiment. During all simulated interactions with the AI system (e.g., when providing inputs or receiving information from the AI), these sections were visually distinguished. The interface featured a blue background, and an AI symbol, depicted as a pulsing icon within a circle, to clearly indicate when the participant was interacting with or receiving information from the AI system.

Participants subsequently followed the same steps to experience and then evaluate four scenarios (task allocation at work, allocation of work time models, allotment garden plot allocation, kindergarten spot allocation; randomized per participant; see the OSF project (https://osf.io/jkf4u/) for the scenario-specific descriptions and corresponding questions), which were selected from a larger set of scenario options (initially developed by the research team) based on an iterative rating (mechanical-human continuum, relevance), selection (aimed at achieving variance both on the mechanical-human continuum and regarding relevance), and optimization process among three members of the research team. Per scenario participants first read a description of the scenario. They then rated the task as more "mechanical" or "human" (visual analogue scale; 0 = "entirely human task", 100 = "entirely mechanical task") and its personal relevance (visual analogue scale; 0 = "very irrelevant", 100 = "very relevant"). Subsequently, participants provided decision-relevant information specific to the scenario (e.g., task preferences, experience, preferred work style for task allocation; 3 questions per scenario; see the Appendix for an English version of the scenario description and scenario-specific questions for one exemplary scenario). Another simulated waiting period, as described above, followed, indicating that the system was waiting for the full group to finish adding their preferences before proceeding to make its decision. Next, participants were exposed to one of the three randomly assigned transparency manipulations (between subjects) for the specific scenario. These three levels were designed to represent distinct conditions: a complete lack of explanation (low transparency), a concise and accessible summary (balanced

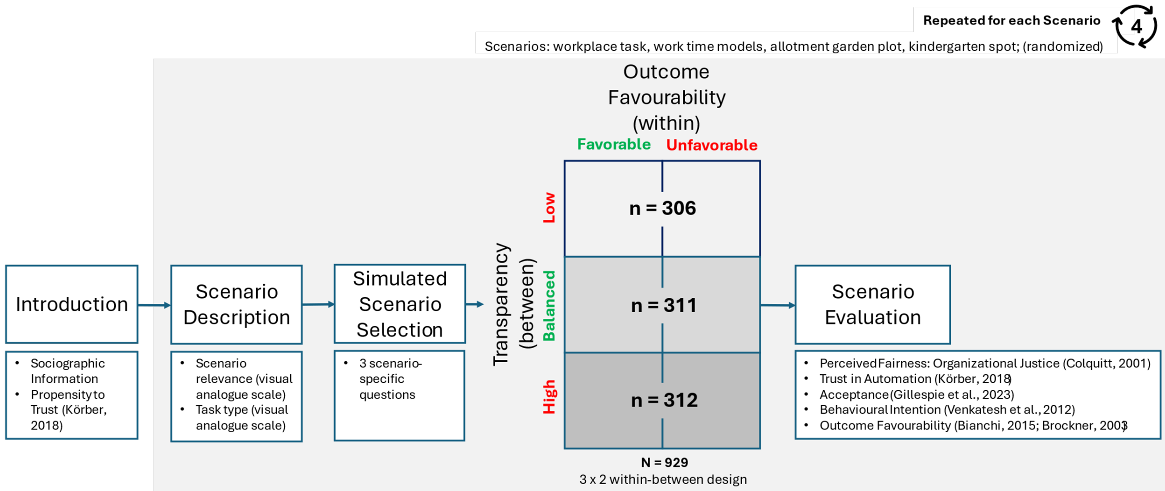

Figure 1: Structure and time course of the experiment.

transparency), and a more complex, technical information (high transparency), reflecting different explainability approaches (own development of transparency levels building on ; see the OSF project (https://osf.io/jkf4u/) for the original transparency manipulations):

Low Transparency: No explanation of the AI's decision-making process was provided. Participants in this condition were shown an empty placeholder screen before the outcome was revealed.

Balanced Transparency: A brief, general description of the parameters the AI considered was given. For example, in the workplace task allocation scenario, participants were told: "The allocation is based on the following factors: desired task, experience and qualifications, and your information on your preferred work style (independent/team). These were weighed in relation to available capacities and the requirements of the open positions."

High Transparency: An extensive and more complex explanation was provided. This included a textual description of the optimization algorithm, a schematic visual representation of a neural network (input layer, hidden layer, output layer), and a table showing aggregated (fictional) preferences of all participants in the current decision round (percentages of participants preferring each task option).

Following the transparency manipulation, participants were 'logged out' of the AI interface. The outcome of the AI's decision was then communicated to participants as an official allocation notification message. This outcome was manipulated within-subjects, with each participant receiving a favorable or unfavorable outcome in 50% of the scenarios (outcomes randomly assigned to scenarios per participant). When receiving a favorable outcome, participants were informed that they received their desired option. When receiving an unfavorable outcome, participants were informed that they did not receive their desired option and were assigned an alternative.

Participants then completed a post-decision questionnaire measuring their perceived procedural and distributive fairness (Organizational Justice scale), trust in the AI system (Trust in Automation scale), acceptance of the decision (Acceptance scale), and their behavioral intention to use the system in the future (Behavioral Intention scale). A manipulation check for outcome favorability was also included, asking participants how much the outcome corresponded to their personal preferences (visual analogue scale; 0 = "not at all", 100 = "completely").

The same process (scenario description, task rating, decision input, waiting for co-participants, transparency information, outcome information, post-decision questionnaires) was repeated for all four scenarios. Two further attention checks, similar in format to the first, were randomly administered during the evaluation of two of the four scenarios (see Figure 1).

Finally, participants completed additional questionnaires for a separate individual differences study and were then fully debriefed about the purpose of the study, the fictional nature of the AI and the other participants, and the different transparency manipulations. They were further given the opportunity to ask questions or provide comments.

2.3 Measures

All scales were presented in German and, where necessary, adapted to the context of AI decision-making for resource allocation. Items belonging to the same construct were averaged to create composite scores. A Bayesian Confirmatory Factor Analysis (BCFA) indicated an acceptable model fit for all variables (see Appendix).

Perceived Fairness: Perceived fairness was assessed using procedural and distributive fairness subscales from the German version of Colquitt's [13] Organizational Justice Questionnaire [38, 40]. Responses were provided on a 5-point Likert scale (1 = "not at all" to 5 = " completely"). Both scales demonstrated high internal consistency in this study (Procedural Fairness α = .91, Distributive Fairness α = .93).

Trust in Automation (TiA): Trust in automation was measured using the two-item TiA subscale of Körber [26], assessing trust in the specific AI system encountered in each scenario. Responses were on a 5-point Likert scale (1 = "do not agree at all" to 5 = "fully agree"). The two items showed a strong correlation (r = .94).

Acceptance: Acceptance was measured using a three-item scale adapted from Gillespie et al. [18]. Responses were provided on a 5-point Likert scale (1 = "not at all" to 5 = " completely"). The scale showed high internal consistency ($\alpha = .95$).

Behavioral Intention (UTAUT2): Behavioral intention was assessed using the three-item behavioral intention subscale of the German version of the UTAUT2 questionnaire [56] (German version by [20]). Responses were provided on a 7-point Likert scale (1 = "absolutely disagree" to 7 = "absolutely agree"). The scale demonstrated excellent internal consistency ($\alpha = .97$).

Task Type: Task type was measured with a single item on a visual analogue scale (0 = "entirely human task" to 100 = "entirely mechanical task"): "How would you categorize the task shown in this scenario?".

Outcome Favorability: The actually perceived outcome favorability was measured with a single item on a visual analogue scale (0 = "not at all" to 100 = "completely"): "How much does the result correspond to your personal preference?".

Relevance: Relevance was assessed with a single item on a visual analogue scale (0 = "Very irrelevant" to 100 = "Very relevant"): "How relevant is this scenario for you personally?".

3 Results

Given that both evidence in favor of as well as against an effect (i.e., the alternative hypothesis) was informative for our research question, we used Bayesian linear mixed-effects models, implemented with the *brms* package [11, 12] in R Version 4.5.0 [45]. Per model, we ran four Markov Chain Monte Carlo (MCMC) chains, each with 12,000 iterations, including a 2,000-iteration warmup period, yielding a total of 40,000 post-warmup draws for posterior inference. Default, weakly informative priors, as specified by brms, were used for all parameters. Model convergence was confirmed by ensuring R-hat ($\hat{R}$) values were ≤ 1.01 for all parameters, visually inspecting the chains, and verifying sufficiently large effective sample sizes (ESS).

All models included random intercepts for participants (N = 929) to account for baseline variability across individuals and random slopes for outcome favorability (manipulated within-subjects) per participant. An additionally preregistered random intercept for scenario (N = 4) accounted for virtually no variance in an initial analysis, indicating that result patterns did not distinctly differ between scenarios. We thus decided to not further consider this random intercept to simplify the tested models. Note, however, that supplementary, exploratory analyses revealed that scenarios moderated the effect of outcome favorability (see Appendix for full analyses). The two categorical predictors, outcome favorability (favorable vs. unfavorable) and transparency (low vs. balanced vs. high), were coded as treatment contrasts. The continuous predictor task type was z-standardized. The structure of the maximum model considered per dependent variable was: dependent variable ~ outcome favorability * transparency * task type + (1 + outcome favorability | participant).

To quantify evidence for or against the alternative hypothesis, we report Bayes Factors (BF_{10}) comparing models including the corresponding effect of interest against models without it. Following common conventions [30], BF_{10} values 1-3 are considered as anecdotal evidence, 3-10 as moderate evidence, 10-30 as strong evidence, 30-100 as very strong evidence, and >100 as extreme evidence for the alternative hypothesis (H_1). As preregistered, we categorize BF_{10} values ≥ 5 as conclusive evidence for the alternative hypothesis. Correspondingly, BF_{10} values ≤ 0.20 were considered as conclusive evidence against the alternative hypothesis and in favor of the null hypothesis. A comprehensive summary of the model parameters and Bayes Factors can be found in Appendix (Section A.3, Table 2).

3.1 Scenario Descriptives

The four scenarios presented to participants were task allocation at work, allocation of work time models, allotment garden plot allocation, and kindergarten spot allocation.

Regarding the task type (where higher scores are more "mechanical"), all scenarios were, on average, rated near the midpoint of the scale: task allocation (M = 46.2, SD = 27.0), work time models (M = 47.5, SD = 27.2), allotment garden plots (M = 49.7, SD = 27.3), and kindergarten spots (M = 44.0, SD = 29.2), but showed substantial inter-individual variance per scenario. This demonstrates the importance of inquiring about individual perceptions of task type and using them in corresponding analyses when investigating the influence of task type. Perceptions of personal relevance also varied across scenarios, with work time models being rated as most relevant (M = 52.8, SD = 32.4) and kindergarten spot allocation as least relevant (M = 39.3, SD = 36.9). The remaining scenarios of task allocation (M = 50.4, SD = 31.2) and garden plots (M = 46.1, SD = 32.7) fell in between. Again, we observed substantial inter-individual variance per scenario.

3.2 Hypotheses Testing

3.2.1 *Outcome Favorability.*

The analysis revealed that outcome favorability had a decisive effect on all measured user perceptions. Receiving a favorable outcome, compared to an unfavorable one, led to substantially higher ratings of perceived procedural fairness ($BF_{10} \approx 2.91 \text{ x } 10^{153}$), distributive fairness ($BF_{10} = \infty$), trust in the AI ($BF_{10} \approx 3.69 \text{ x } 10^{155}$), acceptance ($BF_{10} \approx 7.64 \text{ x } 10^{159}$), and behavioral intention to use ($BF_{10} \approx 5.37 \text{ x } 10^{161}$). See Appendix for evidence that participants' perceived outcome favorability per decision corresponds to the outcome favorability categories.

3.2.2 *Transparency.*

There was decisive evidence against the main effect of transparency on user perceptions. The overall Bayes Factors strongly supported the null hypothesis for procedural fairness ($BF_{10} \approx 0.000$), distributive fairness ($BF_{10} \approx 0.000$), Trust ($BF_{10} \approx 0.000$), acceptance ($BF_{10} \approx 0.003$), and behavioral intention to use ($BF_{10} \approx 0.001$).

3.2.3 *Task Type.*

The perceived nature of the task had a strong, consistent effect on users' evaluations of the AI system. Tasks perceived as more mechanical as compared to more human consistently elicited higher ratings across procedural fairness ($BF_{10} \approx 2426$), distributive fairness ($BF_{10} \approx 127$), trust ($BF_{10} \approx 1315$), acceptance ($BF_{10} \approx 1.03 \times 10^{10}$), and behavioral intention to use ($BF_{10} \approx 2063$).

3.2.4 Interactions. Evidence against an interaction between outcome favorability and transparency was found for procedural fairness ($BF_{10} \approx 0.00$), distributive fairness ($BF_{10} \approx 0.003$), trust ($BF_{10} \approx 0.000$), acceptance ($BF_{10} \approx 0.013$), as well as behavioral intention to use ($BF_{10} \approx 0.001$).

Evidence for/against an interaction between outcome favorability and task type was mixed. Bayes factors provided strong evidence against an interaction of outcome favorability and task type for procedural fairness ($BF_{10} \approx 0.019$) and trust ($BF_{10} \approx 0.00$). For distributive fairness, there was decisive evidence for an interaction between outcome favorability and task type ($BF_{10} \approx 4.37 \times 10^{11}$). A detailed analysis of this interaction showed that the effect of task type on distributive fairness was weaker when the outcome was favorable rather than unfavorable (favorable: $BF_{10} \approx 11$; unfavorable: $BF_{10} \approx 2856$). For acceptance ($BF_{10} \approx 1.49 \times 10^8$) and behavioral intention to use ($BF_{10} \approx 265$), the data showed extreme and strong evidence, respectively, for an interaction between outcome favorability and task type. However, the pattern differed from distributive fairness. A more mechanical task type increased acceptance both under favorable ($BF_{10} = \infty$) and unfavorable outcome conditions ($BF_{10} = \infty$), with a more pronounced effect for favorable outcomes. Similarly, a more mechanical task type also increased behavioral intention in both conditions, with a stronger effect for favorable rather than unfavorable outcomes (favorable: $BF_{10} = \infty$; unfavorable: $BF_{10} \approx 562$).

Finally, for the interaction between transparency and task type, results consistently and strongly supported the null hypothesis for procedural fairness ($BF_{10} \approx 0.000$), distributive fairness ($BF_{10} \approx 0.049$), acceptance ($BF_{10} \approx 0.001$), and behavioral intention to use ($BF_{10} \approx 0.019$). For trust, we found an inconclusive but moderate tendency against the interaction of transparency and task type ($BF_{10} \approx 0.308$).

Finally, we assessed the three-way interaction between outcome favorability, transparency, and task type (see Figure 2). Evidence for/against the three-way interaction was mixed across dependent variables. Strong evidence against the three-way interaction was found for procedural fairness ($BF_{10} \approx 0.008$), trust ($BF_{10} \approx 0.015$), and acceptance ($BF_{10} \approx 0.013$). However, decisive and strong evidence for the three-way interaction emerged for distributive fairness ($BF_{10} \approx 4.88 \times 10^{16}$) and behavioral intention ($BF_{10} \approx 1015$), respectively. For unfavorable outcomes, task type effects on distributive fairness varied across transparency conditions: The slope of task type was conclusive and steepest for high transparency ($BF_{10} \approx 13{,}332$). For low transparency, the task type slope was also conclusive but less steep ($BF_{10} \approx 52.55$), whereas the evidence in favor of a task type slope was inconclusive for the balanced transparency condition ($BF_{10} \approx 1.14$). Conversely, for favorable outcomes, task type slopes showed only weak (inconclusive) to moderate effects across transparency levels (low transparency: $BF_{10} \approx 3.37$; balanced transparency: $BF_{10} \approx 2.14$; high transparency: $BF_{10} \approx 7.70$). That is, task type influences differed less across transparency conditions when outcomes were favorable as compared to unfavorable.

For behavioral intention, when outcomes were unfavorable, the size of task type effects (i.e., the steepness of the task type slope) increased with transparency level from low transparency (BF10 $\approx$ 18.86) to balanced transparency (BF10 $\approx$ 3.21) and high transparency (BF10 $\approx$ 505.33). For favorable outcomes, task type effects were stronger relative to unfavorable outcomes per transparency level. Furthermore, interestingly, task type effects were again most pronounced under high transparency (BF10 = ∞), but intermediate under low transparency (BF10 $\approx$ 309.08) and least pronounced under balanced transparency (BF10 $\approx$ 29.30).

4 Discussion

This study aimed to disentangle the complex interplay of outcome favorability, transparency, and perceived task type on users' perceptions of AI-driven decision-making systems. Our findings reveal a clear hierarchy of influence, showing that users overwhelmingly prioritize personal outcome optimization. The results clearly indicate that what the AI decides (outcome; H1) and what it decides about (task type; H4) are the most powerful, direct predictors of user reactions, while the effect of process descriptions and explanations (e.g., transparency manipulations) appears to be more complex and less direct than anticipated (H2).

Consistent with prior findings [51], the favorability of the decision outcome yielded the strongest influence on participants' perception of AI-driven decision-making. The extreme Bayes Factors in favor of the effect of outcome favorability across all dependent variables underscore that users' primary basis for evaluation was a decision's tangible result. This aligns with the concept of outcome bias, where individuals' judgments of a process are strongly influenced by its result, even if the outcome itself is not a direct indicator of the process's quality [5, 35]. From a practical standpoint, these findings present a double-edged sword. On the one hand, they suggest that designing systems optimized for maximally favorable average user outcomes (outcome optimization) is the most direct path to acceptance and adoption. Yet, on the other hand, this carries the inherent risk of entrenching structural inequities (when individual characteristics like age, gender, or ethnicity are included as AI inputs) if it leads to a narrow focus on majority preferences while marginalizing other critical variables, such as fairness to minorities or disadvantaged groups. Furthermore, our findings indicate that AI-based discrimination can also create a self-perpetuating cycle of disadvantages for disadvantaged groups, as they experience fewer (more) positive (negative) outcomes of AI decisions, they may be less likely to trust and use AI systems. In turn, this could prevent them using AI in the future and, correspondingly, from benefitting from future technological advancements, further perpetuating their marginalization.

Moreover, task type yielded a strong influence on the evaluation of AI-driven decision-making as we had hypothesized (see also [31]). Participants perceived the AI decision-maker far more positively (i.e., more fair, trustworthy, acceptable, and desirable for usage) for tasks they considered more mechanical rather than human-centric. Our findings align with prior research on algorithm aversion and algorithm appreciation [15, 37]. Depending on the decision context, that is, the task type, participants showed more versus less preference for the AI decision-maker [31]. Importantly, however, our assessment captures individual-level variance in how tasks were perceived and the impact these task-perceptions have on the evaluation of the AI decision-maker. Yet, our intentionally chosen global assessment of task characteristics on a continuum from mechanical to human simultaneously presents a limitation,

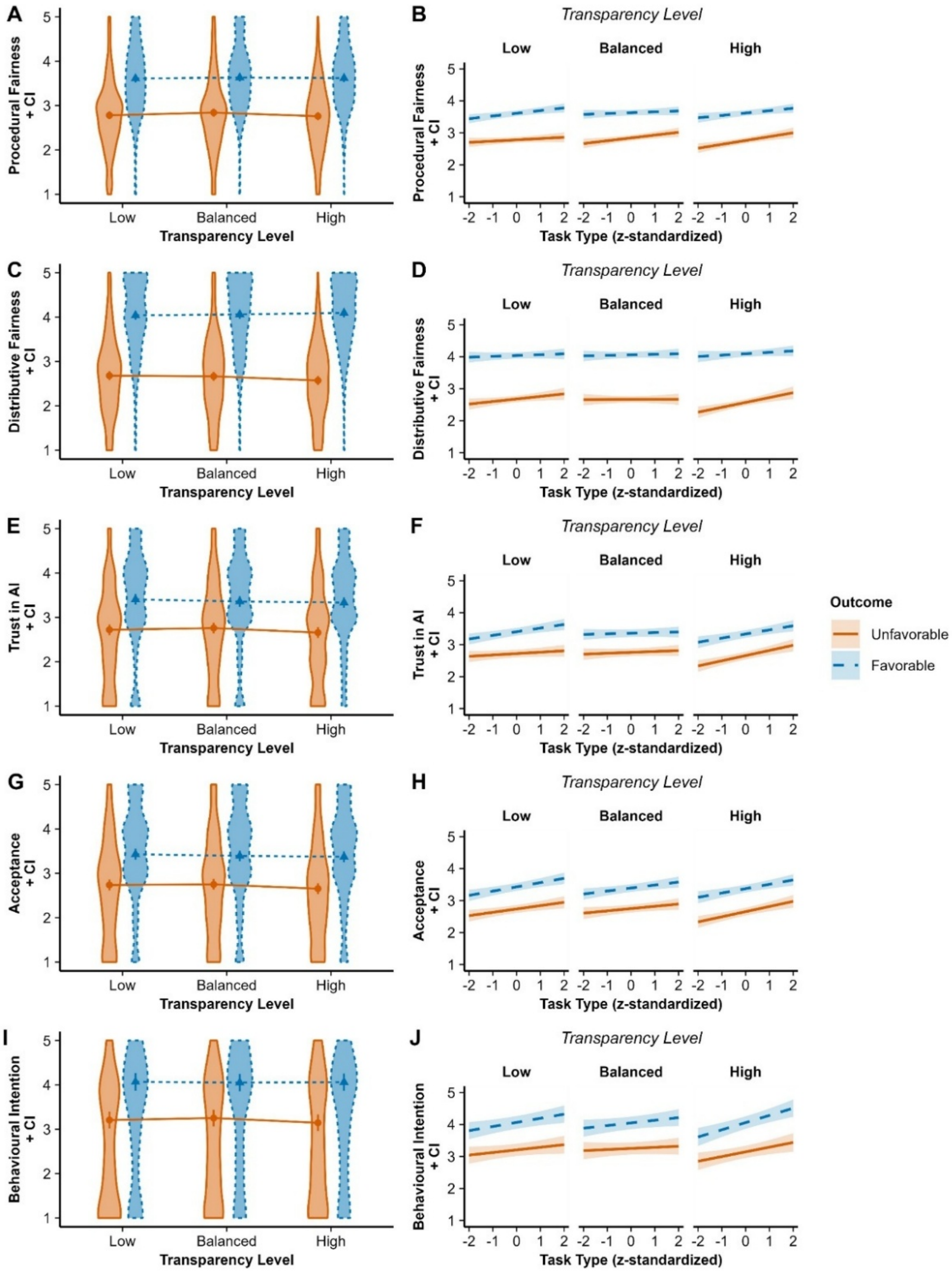

Figure 2: Graphical Illustration of Outcome Favorability by Transparency (left column; A, C, E, G, I) and of all Independent Variables including Task Type (right column; B, D, F, H, J). For the left column, horizontal lines in the violin plots denote the respective mean. For the right column, the coloured bands depict the 95%-confidence interval.

as it does not allow us to disentangle individual features of the multifaceted, inherent task characteristics, such as perceived risk, complexity, or subjectivity [44]. Future work would strongly benefit from developing a more detailed taxonomy of task characteristics beyond the human-mechanical continuum to infer which specific task characteristics most strongly contribute to the perception and evaluation of AI decision-makers.

Our findings regarding transparency are also clear-cut: We predicted an inverted U-shaped effect with the most positive evaluations of the AI occurring for the balanced transparency condition

[25]. Yet, the Bayes factors provided strong evidence against an effect of transparency on any dependent variable. These findings align with prior research suggesting that providing an explanation does not necessarily lead to better evaluations of AI [25, 32, 55], as different types of transparency may elicit different reactions. We had expected that prior discrepancies in the impact of transparency might be better explained by additionally considering interactions with outcome favorability and task type. Yet, contrary to our expectations, we found strong evidence *against* an interaction between transparency and outcome favorability (H3) and between transparency and task type (H6). These consistent null findings, even when accounting for interactions, highlight the need for a systematic re-assessment of the boundary conditions for transparency's effects in AI interaction. In this context, it has to be noted that our operationalization of transparency intentionally reduced the complexity of the transparency assessment for the sake of feasibility. Thus, the present transparency manipulation cannot fully account for all facets of the concept transparency, representing a key limitation of this study. We focused on how a decision was made (i.e. standards clarity), but we did not focus on why it was made (i.e. outcome clarity) [32]. Moreover, further elements of procedural justice, such as voice, accuracy, and correctability [33] likely are also central to AI perception and acceptance. Future research should thus aim to assess the different elements of procedural justice and types of transparency in more detail. Additional qualitative assessments could provide further insights into why we failed to see an impact of transparency in this study.

The most theoretically nuanced finding of this study, however, emerged from the selective nature of the one interaction between outcome favorability and task type (H5). We found decisive evidence for this interaction on three specific outcomes: distributive fairness, acceptance, and behavioral intention to use. In stark contrast, there was decisive evidence *against* this same interaction for procedural fairness and trust. This clear divergence invites a more careful, differentiated view of how users form judgments about AI systems. We cautiously propose that this pattern reflects a distinction between direct, outcome-oriented evaluations and more indirect, process-oriented evaluations. The variables that showed a strong sensitivity to the interaction, distributive fairness (the fairness of the received outcome), acceptance (the willingness to assent to that outcome), and behavioral intention (the willingness to be subject to future outcomes), are all fundamentally concerned with the more direct and personal consequences of the AI's decision. This suggests that these judgments are highly context-sensitive, shaped by the specific interplay of what the AI decides and the perceived appropriateness of the task type for this decision.

Conversely, procedural fairness (the perceived quality of the process) and trust appear to function as more stable, indirect assessments. In this context, they seem less susceptible to the immediate influence between a single outcome and the task type. These findings have important implications for how we conceptualize and measure fairness in AI. The differential responsiveness of procedural versus distributive fairness to this contextual interaction demonstrates that ”fairness” is not a unitary construct. This distinction, well-established in organizational justice theory, is clearly critical in the AI domain as well.

This highlights a crucial avenue for future research and design regarding AI-based decision-making: The need to approach user experience in AI not as a monolithic concept, but as a differentiated set of dimensions. Future work should continue to disentangle these components to explore which design choices most effectively influence the specific aspects of how we perceive and evaluate AI, like acceptance and usage intention. It has to be noted that our findings are at present restricted to a German sample. We thus encourage future cross-cultural research to validate these findings more broadly. Moreover, to make the comparison of four scenarios feasible, we opted for a setting in which hypothetical scenarios were described to participants in a vignette study. This however, meant that participants knew that they would not be affected by the AIs' decisions. In the future, our findings should also be reconfirmed in a scenario in which participants are (or are at least convinced to be) directly affected by the AI's decision.

5 Conclusion

This study underscores that user perceptions of AI-driven decision-making are shaped by a complex interplay of factors. Our findings clearly demonstrate that the tangible consequences of a decision, both what the outcome is and what it is about, are the most powerful drivers of user judgment. While the favorability of an outcome and the perceived nature of the task consistently and strongly predict user reactions, the role of transparency appears far more nuanced and less direct. The selective interaction between outcome favorability and task type on outcome-oriented evaluations but not on process-oriented evaluations provides a first insight into the differentiation of fairness and suggests that more research is needed to untangle the complex interplay of acceptance and use of AI systems.

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Table 1: Results from the Bayesian Confirmatory Factor Analysis

Latent VariableItems	Estimate	Post.SD	95% CI Lower	95%CI Upper	Std.lv	Std.all	Rhat	Prior
Procedural Fairness								
Proc_Fair_1	0.855	0.013	0.829	0.882	0.855	0.855	1.000	normal(0,10)
Proc_Fair_2	0.740	0.014	0.712	0.769	0.740	0.740	1.000	normal(0,10)
Proc_Fair_3	0.688	0.015	0.659	0.717	0.688	0.688	1.000	normal(0,10)
Proc_Fair_4	0.784	0.014	0.757	0.812	0.784	0.784	1.000	normal(0,10)
Proc_Fair_5	0.692	0.015	0.663	0.721	0.692	0.691	1.000	normal(0,10)
Proc_Fair_6	0.832	0.014	0.805	0.859	0.832	0.831	1.000	normal(0,10)
Proc_Fair_7	0.723	0.014	0.695	0.752	0.723	0.723	1.000	normal(0,10)
Distributive Fairness								
Dis_Fair_1	0.816	0.014	0.789	0.843	0.816	0.815	1.000	normal(0,10)
Dis_Fair_2	0.899	0.013	0.874	0.924	0.899	0.898	1.000	normal(0,10)
Dis_Fair_3	0.880	0.013	0.855	0.906	0.880	0.880	1.000	normal(0,10)
Dis_Fair_4	0.913	0.013	0.888	0.938	0.913	0.912	1.000	normal(0,10)
Trust								
TiA_1	0.946	0.012	0.923	0.971	0.946	0.946	1.000	normal(0,10)
TiA_2	0.941	0.012	0.917	0.965	0.941	0.941	1.000	normal(0,10)
Behavioral Intention								
BI_UTAUT2_1	0.956	0.012	0.933	0.980	0.956	0.956	1.000	normal(0,10)
BI_UTAUT2_2	0.968	0.012	0.945	0.992	0.968	0.968	1.000	normal(0,10)
BI_UTAUT2_3	0.959	0.012	0.936	0.983	0.959	0.959	1.000	normal(0,10)
Acceptance								
Acceptance_1	0.906	0.013	0.881	0.931	0.906	0.906	1.000	normal(0,10)
Acceptance_2	0.949	0.012	0.926	0.974	0.949	0.949	1.000	normal(0,10)
Acceptance_3	0.952	0.012	0.928	0.976	0.952	0.952	1.000	normal(0,10)

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A A APPENDICES

A.1 Bayesian Confirmatory Factor Analysis

Before testing our hypotheses, we assessed the psychometric properties of our scales using Bayesian Confirmatory Factor Analysis (CFA) at the within-person level. The analysis was conducted using the *blavaan* package (version 0.5.8), and the model converged after 12,000 iterations. The fit of the measurement model was evaluated using Bayesian fit indices. The posterior predictive p-value (PPP) was 0.000. The Bayesian Root Mean Square Error of Approximation (BRMSEA) was 0.068 (90% CI [0.068, 0.069]), indicating acceptable model fit. Other fit indices also suggested an acceptable fit: the Bayesian Gamma Hat (BGammaHat) was 0.95, and the Bayesian McDonald's Mc fit index was 0.77. The standardized factor loadings for all items on their respective latent variables were substantial (see Table 1), and latent variable correlations were appropriate.

A.2 Manipulation Check

We conducted a linear mixed-effects model (LMM) to confirm the effectiveness of the outcome manipulation. The model predicted the z-standardized ratings on the manipulation check item from the experimental condition (Favorable vs. Unfavorable). Participants in the favorable outcome condition rated the outcome as significantly more favorable than those in the unfavorable condition ($t(3713) = 106.19$, $p < .001$, $\beta = 1.73$).

A.3 Bayesian Linear Mixed Model Results

A.4 Scenario Effects

To address potential differences between our four scenarios, we examined whether our four specific allocation contexts (workplace task allocation, work time models, garden plots, kindergarten spots) were differentially affected by our manipulations. Using linear mixed-effects models, per dependent variable, we tested the following model: Dependent variable ~ scenario * outcome favorability

Table 2: Results

Effect	Parameter	β [95% CI]	BF_{10}	Interaction	As Hypothesized
H1: Outcome Favorability					
Procedural Fairness	Outcome Favorability	0.83 [0.77, 0.89]	$\approx 2.91 \times 10^{153}$	++	H1: ✓
Distributive Fairness	Outcome Favorability	1.44 [1.36, 1.52]	∞	++	H1: ✓
Trust (TiA)	Outcome Favorability	0.65 [0.59, 0.71]	$\approx 3.69 \times 10^{155}$	++	H1: ✓
Acceptance	Outcome Favorability	0.69 [0.62, 0.75]	$\approx 7.64 \times 10^{159}$	++	H1: ✓
Behavioral Intention (BI)	Outcome Favorability	0.86 [0.77, 0.96]	$\approx 5.37 \times 10^{161}$	++	H1: ✓
H2: Transparency					
Procedural Fairness	Overall Effect	—	≈ 0.00	–	H2: X
Distributive Fairness	Overall Effect	—	≈ 0.00	–	H2: X
Trust (TiA)	Overall Effect	—	≈ 0.00	–	H2: X
Acceptance	Overall Effect	—	≈ 0.00	–	H2: X
Behavioral Intention (BI)	Overall Effect	—	≈ 0.00	–	H2: X
H4: Task Type					
Procedural Fairness	Task Type	0.09 [0.05, 0.12]	≈ 2426	++	H4: ✓
Distributive Fairness	Task Type	0.11 [0.06, 0.15]	≈ 127	++	H4: ✓
Trust (TiA)	Task Type	0.08 [0.05, 0.12]	≈ 1315	++	H4: ✓
Acceptance	Task Type	0.13 [0.10, 0.17]	$\approx 1.03 \times 10^{10}$	++	H4: ✓
Behavioral Intention (BI)	Task Type	0.13 [0.08, 0.18]	≈ 2063	++	H4: ✓
H3: Outcome Favorability × Transparency					
Procedural Fairness	Interaction (Overall)	—	≈ 0.00	–	H3: X
Distributive Fairness	Interaction (Overall)	—	≈ 0.00	–	H3: X
Trust (TiA)	Interaction (Overall)	—	≈ 0.00	–	H3: X
Acceptance	Interaction (Overall)	—	≈ 0.01	–	H3: X
Behavioral Intention (BI)	Interaction (Overall)	—	≈ 0.00	–	H3: X
H5: Outcome Favorability × Task Type					
Procedural Fairness	Interaction (Overall)	—	≈ 0.02	–	H5: X
Distributive Fairness	Interaction (Overall)	—	$\approx 4.37 \times 10^{11}$	++	H5: ✓
Trust (TiA)	Interaction (Overall)	—	≈ 0.00	–	H5: X
Acceptance	Interaction (Overall)	—	$\approx 1.49 \times 10^{8}$	++	H5: ✓
Behavioral Intention (BI)	Interaction (Overall)	—	≈ 265	++	H5: ✓
H6: Transparency × Task Type					
Procedural Fairness	Interaction (Overall)	—	≈ 0.00	–	H6: X
Distributive Fairness	Interaction (Overall)	—	≈ 0.05	–	H6: X
Trust (TiA)	Interaction (Overall)	—	≈ 0.31	-	H6: X
Acceptance	Interaction (Overall)	—	≈ 0.00	–	H6: X
Behavioral Intention (BI)	Interaction (Overall)	—	≈ 0.02	–	H6: X
Outcome Favorability × Transparency × Task Type					
Procedural Fairness	Interaction (Overall)	—	≈ 0.01	–	/
Distributive Fairness	Interaction (Overall)	—	$\approx 4.88 \times 10^{16}$	++	/
Trust (TiA)	Interaction (Overall)	—	≈ 0.02	–	/
Acceptance	Interaction (Overall)	—	≈ 0.01	–	/
Behavioral Intention (BI)	Interaction (Overall)	—	≈ 1015	++	/

Results in bold indicate conclusive results. ++ and – refer to conclusive evidence respectively for or against an effect + and – refer to inconclusive tendencies towards or against an interaction.

* transparency * task type + (1 + outcome favorability | participant). We assessed the effect of scenario as well as all interactions involving scenario (see Table 3 for the results overview).

The analysis revealed several significant effects involving the different scenarios. Notably, Scenario 1 showed a significant positive main effect on procedural fairness, distributive fairness, and behavioral intention compared to the reference scenario. Another interaction pattern occurred between scenario and outcome favorability, which significantly influenced perceptions of distributive fairness. Specifically, the effect of a favorable outcome was weaker in Scenario 1 but stronger in Scenario 3.

Beyond this, other significant interactions were more isolated. Transparency interacted with the scenario in two cases: high transparency in Scenario 1 significantly impacted procedural fairness, while balanced transparency in Scenario 3 affected behavioral intention. Finally, three distinct three-way interactions were significant: Scenario 1 × Transparency × Task Type for distributive fairness, Scenario 3 × Transparency × Task Type for Trust in AI, and Scenario 2 × Outcome × Task Type for behavioral intention.

Overall, the analysis did not reveal a systematic pattern of effects for the scenarios across dependent variables. We conclude that, at present, there is no reason to assume that the scenario (beyond its task type) systematically affected the impact of our outcome favorability, transparency, and task type manipulations on the dependent variables.

Table 3: Influence of Scenario

Predictors | DVs	Procedural Fairness	Distributive Fairness	Trust in AI	Acceptance	Behavioral Intention
	β | p	β | p	β | p	β | p	β | p
(Intercept)	2.73 | **<0.001**	2.65 | **<0.001**	2.70 | **<0.001**	2.73 | **<0.001**	3.14 | **<0.001**
Scenario 1	0.13 | **0.003**	0.12 | **0.023**	0.05 | 0.255	0.06 | 0.197	0.16 | **0.019**
Scenario 2	0.03 | 0.550	0.04 | 0.395	0.06 | 0.207	0.05 | 0.297	0.05 | 0.401
Scenario 3	0.00 | 0.928	-0.05 | 0.310	-0.05 | 0.292	-0.09 | 0.063	0.01 | 0.860
Scenario 1 × Outcome	-0.12 | 0.054	-0.23 | **0.002**	-0.02 | 0.718	-0.09 | 0.197	-0.19 | 0.052
Scenario 2 × Outcome	0.06 | 0.322	0.09 | 0.227	0.00 | 0.962	-0.00 | 0.970	-0.02 | 0.808
Scenario 3 × Outcome	0.05 | 0.432	0.19 | **0.011**	0.10 | 0.109	0.09 | 0.175	0.08 | 0.395
Scenario 1 × Trans 1	-0.03 | 0.582	-0.01 | 0.887	0.07 | 0.279	0.01 | 0.832	0.01 | 0.913
Scenario 2 × Trans 1	-0.04 | 0.510	-0.08 | 0.256	-0.02 | 0.732	-0.06 | 0.368	-0.06 | 0.544
Scenario 3 × Trans 1	-0.06 | 0.314	0.02 | 0.819	-0.03 | 0.589	0.01 | 0.933	-0.19 | **0.034**
Scenario 1 × Trans 2	-0.17 | **0.004**	-0.10 | 0.207	-0.07 | 0.312	-0.06 | 0.351	-0.09 | 0.345
Scenario 2 × Trans 2	0.02 | 0.727	-0.02 | 0.745	0.03 | 0.698	0.02 | 0.728	0.12 | 0.183
Scenario 3 × Trans 2	-0.03 | 0.574	0.02 | 0.773	-0.03 | 0.625	0.02 | 0.713	-0.12 | 0.194
Scenario 1 × Task	0.00 | 0.987	0.06 | 0.308	-0.07 | 0.215	-0.03 | 0.548	-0.02 | 0.769
Scenario 2 × Task	0.02 | 0.716	0.03 | 0.575	-0.01 | 0.844	0.02 | 0.669	0.14 | **0.051**
Scenario 3 × Task	-0.01 | 0.887	0.03 | 0.559	-0.09 | 0.065	-0.04 | 0.493	-0.09 | 0.199
Scenario 1 × Outcome × Trans 1	-0.01 | 0.938	0.04 | 0.675	-0.14 | 0.133	-0.02 | 0.863	0.03 | 0.803
Scenario 2 × Outcome × Trans 1	0.04 | 0.675	0.10 | 0.338	0.01 | 0.872	0.10 | 0.327	0.11 | 0.406
Scenario 3 × Outcome × Trans 1	0.02 | 0.849	-0.13 | 0.226	-0.01 | 0.923	0.03 | 0.775	0.17 | 0.200
Scenario 1 × Outcome × Trans 2	0.12 | 0.174	0.11 | 0.295	-0.03 | 0.778	0.02 | 0.851	0.03 | 0.825
Scenario 2 × Outcome × Trans 2	0.02 | 0.823	0.04 | 0.690	0.05 | 0.599	0.06 | 0.574	-0.01 | 0.921
Scenario 3 × Outcome × Trans 2	-0.03 | 0.735	-0.11 | 0.300	-0.08 | 0.385	-0.08 | 0.416	0.03 | 0.839
Scenario 1 × Outcome × Task	-0.00 | 0.975	0.01 | 0.887	0.00 | 0.955	0.02 | 0.749	0.06 | 0.549
Scenario 2 × Outcome × Task	0.01 | 0.893	-0.10 | 0.225	-0.00 | 0.970	-0.03 | 0.657	-0.21 | **0.039**
Scenario 3 × Outcome × Task	-0.02 | 0.791	-0.08 | 0.317	0.09 | 0.183	0.00 | 0.986	0.06 | 0.515
Scenario 1 × Trans 1 × Task	-0.09 | 0.159	-0.16 | **0.048**	-0.01 | 0.920	-0.07 | 0.367	-0.07 | 0.516
Scenario 2 × Trans 1 × Task	0.00 | 0.951	0.03 | 0.747	0.07 | 0.344	0.09 | 0.216	-0.06 | 0.540
Scenario 3 × Trans 1 × Task	0.10 | 0.105	0.12 | 0.126	0.16 | 0.026	0.11 | 0.118	0.11 | 0.286
Scenario 1 × Trans 2 × Task	0.04 | 0.573	0.10 | 0.264	0.10 | 0.199	0.04 | 0.594	0.18 | 0.099
Scenario 2 × Trans 2 × Task	0.06 | 0.355	-0.04 | 0.616	0.05 | 0.524	0.05 | 0.520	-0.02 | 0.850
Scenario 3 × Trans 2 × Task	0.05 | 0.464	-0.08 | 0.332	0.11 | 0.125	-0.00 | 0.959	-0.06 | 0.585
Scenario 1 × Out × Trans 1 × Task	0.07 | 0.414	0.08 | 0.473	0.09 | 0.365	0.05 | 0.622	-0.05 | 0.711
Scenario 2 × Out × Trans 1 × Task	-0.06 | 0.468	-0.05 | 0.623	-0.08 | 0.412	-0.18 | 0.076	0.08 | 0.557
Scenario 3 × Out × Trans 1 × Task	-0.07 | 0.394	-0.08 | 0.463	-0.17 | 0.081	-0.06 | 0.561	-0.07 | 0.628
Scenario 1 × Out × Trans 2 × Task	-0.05 | 0.607	-0.19 | 0.099	0.00 | 0.981	-0.05 | 0.665	-0.12 | 0.395
Scenario 2 × Out × Trans 2× Task	-0.13 | 0.157	0.13 | 0.249	-0.09 | 0.357	-0.08 | 0.422	0.09 | 0.512
Scenario 3 × Out × Trans 2 × Task	0.02 | 0.845	0.12 | 0.260	-0.09 | 0.356	0.12 | 0.241	0.08 | 0.580

All significant effects are marked in bold. Explanation of abbreviations: Scenario 1: contrast workplace tasks vs. kindergarten spots; Scenario 2: contrast work time models vs. kindergarten spots; Scenario 3: contrast garden plots vs. kindergarten spots; Outcome: Outcome Favorability; Trans 1: Transparency, contrast low vs. balanced; Trans 2: Transparency, balanced vs. high; Task: Task Type (z-standardized).