GIZEM YALCIN

Consumers in the Age of AI

Understanding Reactions Towards Algorithms and Humans in Marketing Research

Consumers in the Age of AI:
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Understanding Reactions Towards Algorithms and Humans in Marketing Research

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Inzicht in reacties op algoritmes en mensen in marketingonderzoek

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Now… Onto the next adventure!

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CHAPTER 1

Introduction

Companies are increasingly deploying algorithms to accomplish tasks that are previously managed by humans. Today, algorithms (i.e., computer systems programmed to follow a set of steps to perform a specific task; Castelo, Bos, and Lehman 2019) are commonly utilized by businesses to accomplish a wide variety of tasks: they can provide consumers with personalized recommendations (e.g., recommend what to watch; Netflix), make decisions about consumers (e.g., decide whom to admit to a company's platform; Rayatheapp) and interact with customers (e.g., provide customers with service assistance; Amazon). Demonstrating their increasing adoption among businesses, the market for artificial intelligence (AI) is projected to be worth over $300 billion by 2026 (Markets and Markets 2021). In addition to pervading the business world, algorithms and AI technologies have been increasingly adopted by governments and social institutions: Today algorithms are given a profound role to play in the judicial system, labor markets, and many other core public functions spanning healthcare, education, and military (e.g., Fry 2018; Longoni et al. 2019; Tuomi et al. 2018). This widespread adoption of algorithms in private and public sectors raises important practical and theoretical questions for consumers, companies, policymakers and academics.

The expanding importance of algorithms in our lives has encouraged marketing scholars to investigate the perceptions and use of algorithmic and human decision-makers. Despite their widespread adoption in practice, marketing scholars have repeatedly documented consumers' dislike for algorithms. For instance, consumers have been found to prefer humans over algorithms (e.g., Dietvorst, Simmons, and Macey 2015; Longoni, Bonezzi, and Morewedge 2019; Yeomans et al. 2019) and to perceive algorithms to have various weaknesses compared to humans, such as neglecting consumers' unique characteristics (Longoni et. 2019), being less authentic (Jago 2019), less intuitive (Yeomans et al. 2019), and less moral (Bigman and Gray 2018). This inconsistency between practice and academia raises the following question: if individuals are averse to algorithms, why are companies and government organizations still adopting them?

The purpose of this dissertation is twofold: First, it aims to provide a *systematic* and *comprehensive* understanding of human and algorithmic decision-making and provide managerial and theoretical insights on how consumers process and react to the same description of an output or a service that is framed to be provided by an algorithm versus a human. To provide a comprehensive understanding of consumer reactions towards algorithms and humans, this dissertation focuses on various application contexts (e.g., customer requests, product recommendations), employs different methods (e.g., experiments, secondary data analysis), and draws from a variety of literatures and theories (e.g., motivated reasoning, advice-taking). Second, this dissertation aims to offer a *nuanced* perspective on consumers' reactions towards algorithms and humans and introduces three contextual factors that impact consumers' reactions towards algorithmic and human decision-makers. Each chapter zooms into the role of an important factor that is relevant when a decision is being made, namely *the outcome of a decision* (i.e., whether the decision outcome is favorable or unfavorable; Chapter 2), *the recipient of a decision* (i.e., characteristics of the individual who receives the decision; Chapter 3), and *the role of decision complexity* (i.e., complexity is technical or emotional in nature; Chapter 4). Doing so, the dissertation offers a counterpoint to the pervasive algorithms-are-bad rhetoric in much contemporary marketing literature and provides managerial and theoretical insights into the deployment of algorithms and AI technologies. Figure 1 illustrates the focus of each chapter.

Figure 1. Overview of Chapters in this Dissertation

	Chapter 2 **Yalcin,** Lim, Puntoni, and van Osselaer	**Chapter 3** **Yalcin,** Klesse, and Dahl	**Chapter 4** **Yalcin,** Puntoni, Themeli, Philipsen, and Stamhuis
APPLICATION CONTEXT	Customer requests/feedback	Product recommendations	Judicial decision-making
METHODOLOGY	Experiments, secondary data analysis	Experiments	Experiments
FOCUS	Decision outcome	Decision recipient	Decision complexity

Chapter 2 examines how consumers react to decision outcomes about them that are framed as being made by algorithms versus humans. Companies are increasingly adopting algorithms to make decisions that affect potential and existing customers, such as accepting and rejecting applications or customer requests. Today, algorithms are commonly used to decide whose applications to accept (e.g., rayatheapp.com) or whom to lend money to (e.g., Upstart). This growing trend calls for marketing researchers to gain a better understanding of customers' reactions to decisions made by algorithms and humans. Previous research, however, has predominantly focused on how individuals choose between an algorithmic and a human service provider (Castelo et al. 2019; Logg et al. 2019; Longoni et al. 2019). Unlike this line of research, Chapter 2 investigates the responses of individuals as a recipient of decisions made by either an algorithm or a human. Specifically, this chapter investigates the effect of favorable and unfavorable decision outcomes by employing different methodological approaches (e.g., online panel studies, field experiment, secondary data analysis, in-depth interviews). Across ten studies, conducted in various domains (e.g., loan application, membership application), Chapter 2 reveals that consumers react less positively to favorable decision outcomes by algorithms (vs. humans). This negative effect of algorithms, however, is mitigated when the decision outcome is unfavorable. This chapter also demonstrates that this interactive effect is driven by distinct attribution processes: it is easier for consumers to internalize a favorable decision outcome that is rendered by a human (vs. an algorithm), while it is easy to externalize an unfavorable decision outcome regardless of the decision-maker type.

Another important decision-making element is the recipient of a decision: in this case, consumers. Do consumers' reactions to algorithms and humans depend on consumer characteristics? Which characteristics impact reactions to services that deploy algorithms? Chapter 3 examines the role of an important consumer characteristic, consumers' perceived knowledge, in the highly relevant application context of product recommendations. An increasing number of companies are deploying algorithms in addition to, or instead of, human experts to provide consumers with recommendations (e.g., about what to eat or where to go on holiday). Although past work has investigated the impact of recommendation source on the valuation of recommendations (e.g., consumers' willingness to use a recommendation), it has mostly neglected to explore the role of recommendation recipients' characteristics. Across seven studies and in various domains (e.g., road trip recommendations, coffee recommendations), Chapter 3 demonstrates that recipients' perceived knowledge in a focal domain moderates their valuation of recommendations that are told to be generated by algorithms (vs. human experts). Specifically, consumers with high subjective knowledge value recommendations from algorithms (vs. human experts) more as they believe they can engage in more meaningful collaboration with an algorithm (vs. a human expert). This greater valuation of algorithmic recommendations, however, is mitigated for consumers with low subjective knowledge in a focal domain.

The widespread adoption of algorithms is not only changing the nature of businesses but also social institutions, including the justice system. Nowadays many governments (e.g., Estonia, Netherlands) and international organizations (e.g., the Council of Europe) have been formulating policies related to the application of AI in courts. Complementing the previous chapters and in collaboration with law scholars, Chapter 4 studies the role of algorithms beyond traditional marketing contexts and examines individuals' perceptions towards algorithms versus humans making legal decisions. Additionally, this chapter investigates the role of another important element of decision-making, that is especially highly relevant for judicial decision-making: type of decision complexity. Two experiments and an internal meta-analysis demonstrate that people trust a human (vs. an algorithmic) judge more and have greater intentions to go to the court when a human (vs. an algorithmic) judge adjudicates. Importantly, these perceptions also depend on the nature of the case: trust for algorithmic judges is especially penalized when cases involve emotional complexities (vs. simple cases or technical complex ones).

Finally, Chapter 5 concludes the dissertation by summarizing the main findings of the research conducted in each chapter and by providing directions for future research.

Declaration of Contributions

Chapters 1 and 5. I have written these chapters and implemented my supervisors' feedback.

Chapter 2. I formulated the research question, reviewed the literature, designed the studies, collected, and analyzed the data. I wrote the manuscript together with Dr. Sarah

Lim. My co-authors Prof. dr. Stefano Puntoni and Prof. dr. Stijn van Osselaer provided feedback at each stage of the process.

Chapter 3. I formulated the research question together with my co-author Dr. Anne-Kathrin Klesse. I reviewed the literature, designed the studies, collected, and analyzed the data. I wrote the manuscript in collaboration with Dr. Anne-Kathrin Klesse. Dr. Anne-Kathrin Klesse and Prof. dr. Darren W. Dahl provided feedback at each stage of the process.

Chapter 4. I formulated the research question in collaboration with my co-authors. I reviewed the literature with Dr. Erlis Themeli. I then designed the studies, collected, and analyzed the data. I wrote the manuscript together with Dr. Erlis Themeli. My co-authors Prof. dr. Stefano Puntoni, Dr. Stefan Philipsen, and Prof. dr. Evert Stamhuis provided feedback at each stage of the process.

CHAPTER 2

Thumbs Up or Down: Consumer Reactions to Decisions by Algorithms Versus Humans

A growing number of companies are using algorithms to make business decisions that directly affect potential and existing customers. For example, algorithms are now used to decide which applicants should be admitted to platforms (e.g., Raya) and who should receive loans (e.g., Upstart; see Appendix 1A for more examples). As the prevalence of algorithms in consumer-facing decisions increases, so does the managerial importance of understanding consumers' reactions to algorithmic versus human decisions. We investigate consumers' reactions toward a company following a decision (favorable or unfavorable) made by an algorithmic versus a human decision-maker. Specifically, we focus on contexts where the decision outcome is considered diagnostic of the consumer's qualifications, deservingness, or merit, such as when consumers submit an application to access a valued service or other benefits.

We demonstrate that consumers react less positively when a favorable decision (e.g., the acceptance of an application) is made by an algorithm rather than by a human. This difference, however, is attenuated for an unfavorable decision (e.g., the rejection of an application). We explain this interaction between the decision-maker type and decision outcome favorability by drawing on attribution theory (Jones and Davis 1965; Kelley 1967). Consumers are motivated to internalize favorable decisions, but internal attribution is more difficult when the decisions are made by an algorithm (vs. a human), so consumers react less positively (e.g., form less positive attitudes toward the company). By contrast, consumers are motivated to externalize unfavorable decisions, and this is similarly easy with algorithmic and human decision-makers, so consumers' subsequent reaction is relatively indifferent to the decision-maker type.

The current research makes three primary contributions (see Table 1 for a comprehensive literature review). First, our research addresses an underexplored question: how do consumers' attitudes (and related constructs) change as a function of a company's use of algorithmic versus human decision-makers in consumer-facing tasks? Past work has focused on *consumers' choices*, such as for advice, between an algorithmic and a human decision-maker (Dietvorst, Simmons, and Massey 2015; Longoni, Bonezzi, and Morewedge 2019). However, companies usually decide whether to rely on algorithms or humans for a given task; consumers are more often in the position of decision recipients. Unlike prior research, the current research focuses on *consumers' reactions to algorithmic versus human decisions about themselves*. This distinction is important because the two situations may elicit different psychological processes. Decision recipients face the task of interpreting a decision outcome reflective of one's worth in the eye of others. In such a context, one's reaction to the decision outcome often involves self-serving interpretations and motivated reasoning (Taylor and Brown 1988), a topic that has not been examined in prior research on algorithmic decisions. More generally, as consumers' choices often diverge from their reactions to the given options (Botti and Iyengar 2006), we argue that it is unclear whether findings about consumers' choice behavior (e.g., reluctance to rely on algorithmic advice) are generalizable to the reactions of consumers as decision recipients (e.g., negative reactions to algorithmic decisions made about the consumers themselves).

Second, we examine an important factor that influences consumers' reactions to different decision-makers: the favorability of decision outcomes, which is known to affect people's attitudes and behaviors (e.g., Barry, Chaplin, and Grafeman 2006; Rhodewalt and

Davison 1986). Both types of decision outcomes are common; companies may deliver approvals or acceptances as well as denials or rejections to existing or potential customers—and yet, the consequences of decision outcome favorability are underexplored in the research on algorithmic (vs. human) decision-making. We find that most managers believe that consumers react more positively to decisions made by humans (vs. algorithms) regardless of the decision outcome (see the managerial intuitions study and Appendix 1B). We demonstrate, however, that favorable decision outcomes elicit divergent reactions to algorithmic versus human decision-makers, while such difference is attenuated for unfavorable decision outcomes.

Third, in examining the process underlying the proposed effect, we elucidate how consumers interpret decisions made by algorithms versus by humans. Unlike prior work that focuses on consumers' diverging perceptions of humans and algorithms (e.g., moral authenticity: Jago 2019; trustworthiness: Lee 2018), the current work examines consumers' differential attribution of a given decision outcome. Specifically, we demonstrate that for a favorable decision, a human (vs. an algorithmic) decision-maker facilitates stronger internal attribution of the decision outcome, whereas for an unfavorable decision, consumers readily engage in external attribution regardless of the type of decision-maker. The current research thus marries the psychological literature on attribution (McFarland and Ross 1982; Olcaysoy Okten and Moskowitz 2018) with the marketing literature on algorithms (Castelo, Bos, and Lehmann 2019; Puntoni et al. 2021), offering a novel contribution to both.

In the following sections, we review the extant work on algorithmic and human decision-making. We draw on attribution theory to make theoretical predictions about how consumers respond to favorable and unfavorable decisions made by algorithms versus humans.

Theoretical Background

An algorithm is "a set of steps that a computer can follow to perform a task" (Castelo et al. 2019). A growing number of companies rely on algorithms; the market for artificial intelligence is expected to be worth over $300 billion by 2026 (Markets and Markets 2021). The widespread adoption of algorithms has encouraged researchers to investigate how consumers perceive algorithms versus humans. Existing work has demonstrated that consumers perceive algorithmic and human decision-makers to have different strengths and weaknesses. For instance, compared to humans, algorithms are perceived as more objective (Lee 2018; Sundar and Nass 2001) but also as less authentic, less intuitive, and less moral (Bigman and Gray 2018; Jago 2019; Yeomans et al. 2019).

Extant work has examined consumers' choices between algorithmic and human decision-makers and has documented an aversion to algorithms (see Logg, Minson, and Moore 2019 for an exception). For instance, consumers are often reluctant to use algorithms to predict stock prices (Onkal et al. 2009), solicit medical advice (Cadario, Longoni, and Morewedge 2021; Longoni et al. 2019; Promberger and Baron 2006), and predict people's performance (Dietvorst et al. 2015). Additionally, *algorithm aversion* varies with contextual factors such as the nature of the task (subjective vs. objective: Castelo et al. 2019) and the product (hedonic vs. utilitarian: Longoni and Cian 2020).

The current research is the first to examine consumers' attitudes toward a company in the context in which 1) a decision-maker (algorithm vs. human) is already chosen, 2) the decision is made by the company about the consumers themselves (i.e., the decision is self-diagnostic), and 3) a decision outcome is known (see Table 1). Our research context is of managerial importance. Companies often deliver both types of decision outcomes—favorable (e.g., approval, acceptance) and unfavorable (e.g., denial, rejection)—to existing or potential customers. Our in-depth interviews with practitioners confirm the prevalence of algorithms in many consumer-facing tasks such as consumer application evaluations (see Appendix 1C: interviews #1 and #11), insurance premium decisions (#1), and loan application decisions (#5). Such decisions are often based on personal information provided by the consumers, and decision outcomes are thus reflective of consumers' qualifications.

Table 1. Overview of Research on Consumers' Responses to Decisions by Algorithms

Authors	**Year**	**Main Comparison**	**Main Dependent Variable**	**Decision Context** Decision-maker is already chosen	 Self-diagnostic decision	 Decision outcome is known	**Main Finding**
Bigman and Gray	2018	Computer vs. human	Perceived permissibility	✓		✓	It is less permissible for computers (vs. humans) to make moral decisions.
Bonezzi and Ostinelli	2021	AI vs. human	Perceived bias	✓		✓	Algorithmic (vs. human) decision-makers are less likely to be perceived as biased.
Cadario et al.	2021	Algorithm vs. human	Subjective understanding of decision-making, preference	✓	✓		People display an illusory understanding of human (vs. algorithmic) decision-making, which makes them more reluctant to use algorithms.
Castelo et al.	2019	Algorithm vs. human	Trust and preference		✓		People rely on algorithms less for subjective (vs. objective) tasks.
Diab et al.	2011	Formula vs. interview	Perceived usefulness	✓	✓		Thorough discussions are viewed as more useful than a formula.
Dietvorst and Bharti	2020	Statistical model vs. self	Preference				People prefer riskier decision-making methods (humans instead of statistical models) in inherently uncertain decision domains.
Dietvorst et al.	2015	Statistical model vs. self	Preference			✓	Seeing an algorithm err decreases people's willingness to rely on it.
Dietvorst et al.	2016	Statistical model vs. self	Preference			✓	People are more willing to use an algorithm when it is modifiable.
Eastwood et al.	2012	Expert using a formula vs. personal experience	Preference and perceived accuracy		✓		Using an experience is preferred and seen as more accurate than using a formula.
Efendic et al.	2020	Algorithm vs. human	Perceived accuracy and trust	✓		✓	People judge slow predictions from algorithms (vs. humans) as less accurate and are less willing to rely on them.
Jago	2019	Algorithm vs. human	Perceived authenticity	✓			People believe that algorithms (vs. humans) are less authentic.
Kim and Duhachek	2020	Artificial agent vs. human	Perceived appropriateness and compliance	✓		✓	Persuasive messages by artificial agents (vs. humans) are more appropriate and effective when the messages have low (vs. high) level construal features.
Lee	2018	Algorithm vs. human	Trust and perceived fairness	✓			For tasks that require human (vs. mechanical) skills, algorithms are perceived as less fair and trustworthy.
Logg et al.	2019	Algorithm vs. human/self	Weight on advice			✓	People adhere more to advice when it comes from algorithms (vs. humans).
Longoni and Cian	2020	AI vs. human	Preference			✓	People prefer AI (vs. human) recommenders when utilitarian (vs. hedonic) attributes of a product are more important or salient.
Longoni et al.	2019	AI vs. human	Preference		✓		People prefer to receive medical care from humans (vs AI).
Newman et al.	2020	Algorithm vs. human	Perceived fairness	✓		✓	People perceive algorithms as less fair than humans.
Onkal et al.	2009	Statistical model vs. human	Weight on advice			✓	People place greater weight on human (vs. algorithmic) advice.
Promberger and Baron	2006	Computer vs. human	Acceptance of advice and trust		✓	✓	Acceptance/trust is greater for humans than computers.
Shaffer et al.	2013	Doctor soliciting advice from computers vs. humans	Perceived ability	✓		✓	Soliciting aid from computers (but not from humans) reduces doctors' perceived ability, professionalism, and thoroughness.
Srinivasan and Sarial-Abi	2021	Algorithm vs. human	Brand evaluation	✓		✓	Consumers respond less negatively to a brand harm crisis when it is caused by an algorithmic (vs. a human-based) error.
Yeomans et al.	2019	Algorithm vs. human	Preference		✓	✓	People prefer to receive joke recommendations by humans (vs. algorithms) for themselves as well as for others.
Current research	2022	Algorithm vs. human	Attitudes toward the company	✓	✓	✓	Consumers who receive a favorable decision form less positive attitudes toward the company if the decision was made by an algorithm (vs. human). This difference is mitigated for unfavorable decisions.

Decision-maker is already chosen: whether the decision-maker type (algorithm vs. human) has been already chosen; if not, consumers (participants) are asked to choose between them
Self-diagnostic decision: whether the decisions are about the consumers themselves (i.e., reflect on the consumer's self)
Decision outcome is known: whether the decision outcome is known to consumers

We posit that the self-diagnostic nature of many consumer-facing decisions motivates consumers to make different attributions for favorable and unfavorable outcomes. The type of decision-maker (algorithm vs. human) affects consumers' internal and external attributions, leading to an interaction effect between the decision-maker type and decision outcome favorability on consumers' attitudes toward the company.

Attribution of Favorable and Unfavorable Decisions as a Function of the Decision-Maker Type

Consumers often make inferences about the causes of events, actions, and behaviors (Heider 1958; Jones and Davis 1965) and attribute behaviors or outcomes to either internal or external causes (Kelley 1967). Attribution theory proposes that people are motivated to attribute self-relevant outcomes in a self-serving way: to maintain or enhance their self-worth, people are motivated to attribute favorable outcomes to themselves (i.e., "internal attribution"; Baumeister 1999; Zuckerman 1979) and to attribute unfavorable outcomes to external factors (i.e., "external attribution"; Kelley and Michela 1980; Miller and Ross 1975). In marketing research, attribution theory has been used to explain consumers' perceptions of a company's performance (Dunn and Dahl 2012; Folkes 1984; Wan and Wyer 2019), other consumers' behavior (He and Bond 2015; O'Laughlin and Malle 2002), and one's own behavior (Leung, Paolacci, and Puntoni 2018; Yoon and Simonson 2008). We contribute to this literature by demonstrating that the decision-maker type (algorithm vs. human) affects how consumers attribute favorable versus unfavorable decision outcomes.

Consumers who receive a favorable decision are motivated to make an internal attribution (Luginbuhl, Crowe, and Kahan 1975), and we argue that they find it easier to do so when the decision is made by a human (vs. an algorithm). Consumers often define themselves based on personal characteristics (e.g., abilities, attitudes) that make them feel unique (Brewer 1991; Fromkin and Snyder 1980). Human (vs. algorithmic) decision-makers are perceived as more adept at considering individuals' unique characteristics and qualifications (Longoni et al. 2019). In contrast, algorithms usually rely on a set of pre-coded categories of characteristics and qualifications that are shared by many (note that an algorithm probably would not recognize characteristics that are unique to a single person) and reduce individuals into a number (Newman, Fast, and Harmon 2020). Thus, we predict that consumers view a favorable decision made by a human (vs. an algorithm) as more reflective of their individuality (i.e., unique self) and deservingness (e.g., "My application was accepted because of who I am"), so they would more easily make strong internal attributions for a favorable decision made by a human (vs. an algorithm). It is easier to attribute a good outcome to "me" when the decision-maker relied on characteristics and achievements that are "uniquely me". Put differently, it is more difficult to attribute a positive outcome to something about oneself if those qualities or that something is shared with many others.

On the other hand, consumers who receive an unfavorable decision are motivated to make an external attribution, and we argue that consumers would find no difference in difficulty to do so regardless of whether the decision is made by a human or an algorithm. The decision-maker is easily blamed for making a bad decision whether that decision-maker is a human or an algorithm, but for different reasons. For instance, an algorithm can be easily blamed for ignoring consumers' uniqueness (Longoni et al. 2019), while a human can easily be blamed for not being objective (Lee 2018).

If the type of decision-maker affects consumers' ability to make attributional inferences for different decision outcomes, this should be expected to have repercussions for consumer attitudes. Causal reasoning—reasoning about what or who is responsible for a given outcome—is a key factor in attitude formation and change (e.g., Forsyth 1980; Kelley 1973) and the marketing literature contains many demonstrations that attributions are an important determinant of attitudes toward companies (e.g., Dunn and Dahl 2012). In the context of automation, Leung et al. (2018) show that the extent to which the consumption context enables people to make internal or external attributions explains their product preferences. For example, in their study 6, the authors demonstrate that framing an automated product in a way that makes it easier for people to internally attribute favorable consumption outcomes leads to more positive attitudes towards the product.

Summary of Key Predictions and Overview of Studies

We present ten studies that examine our theory (see Table 2 for a summary). While most managers predict (in interviews and surveys) that consumers react more positively to human (vs. algorithmic) decision-makers regardless of decision outcome favorability, we demonstrate a robust interaction effect on attitudes toward the company (studies 1a–8) and Word-of-Mouth (WoM) intentions (specifically, the Net Promoter Score measure, study 1b). Furthermore, we examine the underlying attribution processes through both mediation (studies 4 and 6) and moderation (study 5). We also rule out alternative explanations including attention (study 2), social presence (study 7), and perceived fairness (a follow-up study in the General Discussion). Finally, we offer managerial insights into strategies for improving reactions to favorable decisions made by algorithms (study 8). We report all conditions and all measures. Some studies included an exploratory measure, for which we report analyses in Appendix 1O. For some of our studies, we screened participants before access to the study by using an attention check, such as an instructional manipulation check (IMC; Oppenheimer, Meyvis, and Davidenko 2009). Those who failed the attention check were not allowed to proceed to the actual study. Our reports of the studies include only those who participated in the actual study. Sample sizes were determined prior to data collection. All data and study materials are available on osf.io/3bnsz.

Managerial Intuitions

To evaluate the managerial importance of our findings, we examined how practitioners would predict customers' reactions to favorable versus unfavorable decisions made by humans versus algorithms. We started with a series of in-depth interviews with fourteen managers, and none correctly predicted our hypothesized interaction effect. Motivated by this preliminary result, we conducted a survey with a larger group of experienced professionals.

We report the results of the in-depth interviews in Appendix 1C and the results of the survey below.

Method. We recruited eighty-eight managers (M_{age}= 35.05, 24 females, $M_{work\ experience}$ = 11 years) from an executive MBA program at a major European business school.

We described a business situation involving consumer applications (see Appendix 1B), and we asked the managers to predict how the type of decision-maker would influence customer satisfaction in response to an acceptance and in response to a rejection (getting [accepted/rejected] by an algorithm would be better than getting accepted/rejected by an employee vs. getting [accepted/rejected] by an algorithm would be equally good as getting [accepted/rejected] by an employee vs. getting [accepted/rejected] by an employee would be better than getting [accepted/rejected] by an algorithm).

Results and Discussion. Managers expected that an algorithmic (vs. a human) decision-maker would lead to lower satisfaction regardless of decision outcome favorability (B = -.09, z = -.31, p = .76). Specifically, 61% of the managers predicted that participants would be less satisfied with an acceptance from an algorithm (vs. a human; see Figure 1). Similarly, 59% of the managers predicted that consumers would be less satisfied with a rejection from an algorithm (vs. a human).

Study 1*a:* *Effect of Decision-Maker Type as a Function of Decision Outcome Favorability: Attitudes Toward the Company (Country Club Application; N = 993; Mturk)*				
2 (Decision-maker Type) x 2 (Decision Outcome Favorability)	Favorable Decision Outcome (N = 494)		Unfavorable Decision Outcome (N = 499)	
	Algorithm (N = 253)	Human (N = 241)	Algorithm (N = 243)	Human (N = 256)
DV: Attitudes Toward the Company	7.13 (2.59)	7.88 (2.58)	3.12 (2.11)	3.02 (1.82)
Key Finding: Attitudes toward the company were more positive among participants whose applications were accepted by a human (vs. an algorithm). This effect of the decision-maker type was attenuated for participants whose applications were rejected.				
Study 1b: *Effect of Decision-Maker Type as a Function of Decision Outcome Favorability: WoM Intentions (Business Loan Application; N = 500; Prolific)*				
2 (Decision-maker Type) x 2 (Decision Outcome Favorability)	Favorable Decision Outcome (N = 249)		Unfavorable Decision Outcome (N = 251)	
	Algorithm (N = 126)	Human (N = 123)	Algorithm (N = 124)	Human (N = 127)
DV: Attitudes Toward the Company	8.06 (2.51)	9.40 (1.51)	3.39 (1.79)	3.71 (1.97)
DV: WoM Intentions	6.54 (2.27)	7.77 (1.75)	2.10 (1.81)	2.52 (2.18)
Key Finding: We replicated the interaction effect on both DVs.				
Study 2: *Replication with a Real Application Process* (Research Participant Pool Application; N = 303; Prolific)				
2 (Decision-maker Type) x 2 (Decision Outcome Favorability)	Favorable Decision Outcome (N = 152)		Unfavorable Decision Outcome (N = 151)	
	Algorithm (N = 74)	Human (N = 78)	Algorithm (N = 75)	Human (N = 76)
DV: Attitudes Toward the Company	4.57 (1.23)	5.47 (1.19)	2.88 (1.45)	3.01 (1.54)
Key Finding: We replicated the interaction effect in a real application experience, and we provided evidence against the alternative account based on inattention.				
Study 3a: *Effect of (Not) Disclosing the Decision-Maker* (Country Club Application; N = 403; Prolific)				
3-cell (Decision-maker Type)	Favorable Decision Outcome			
	Algorithm (N = 132)	Human (N = 135)		Unspecified (N = 136)
DV: Attitudes Toward the Company	6.04 (2.70)	7.21 (2.83)		6.97 (2.69)
Study 3b: *Effect of (Not) Disclosing the Decision-Maker (Loan Application; N = 402; Prolific)*				
3-cell (Decision-maker Type)	Favorable Decision Outcome			
	Algorithm (N = 135)	Human (N = 133)		Unspecified (N = 134)
DV: Attitudes Toward the Company	7.38 (2.39)	8.50 (1.94)		8.59 (1.98)
Key Findings of Studies 3a & 3b: An algorithmic decision-maker led to worse attitudes than both a human decision-maker and an unspecified decision-maker.				
Study 4: *Mediation by Internal Attribution (Country Club Application; N = 571; Prolific)*				
2 (Decision-maker Type) x 2 (Decision Outcome Favorability)	Favorable Decision Outcome (N = 287)		Unfavorable Decision Outcome (N = 284)	
	Algorithm (N = 132)	Human (N = 155)	Algorithm (N = 154)	Human (N = 130)
DV: Attitudes Toward the Company	6.49 (2.88)	7.54 (2.79)	3.74 (2.36)	3.97 (2.23)
Mediator: Internal Attribution	6.82 (2.54)	8.15 (2.24)	6.30 (2.98)	6.22 (2.81)
Key Finding: Our core interaction effect on attitudes was mediated by the strength of internal attribution of the decision outcome.				

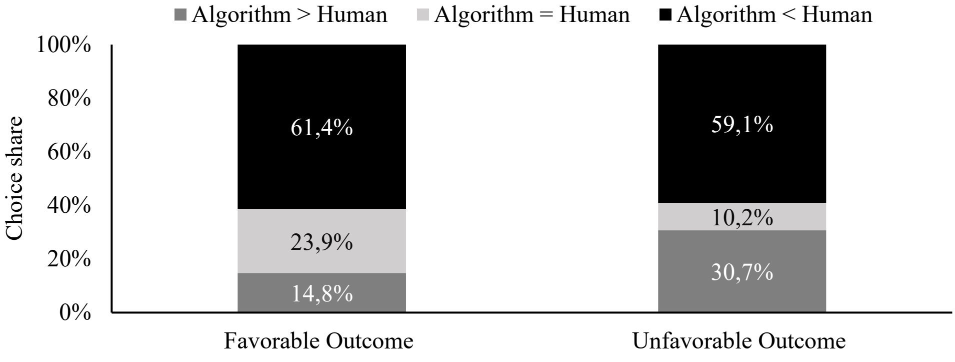
Study 5: Moderated Mediation by Internal Attribution of a Favorable Outcome (Networking Community Application; N = 443; Prolific)				
	Favorable Decision Outcome			
2 (Decision-maker Type) x 2 (Decision Method)	Evaluation (N = 222)		Raffle (N = 221)	
	Algorithm (N = 123)	Human (N = 99)	Algorithm (N = 102)	Human (N = 119)
DV: Attitudes Toward the Company	6.98 (2.34)	7.70 (2.49)	5.80 (2.74)	5.60 (2.73)
Mediator: Internal Attribution	6.84 (2.29)	8.25 (1.96)	4.08 (3.04)	4.25 (3.07)
Key Finding: The self-diagnosticity of the decision method moderates the mediation effect of internal attribution in the setting of a favorable decision outcome.				

Study 6: External Attribution of an Unfavorable Decision Outcome (Country Club Application; N = 626; Mturk)		
2-cell (Decision-maker Type)	Unfavorable Decision Outcome	
	Algorithm (N = 316)	Human (N = 310)
DV: Attitudes Toward the Company	4.84 (2.62)	4.78 (2.61)
Mediator 1: Perceived Objectiveness	7.07 (2.28)	5.95 (2.47)
Mediator 2: Uniqueness Consideration	4.41 (2.81)	5.35 (2.74)
Key Finding: Participants engaged in external attribution (blaming the algorithm [human] for its lack of consideration of individual uniqueness [for their lack of objectivity]), resulting in a relative indifference to the decision-maker type.		

Study 7: Effect of Human Decision Making versus Mere Human Observation (Country Club Application; N = 597; Mturk)						
3 (Decision-maker Type) x 2 (Decision Outcome Favorability)	Favorable Decision Outcome (N = 299)			Unfavorable Decision Outcome (N = 298)		
	Algorithm Only (N = 95)	Human (N = 98)	Algorithm with Human Monitoring (N = 106)	Algorithm Only (N = 103)	Human (N = 101)	Algorithm with Human Monitoring (N = 94)
DV: Attitudes Toward the Company	7.09 (2.68)	7.82 (2.59)	6.68 (2.65)	4.04 (2.47)	3.76 (2.29)	3.46 (1.90)
Key Finding: Participants had less positive attitudes toward the company when their applications were accepted by a human (vs. an algorithm) regardless of whether a human observed the algorithm's decision, contradicting the alternative account based on social presence.						

Study 8: Humanizing Algorithms to Mitigate Negative Consequences (Country Club Application; N = 601; Prolific)			
3-cell (Decision-maker Type)	Favorable Decision Outcome		
	Algorithm (N = 199)	Human (N = 201)	Human-like Algorithm (N = 201)
DV: Attitudes Toward the Company	7.07 (2.67)	7.87 (2.52)	7.64 (2.82)
Key Finding: Participants had similarly positive attitudes toward the company when their applications were accepted by a human and by a human-like algorithm, suggesting that anthropomorphization can mitigate the negative consequences of an algorithmic decision-maker.			

Figure 1. Managers' Predictions About Our Interaction Effect on Consumers' Reactions



Only 5% (i.e., four managers) generated our predicted interaction effect: consumers would react more favorably to an acceptance made by a human (vs. an algorithm) and would be similarly satisfied with a rejection made by a human and by an algorithm. Interestingly, managers also predicted that the decision-maker type would matter less for acceptance decisions than for rejection decisions (choice share of "algorithm = human": $M_{favorable}$ = 23.9% vs. $M_{unfavorable}$ = 10.2%; B = -1.39, z = -2.28, p = .02), the opposite of our hypothesized pattern.

How are Consumers' Attitudes Toward the Company Affected by the Decision-Maker Type and Decision Outcome Favorability?

The first set of studies tested the managers' prediction (i.e., consumers respond more positively to a human [vs. an algorithmic] decision-maker regardless of the outcome) against our own (proposed interaction effect). In studies 1a–b, we examined our hypothesized interaction effect on two dependent variables: consumers' attitudes toward the company and WoM intentions. We predicted that consumers would react less positively when a favorable decision was made by an algorithm (vs. a human); the differential reaction would be mitigated for an unfavorable decision.

Study 1a: Effect of the Decision-Maker Type as a Function of Decision Outcome Favorability: Attitudes Toward the Company

Method. In this pre-registered study (aspredicted.org/j7da3.pdf), we randomly assigned 993 Amazon Mechanical Turk (Mturk) workers ($M_{age} = 40.06$, 531 females)[1] to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design.

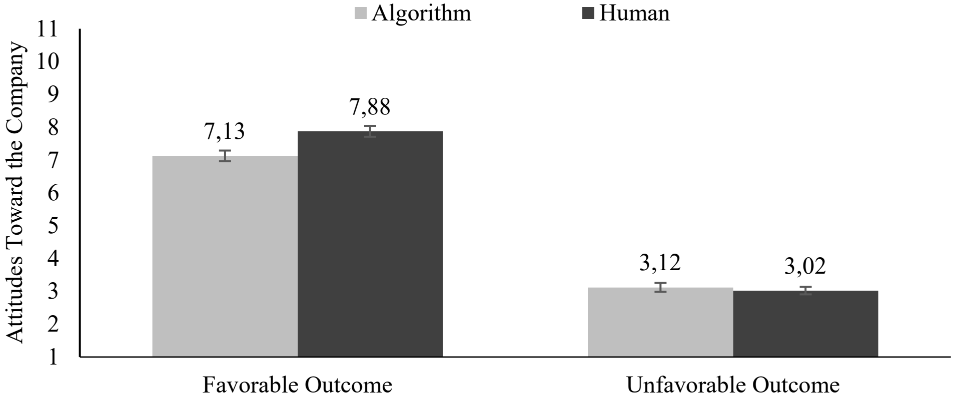
Participants read that they were applying for membership at a country club, *Violethall Country Club* (see Appendix 1D). Participants learned that their applications were either accepted (favorable decision condition) or rejected (unfavorable decision condition); we told participants that the decision was made by either a country club algorithm (algorithm condition) or by a country club coordinator (human condition). We also told all participants that the decision was final and could not be appealed. After learning the outcome, participants indicated their attitudes toward the country club ("What is your general opinion about Violethall Country Club?") on three bipolar items (1 = dislike a great deal / very

[1]One participant did not complete the demographic variables. Although in subsequent studies, we included only participants who completed all measures in our analysis, we included this one person in this study to be consistent with our pre-registration. Our results held significant regardless of whether or not we included this participant in our analysis (see Appendix 1D). As stated in our preregistration form, we targeted 1,000 participants, but the actual sample size differed for reasons beyond our control (e.g., more people claimed their participation on Mturk than the actual number of participants).

negative / not favorable at all, 11 = like a great deal / very positive / very favorable; $\alpha = .99$; adapted from Park et al. 2010).

Results. A 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA revealed a significant main effect of the decision-maker type ($M_{algorithm} = 5.16$, $SD_{algorithm} = 3.10$ vs. $M_{human} = 5.38$, $SD_{human} = 3.29$; $F(1, 989) = 4.98$, $p = .03$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable} = 7.49$, $SD_{favorable} = 2.61$ vs. $M_{unfavorable} = 3.07$, $SD_{unfavorable} = 1.96$; $F(1, 989) = 924.46$, $p < .001$, $\eta_p^2 = .48$). Consistent with our theory and inconsistent with the managers' predictions, we found a significant interaction effect ($F(1, 989) = 8.46$, $p = .004$, $\eta_p^2 = .01$; see Figure 2): attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 7.13$, $SD_{algorithm} = 2.59$ vs. $M_{human} = 7.88$, $SD_{human} = 2.58$; $F(1, 989) = 13.15$, $p < .001$, $\eta_p^2 = .01$). Meanwhile, the effect of the decision-maker type was significantly mitigated when participants' applications were rejected ($M_{algorithm} = 3.12$, $SD_{algorithm} = 2.11$ vs. $M_{human} = 3.02$, $SD_{human} = 1.82$; $F(1, 989) = .23$, $p = .63$).

Figure 2. Study 1a Results



Study 1b: Effect of Decision-Maker Type as a Function of Decision Outcome Favorability: Word-of-Mouth (WoM) Intentions

Study 1b aimed to replicate study 1a with two key changes. First, we tested whether our effect generalizes to a non-social context: business loan applications. To further remove social cues, we used "approved" and "denied" instead of "accepted" and "rejected." Second, we measured participants' Word-of-Mouth (WoM) intentions, another managerially important dependent variable.

Method. We randomly assigned 500 Prolific workers (M_{age} = 33.97, 264 females) to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design.

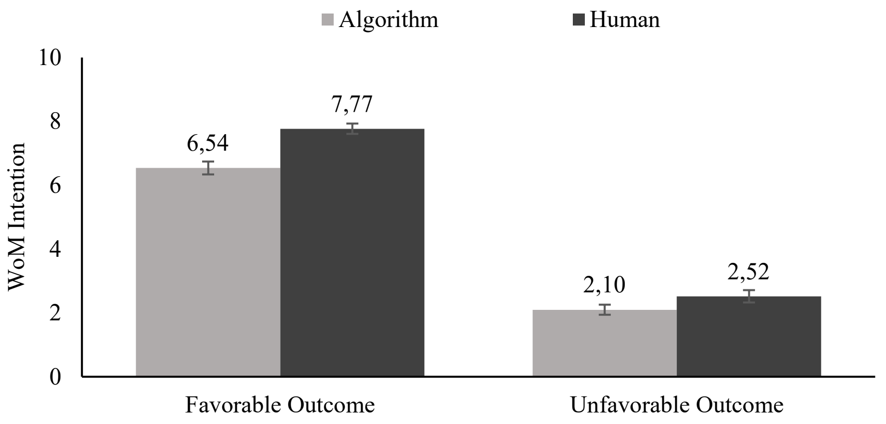
Participants read that they were applying for a business loan (see Appendix 1E). We told participants that their loan applications were either approved or denied by either a loan algorithm or a loan officer. Next, participants indicated their attitudes toward the bank (a = .99), as in study 1a. We also measured participants' WoM intentions using the item made famous by the Net Promoter Score ("On a scale from 0-10, how likely are you to recommend this bank to a friend or colleague?"; 0 = extremely unlikely, 10 = extremely likely).

Results. We first conducted a 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA on attitudes toward the bank. We found a significant main effect of the decision-maker type ($M_{algorithm} = 5.74$, $SD_{algorithm} = 3.20$ vs. $M_{human} = 6.51$, $SD_{human} = 3.35$; $F(1, 496) = 22.17$, $p < .001$, $\eta_p^2 = .04$) and of decision outcome favorability ($M_{favorable} = 8.72$, $SD_{favorable} = 2.18$ vs. $M_{unfavorable} = 3.55$, $SD_{unfavorable} = 1.89$; $F(1, 496) = 853.09$, $p < .001$, $\eta_p^2 = .63$). Crucially, we replicated the significant interaction effect on consumers' attitudes ($F(1, 496) = 8.21$, $p = .004$, $\eta_p^2 = .02$): attitudes toward the bank were less positive among participants whose applications were approved by the algorithm than among participants whose applications were approved by the loan officer ($M_{algorithm} = 8.06$, $SD_{algorithm} = 2.51$ vs. $M_{human} = 9.40$, $SD_{human} = 1.51$; $F(1, 496) = 28.56$, $p < .001$, $\eta_p^2 = .05$). Meanwhile, the effect of the decision-maker type was significantly attenuated when the applications were denied ($M_{algorithm} = 3.39$, $SD_{algorithm} = 1.79$ vs. $M_{human} = 3.71$, $SD_{human} = 1.97$; $F(1, 496) = 1.71$, $p = .19$).

Next, we conducted an analogous ANOVA on WoM intentions. We found a significant main effect of the decision-maker type ($M_{algorithm} = 4.34$, $SD_{algorithm} = 3.02$ vs. $M_{human} = 5.10$, $SD_{human} = 3.29$; $F(1, 496) = 21.01$, $p < .001$, $\eta_p^2 = .04$) and of decision outcome favorability ($M_{favorable} = 7.15$, $SD_{favorable} = 2.12$ vs. $M_{unfavorable} = 2.31$, $SD_{unfavorable} = 2.01$; $F(1, 496) = 722.11$, $p < .001$, $\eta_p^2 = .59$). More importantly, we found a significant interaction effect ($F(1, 496) = 5.04$, $p =$

.03, $\eta_p^2 = .01$; see Figure 3): the bank was less likely to be recommended to others by participants whose applications were approved by the algorithm than participants whose applications were approved by the loan officer ($M_{algorithm} = 6.54$, $SD_{algorithm} = 2.27$ vs. $M_{human} = 7.77$, $SD_{human} = 1.75$; $F(1, 496) = 23.25$, $p < .001$, $\eta_p^2 = .04$). Again, however, the effect of the decision-maker type on WoM intentions was significantly mitigated when participants' applications were denied ($M_{algorithm} = 2.10$, $SD_{algorithm} = 1.81$ vs. $M_{human} = 2.52$, $SD_{human} = 2.18$; $F(1, 496) = 2.76$, $p = .10$, $\eta_p^2 = .01$).

Figure 3. Study 1b Results



Discussion of Studies 1a–b. Studies 1a–b demonstrated that the effect of the decision-maker type (algorithm vs. human) on consumers' reactions to the company is a function of decision outcome favorability. When participants received a favorable decision outcome, the algorithm (vs. human) decision-maker led to less positive reactions toward the company. However, this effect was significantly mitigated when participants received an unfavorable decision outcome.

We note the robustness of our effect thus far: it held in both social (club membership application) and non-social contexts (bank loan application) and with two managerially relevant measures of consumers' reactions (attitudes toward the company, WoM intentions). Additionally, we demonstrated that our effect is not driven by consumers' assumption on algorithmic (vs. human) decisions as less conclusive. We consistently observed the key interaction effect regardless of whether we explicitly emphasized that the decision is final.

Note that our findings contradict the managers' intuitions, so they are managerially informative. Furthermore, it is noteworthy that our interaction effect cannot be explained by the algorithm aversion literature (e.g., Longoni et al. 2019), which documents consumers' avoidance of algorithms (vs. humans) without consideration of decision outcome favorability. The interaction effect is therefore distinct from prior findings on general algorithm aversion.

Study 2: Replication with a Real Application Process

The purpose of study 2 was twofold. First, study 2 aimed to provide a field test of the predicted effect. Participants applied to join a research participant pool run by a research company, Johnson Customer Insight. We examined participants' attitudes toward the research company when their applications were accepted or rejected by either a human or an algorithm. Second, we aimed to rule out an alternative account: inattention to unfavorable information. People tend to avoid unfavorable information that can hurt their self-esteem (Trope and Neter

1994), so they may pay less attention to information (including the decision-maker type) that is related to an unfavorable decision outcome. Accordingly, inattention may explain the apparent indifference to the decision-maker type for unfavorable decision outcomes. To address this possibility, we directed participants' attention to the decision-maker type in all conditions before measuring attitudes toward the company.

Method. We randomly assigned 303 Prolific workers ($M_{age} = 34.19$, 184 females) to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design.

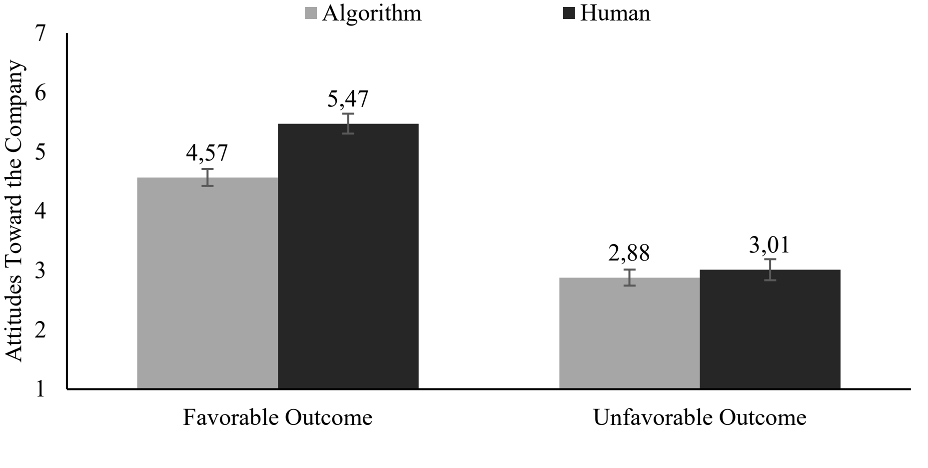
We created a Prolific researcher account under the name *Johnson Customer Insight* and told Prolific workers (who are essentially gig economy workers whose gig is to be a paid research participant) that the company was creating a research participant pool. Furthermore, we told participants that Johnson Customer Insight was dedicating that particular day to determining the eligibility of applicants for future surveys with generous compensation (see Appendix 1F). Participants were invited to complete an application form, which included questions about their cognitive abilities and their Prolific history; participants were told that the information reflected their diligence and attractiveness as a research participant. After submitting the application, each participant received an application number and was asked to wait while their applications were evaluated; after a few minutes, they received either an acceptance (favorable decision outcome) or a rejection (unfavorable decision outcome). Participants then rated their overall attitude toward the research company ("What is your overall evaluation of Johnson Customer Insight?") on a 10-point star scale.

On the next page, we informed participants of the type of decision-maker: Either one of the coordinators or a computer program designed by the IT team. Participants completed another measure of attitude: "How do you feel about Johnson Customer Insight now?" (1 = less positive, 7 = more positive). Finally, we thanked and debriefed participants (including telling them that Johnson Customer Insight was a fictional company) and paid the promised bonus to all participants.

Attitudes Before Receiving Information about the Decision-Maker Type. As expected, a 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA on the initial rating of the research company indicated a significant main effect of decision outcome favorability ($M_{favorable} = 8.30$, $SD_{favorable} = 1.67$ vs. $M_{unfavorable} = 4.20$, $SD_{unfavorable} = 2.78$; $F(1, 299) = 243.30$, $p < .001$, $\eta_p^2 = .45$). Unsurprisingly, as this measure was taken before the manipulation of the decision-maker type, we found neither a main effect of the decision-maker type ($F(1, 299) = 1.29$, $p = .256$) nor an interaction effect between the decision-maker type and decision outcome favorability ($F(1, 299) = .53$, $p = .47$), indicating successful random assignment.

Core Results. Central to our hypothesis, we tested how the decision-maker type affected participants' attitudes as a function of decision outcome favorability. An ANOVA revealed a significant main effect of the decision-maker type ($M_{algorithm} = 3.72$, $SD_{algorithm} = 1.59$ vs. $M_{human} = 4.26$, $SD_{human} = 1.85$; $F(1, 299) = 11.04$, $p = .001$, $\eta_p^2 = .04$) and of decision outcome favorability ($M_{favorable} = 5.03$, $SD_{favorable} = 1.29$ vs. $M_{unfavorable} = 2.95$, $SD_{unfavorable} = 1.50$; $F(1, 299) = 175.69$, $p < .001$, $\eta_p^2 = .37$). Crucially, we replicated the key interaction effect ($F(1, 299) = 6.11$, $p = .014$, $\eta_p^2 = .02$; Figure 4): attitudes toward the research company were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 4.57$, $SD_{algorithm} = 1.23$ vs. $M_{human} = 5.47$, $SD_{human} = 1.19$; $F(1, 299) = 16.84$, $p < .001$, $\eta_p^2 = .05$). Meanwhile, the effect of the decision-maker type on the attitudes was significantly mitigated when participants' applications were rejected ($M_{algorithm} = 2.88$, $SD_{algorithm} = 1.45$ vs. $M_{human} = 3.01$, $SD_{human} = 1.54$; $F(1, 299) = .36$, $p = .548$). The key interaction effect remained significant after controlling for the initial rating of the research company ($F(1, 298) = 5.90$, $p = .02$, $\eta_p^2 = .02$).

Figure 4. Study 2 Results



Discussion. Study 2 replicated our key findings in a realistic setting where participants ostensibly were applying to a research company. Furthermore, study 2 ruled out the alternative account based on inattention to unfavorable information by separating the decision outcome from the decision-maker, thereby ensuring attention to the latter.

Studies 3a and 3b: Effect of (Not) Disclosing Decision-Maker

Studies 3a and 3b focused on favorable decision outcomes (as we did not observe a significant effect of the decision-maker type for unfavorable decision outcomes in our previous studies). We aimed to clarify whether the effect of the decision-maker type on reactions is driven by a positive effect of the human decision-maker, a negative effect of the algorithmic decision-maker, or both. The distinction is important from the perspectives of managers and business ethics because it has implications for the consequences of disclosing (vs. not disclosing) the decision-maker type. Studies 3a–b included a third condition in which consumers are not informed of the decision-maker, creating a baseline for assessing the effect of the decision-maker type.

Methods. We randomly assigned 403 Prolific workers (M_{age} = 32.75, 251 females, study 3a) and 402 Prolific workers (M_{age} = 34.98, 259 females, study 3b) to one of three conditions (decision-maker type: algorithm vs. human vs. unspecified) in a between-participants design.

In study 3a, participants were applying for membership at a country club, *Violethall Country Club* (see Appendix 1G); depending on the condition, participants learned that their applications were accepted by the club algorithm

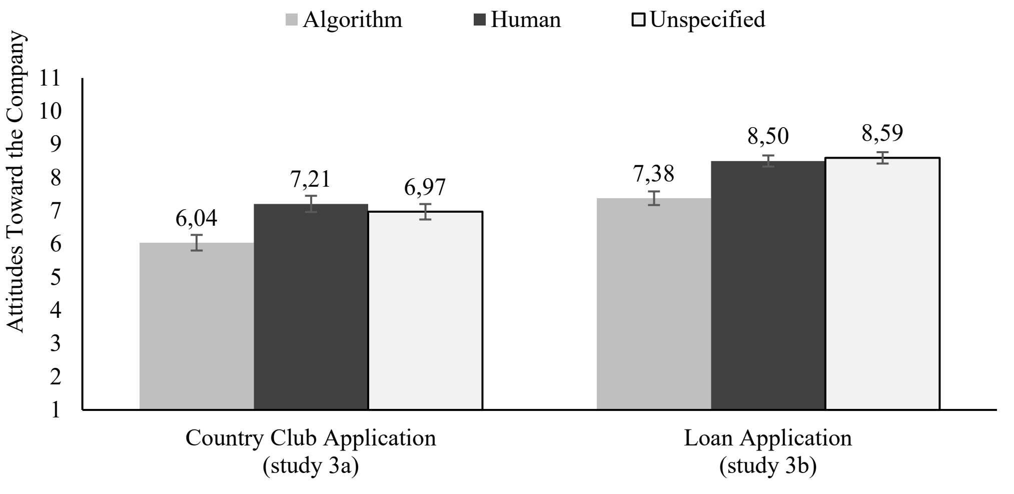
(algorithm condition), accepted by the club coordinator (human condition), or accepted (unspecified decision-maker condition). Participants completed the same attitude items (a = .98) as in study 1a. Study 3b was a conceptual replication of study 3a with one difference: participants read that they were applying for a bank loan (see Appendix 1G). Similar to study 3a, participants learned that their applications were accepted by a loan algorithm, accepted by a loan officer, or accepted by an unspecified decision-maker. Participants rated their attitudes toward the bank (a = .98).

Study 3a Results. We observed a significant effect of the decision-maker type ($F(2, 400) = 6.78$, $p = .001$, $\eta_p^2 = .03$). Replicating our previous findings, attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 6.04$, $SD_{algorithm} = 2.70$ vs. $M_{human} = 7.21$, $SD_{human} = 2.83$; $F(1, 400) = 12.14$, $p < .001$, $\eta_p^2 = .03$). Attitudes were significantly less positive in the algorithm condition than in the unspecified condition ($M_{algorithm} = 6.04$, $SD_{algorithm} = 2.70$ vs. $M_{unspecified} = 6.97$, $SD_{unspecified} = 2.69$; $F(1, 400) = 7.79$, $p = .006$, $\eta_p^2 = .02$), but attitudes were similar in the human and unspecified conditions ($M_{human} = 7.21$, $SD_{human} = 2.83$ vs. $M_{unspecified} = 6.97$, $SD_{unspecified} = 2.69$; $F < 1$, $p = .48$; Figure 5).

Study 3b Results. We observed a significant effect of the decision-maker type ($F(2, 399) = 13.79$, $p < .001$, $\eta_p^2 = .06$). Participants whose loan applications were accepted by the algorithm indicated less positive attitudes toward the bank than both participants whose loan applications were accepted by the loan officer

($M_{algorithm} = 7.38$, $SD_{algorithm} = 2.39$ vs. $M_{human} = 8.50$, $SD_{human} = 1.94$; $F(1, 399) = 18.85$, $p < .001$, $\eta_p^2 = .05$) and participants whose loan applications were accepted by an unspecified decision-maker ($M_{algorithm} = 7.38$, $SD_{algorithm} = 2.39$ vs. $M_{unspecified} = 8.59$, $SD_{unspecified} = 1.98$; $F(1, 399) = 22.29$, $p < .001$, $\eta_p^2 = .05$). Again, the difference between the human and unspecified conditions was not significant ($M_{human} = 8.50$, $SD_{human} = 1.94$ vs. $M_{unspecified} = 8.59$, $SD_{unspecified} = 1.98$; $F < 1$, $p = .71$; Figure 5).

Figure 5. Results of Studies 3a and 3b



Discussion of Studies 3a and 3b. Studies 3a and 3b clarify that the effect of the decision-maker type in favorable decisions occurs because the disclosure of an algorithmic decision-maker hurts consumers' attitudes relative to a baseline of an undisclosed decision-maker. These findings have implications for decision transparency, which we discuss in the General Discussion.

What Psychological Mechanisms Differentiate Consumers' Reactions to Algorithmic and Human Decision-Makers?

We proposed that consumers react less positively when their applications are accepted by algorithms (vs. humans) because they find it relatively more difficult to internalize an acceptance made by an algorithm (vs. by a human). By contrast, when a decision outcome is unfavorable, consumers readily externalize the decision outcome, so they react similarly toward the company regardless of the decision-maker. We directly examined this attribution mechanism through mediation (studies 4 and 6) and moderation (study 5).

Study 4: Mediation by Internal Attribution

Study 4 examined the mediating role of attribution. We predicted that algorithmic (vs. human) decision-makers would elicit distinct attributions as a function of decision outcome favorability, and the attributions would mediate our key interaction effect on attitudes toward the company.

Method. We randomly assigned 600 Prolific workers to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design. Our final dataset consisted of 571 participants (M_{age} = 33.84, 249 females) who passed our attention check.[2]

As in study 3a, participants read that they were applying for membership at a country club (see Appendix 1H); participants learned that their applications were either accepted or rejected by either the country club algorithm or the

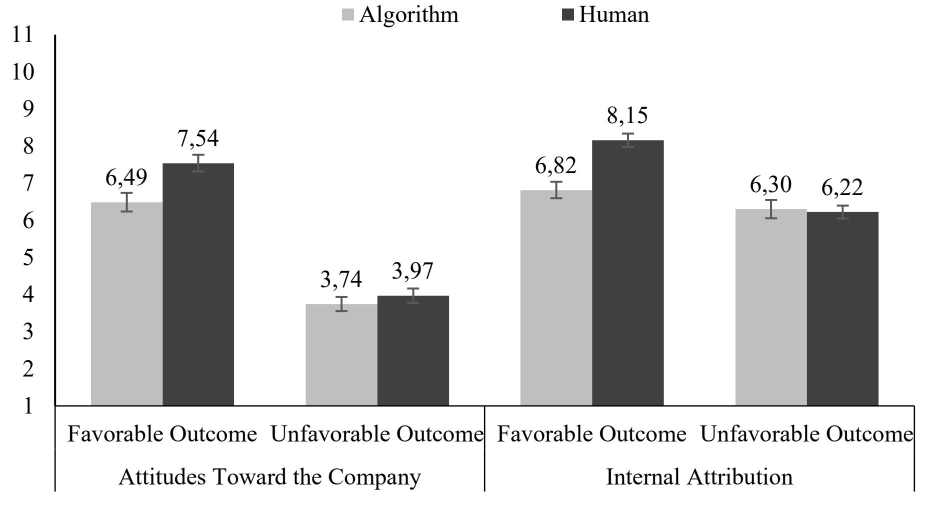
[2] We added an IMC attention check due to the concern about poor data quality during the COVID-19 crisis. In all studies, we found the same results regardless of whether we filter out those who failed the attention check (see Appendices 1H and 1I for details).

country club coordinator, and they indicated their attitudes toward the country club ($\alpha = .99$) as in study 3a. Next, we measured internal attributions (adapted from Russell 1982): "To what extent do you feel this decision [reflects something about yourself / can be attributed to something about yourself / is due to your personal qualities or behaviors]?" (1 = not at all, 11 = very much; $\alpha = .91$).

Results. We conducted a 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA on attitudes toward the country club. We found a significant main effect of the decision-maker type ($M_{algorithm}$= 5.01, $SD_{algorithm}$ = 2.95 vs. M_{human} = 5.91, SD_{human} = 3.11; $F(1, 567) = 8.62$, $p = .003$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable}$ = 7.06, $SD_{favorable}$ = 2.88 vs. $M_{unfavorable}$ = 3.85, $SD_{unfavorable}$ = 2.30; $F(1, 567) = 211.62$, $p < .001$, $\eta_p^2 = .27$). Again, we found a marginally significant interaction between the decision-maker type and decision outcome favorability ($F(1, 567) = 3.66$, $p = .056$, $\eta_p^2 = .01$; see Figure 6): attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the coordinator ($M_{algorithm}$ = 6.49, $SD_{algorithm}$ = 2.88 vs. M_{human} = 7.54, SD_{human} = 2.79; $F(1, 567) = 11.82$, $p < .001$, $\eta_p^2 = .02$). Meanwhile, this difference was significantly mitigated among participants whose applications were rejected ($M_{algorithm}$= 3.74, $SD_{algorithm}$ = 2.36 vs. M_{human} = 3.97, SD_{human} = 2.23; $F < 1$, $p = .47$).

We conducted an analogous ANOVA on internal attributions. We found a significant effect of the decision-maker type ($M_{algorithm}$ = 6.54, $SD_{algorithm}$ = 2.79 vs. M_{human} = 7.27, SD_{human} = 2.69; $F(1, 567) = 8.01$, $p = .005$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable}$ = 7.54, $SD_{favorable}$ = 2.47 vs. $M_{unfavorable}$ = 6.27, $SD_{unfavorable}$ = 2.90; $F(1, 567) = 30.15$, $p < .001$, $\eta_p^2 = .05$). Importantly, we found a significant interaction effect ($F(1, 567) = 10.11$, $p = .002$, $\eta_p^2 = .02$; see Figure 6): the internal attribution was weaker when the acceptance decision was made by the algorithm than when it was made by the club coordinator ($M_{algorithm}$ = 6.82, $SD_{algorithm}$ = 2.54 vs. M_{human} = 8.15, SD_{human} = 2.24; $F(1, 567) = 18.17$, $p < .001$, $\eta_p^2 = .03$). The effect of the decision-maker type was significantly mitigated for the internal attribution of the rejection decision ($M_{algorithm}$ = 6.30, $SD_{algorithm}$ = 2.98 vs. M_{human} = 6.22, SD_{human} = 2.81; $F < 1$, $p = .81$).

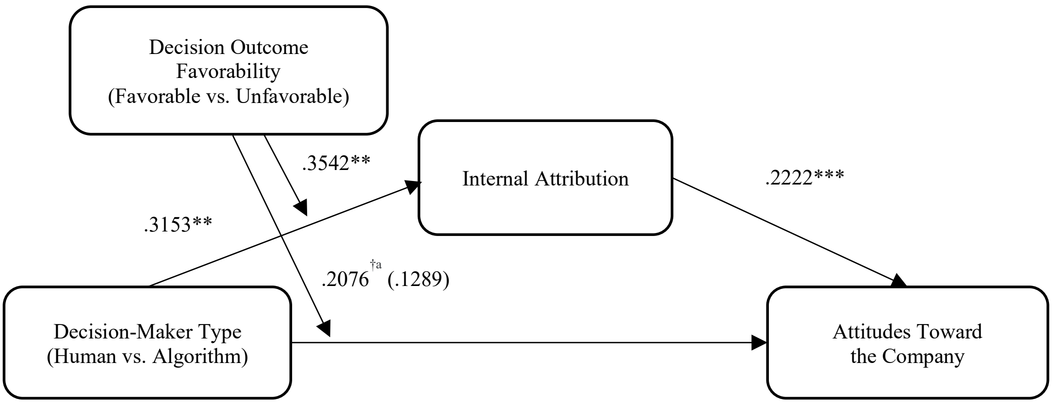
Figure 6. Study 4 Results



Finally, we ran a moderated mediation analysis (Process Model 8, 10,000 bootstrapped samples; Hayes 2013) with attitudes toward the country club as the dependent variable, decision-maker type (-1 = algorithm, 1 = human) as the independent variable, decision outcome favorability (-1 = unfavorable, 1 =

favorable) as the moderator, and internal attribution as the mediator (see Figure 7).[3] As we predicted, we found a significant moderated mediation effect (B = .16, 95% CI [.0536, .2780]). For a favorable decision outcome, the indirect effect of the decision-maker type through internal attribution was significant (B = .15, 95% CI [.0720, .2392]), suggesting that the less positive reaction to the country club after receiving a decision from an algorithm (vs. a human) was driven by the weaker internal attribution of the favorable decision. For an unfavorable decision outcome, however, the corresponding indirect effect was not significant (B = -.01, 95% CI [-.0864, .0694]).

Figure 7. Study 4 Results (Moderated Mediation Model)



NOTE.— †*p* < .06; **p* < .05; ***p* < .01; ****p* < .001
[a] estimated coefficient for the decision outcome favorability by decision-maker type interaction in the model without (with) the mediator

In sum, study 4 directly examined the proposed mechanism and found evidence that decision outcome favorability affects the internal attribution process

[3] The reported mediation model is in line with the criteria for meaningful mediation proposed by Pieters (2017).

of algorithmic versus human decisions, thereby leading to divergent reactions to the decisions made by the different decision-makers.

Study 5: Moderated Mediation by Internal Attribution of a Favorable Outcome

We proposed that consumers react more positively when a favorable decision is made by a human (vs. an algorithm) because a human decision-maker facilitates the internal attribution of the decision outcome more. If this is the case, this effect should be mitigated when the decision outcome is not diagnostic of consumers' personal characteristics (e.g., the decision was made at random), in which case there is little justification for internal attribution regardless of the decision-maker type. Study 5 tested this prediction by manipulating self-diagnosticity; the decision was based on either an evaluation of the consumer's application or a raffle. Furthermore, study 5 increased the generalizability of our effect by replicating it in another managerially relevant context: networking platforms.

Method. We randomly assigned 501 Prolific workers to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision method: evaluation vs. raffle) between-participants design. Our final dataset consisted of 443 participants (M_{age} = 39.33, 222 females) who passed our attention check.

Participants read that they were applying to join a business networking community, *NetWorkLink* (see Appendix 1I). Participants learned that their applications were accepted by either the club algorithm or the club coordinator, and the decision method involved either an evaluation of the applications or a raffle (i.e., random selection). Finally, we measured participants' attitudes toward the networking club ($\alpha = .98$) and internal attributions ($\alpha = .95$) by using the same items as in study 4.

Results. A 2 (decision-maker type) x 2 (decision method) ANOVA on attitudes revealed no significant main effect of the decision-maker type ($M_{algorithm} = 6.44$, $SD_{algorithm} = 2.59$ vs. $M_{human} = 6.55$, $SD_{human} = 2.82$; $F(1, 439) = 1.12$, $p = .29$), but a significant effect of the decision method ($M_{evaluation} = 7.30$, $SD_{evaluation} = 2.43$ vs. $M_{raffle} = 5.69$, $SD_{raffle} = 2.73$; $F(1, 439) = 44.54$, $p < .001$, $\eta_p^2 = .09$). Importantly, we found a marginally significant interaction effect ($F(1, 439) = 3.44$, $p = .064$, $\eta_p^2 = .01$; see Figure 8). When the acceptance decision was based on an evaluation of the applications (i.e., when the decision was self-diagnostic), we replicated our previous findings: attitudes toward the networking club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 6.98$, $SD_{algorithm} = 2.34$ vs. $M_{human} = 7.70$, $SD_{human} = 2.49$; $F(1, 439) = 4.25$, $p = .04$, $\eta_p^2 = .01$). However, when the acceptance decision was based on a raffle (i.e., when the decision was not self-diagnostic), the decision-maker type did not significantly affect participants' attitudes ($M_{algorithm} = 5.80$, $SD_{algorithm} = 2.74$ vs. $M_{human} = 5.60$, $SD_{human} = 2.73$; $F < 1$, $p = .57$).

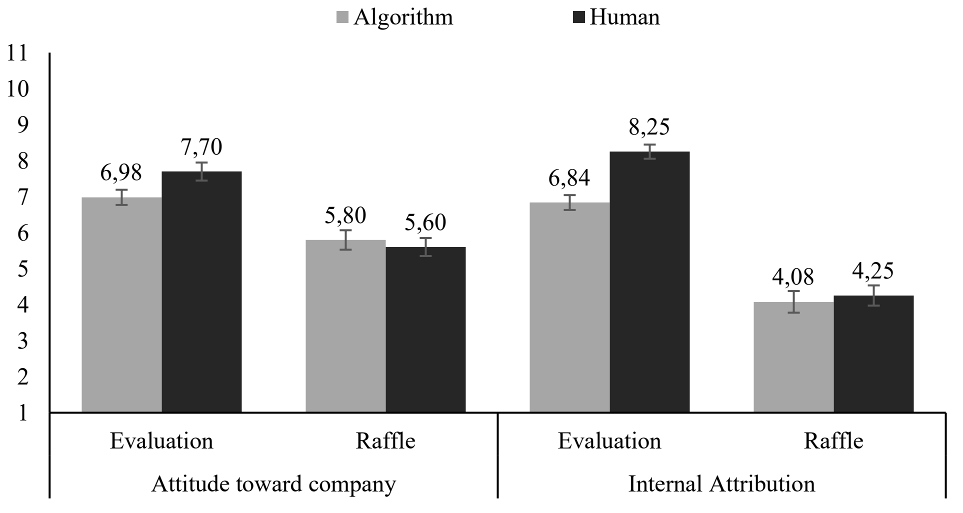
An analogous ANOVA on internal attribution revealed a significant main effect of the decision-maker type ($M_{algorithm} = 5.59$, $SD_{algorithm} = 2.99$ vs. $M_{human} = 6.07$, $SD_{human} = 3.29$; $F(1, 439) = 9.93$, $p = .002$, $\eta_p^2 = .02$) and of the decision method ($M_{evaluation} = 7.47$, $SD_{evaluation} = 2.26$ vs. $M_{raffle} = 4.17$, $SD_{raffle} =$

3.05; $F(1, 439) = 179.62$, $p < .001$, $\eta_p^2 = .29$). Crucially, we again found a significant interaction effect ($F(1, 439) = 6.01$, $p = .02$, $\eta_p^2 = .01$; Figure 8): when the decision was based on an evaluation of the applications, the internal attribution of the acceptance was weaker among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 6.84$, $SD_{algorithm} = 2.29$ vs. $M_{human} = 8.25$, $SD_{human} = 1.96$; $F(1, 439) = 15.69$, $p < .001$, $\eta_p^2 = .03$). However, when the acceptance decision was based on a raffle, the decision-maker type did not significantly affect the internal attribution made by participants ($M_{algorithm} = 4.08$, $SD_{algorithm} = 3.04$ vs. $M_{human} = 4.25$, $SD_{human} = 3.07$; $F < 1$, $p = .62$).

To test whether our key effect is mediated by the internal attribution of the favorable decision outcome, we conducted a moderated mediation analysis (Process Model 8, 95% CI, 10,000 bootstrapped samples; Hayes 2013) with attitudes toward the networking club as the dependent variable, decision-maker type (-1 = algorithm, 1 = human) as the independent variable, decision method (-1 = raffle, 1 = evaluation) as the moderator, and internal attribution as the mediator. In line with our theory, we found a significant moderated mediation effect (B = .26, 95% CI [.0516, .4765]): when the decision was based on an evaluation of the applications and thus self-diagnostic (such that participants were motivated or able to internally attribute the favorable outcome), the indirect effect through internal attribution was significant (B = .29, 95% CI [.1668, .4344]), suggesting that the more positive reaction to the networking club after receiving a decision from the human (vs. algorithm) was driven by the stronger internal attribution of the favorable decision. When the decision was based on a raffle and thus was not self-diagnostic, however, the indirect effect was not significant (B = .04, 95% CI [-.1327, .2088]).

In sum, study 5 corroborates our attribution mechanism by demonstrating moderation by the self-diagnosticity of the decision. Together, the results of studies 4 and 5 provide converging evidence that supports our attribution mechanism.

Figure 8. Study 5 Results



Study 6: External Attribution of an Unfavorable Decision Outcome

We proposed that the decision-maker type has an attenuated effect on consumers' reactions following an unfavorable decision outcome because consumers can readily engage in external attribution of an unfavorable decision outcome regardless of the decision-maker. Consumers perceive both algorithmic and human decision-makers to have weaknesses: humans are less objective (Lee

2018), and algorithms neglect the uniqueness of each individual (e.g., Longoni et al. 2019). Accordingly, when consumers receive an unfavorable decision outcome, they can blame a human decision-maker for a lack of objectivity and blame an algorithmic decision-maker for neglecting their individual uniqueness. We argued that these countervailing effects cancel each other out, resulting in consumers' relative indifference to the type of decision-maker. In study 6, we tested this proposition by measuring consumers' perceptions of the decision-maker's objectivity and consideration of individual uniqueness.

Method. In this preregistered study (aspredicted.org/ah2sc.pdf), we randomly assigned 626 Mturk workers (M_{age} = 35.51, 332 females) to one of two conditions (decision-maker type: algorithm vs. human) in a between-participants design.[4]

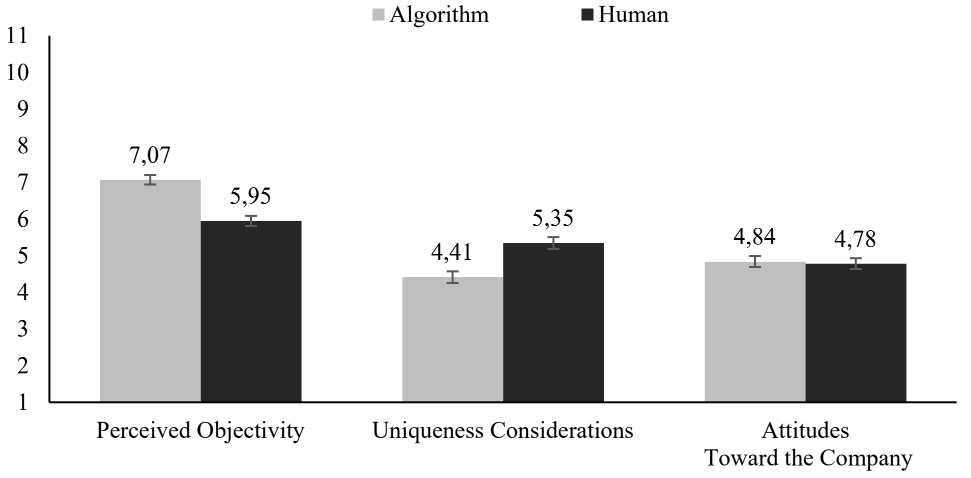
Participants read that they were applying for membership at a country club and their applications were rejected by either the club algorithm or the club coordinator (see Appendix 1J). Participants then assessed the decision-maker's objectivity and consideration of the applicant's uniqueness (the order of the measures was randomized). Specifically, participants answered three items about the decision-maker's objectivity: "To what extent do you think [this algorithm/club coordinator] [made an unbiased assessment of your application / made an unemotional assessment of your application / assessed your application rationally]?" (1 = not at all, 11 = very much; α = .71). Participants also answered

[4] As stated in our preregistration form, we targeted 600 participants, but the actual sample size differed for reasons beyond our control (e.g., participants not claiming their participation on Mturk).

three items about the decision-maker's consideration of their application's uniqueness: "To what extent do you think this [algorithm/club coordinator] [recognized the uniqueness of your application / considered the unique aspects of your application / tailored the decision to your unique case]?" (adapted from Longoni et al. 2019; 1 = not at all, 11 = very much; α = .93). Lastly, participants completed the same attitude items as in study 5 (α = .97).

Results. In line with our previous findings, and as preregistered, there was no significant effect of the decision-maker type on attitudes toward the country club ($M_{algorithm}$= 4.84, $SD_{algorithm}$ = 2.62 vs. M_{human} = 4.78, SD_{human} = 2.61; $F(1, 624) < 1$, $p = .78$; see Figure 9). Crucially, we found a significant effect of the decision-maker type on participants' perceptions of the decision-maker's objectivity and consideration of uniqueness: the club coordinator (vs. algorithm) was perceived as less objective (M_{human}= 5.95, SD_{human} = 2.47 vs. $M_{algorithm}$ = 7.07, $SD_{algorithm}$ = 2.28; $F(1, 624) = 34.76$, $p < .001$, $\eta_p^2 = .05$), whereas the algorithm (vs. club coordinator) was perceived as less sensitive to the applicant's uniqueness ($M_{algorithm}$ = 4.41, $SD_{algorithm}$ = 2.81 vs. M_{human} = 5.35, SD_{human} = 2.74; $F(1, 624) = 17.67$, $p < .001$, $\eta_p^2 = .03$).

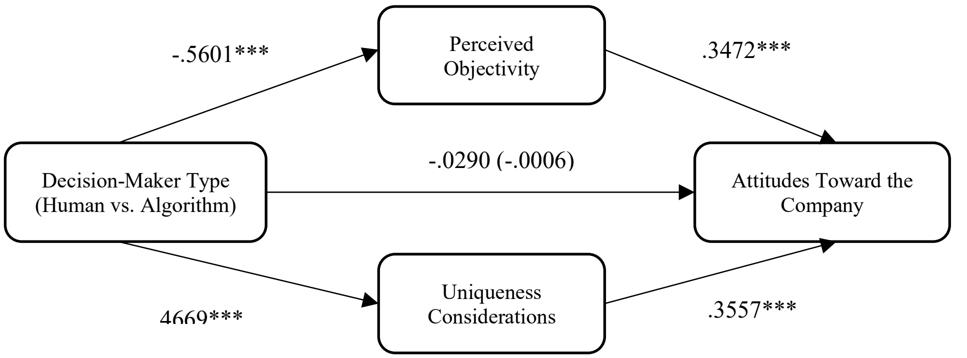
Figure 9. Study 6 Results



In sum, study 6 corroborates our theory that consumers make external attributions about unfavorable decision outcomes for both human and algorithmic decision-makers, facilitated by the perceived weakness of the decision-maker—human decision-makers have poor objectivity, while algorithmic decision-makers do not consider each applicant's unique characteristics.

In addition, these results contradict an alternative explanation based on psychological numbness following a rejection, which could plausibly lead to an indifference to the type of decision-maker for unfavorable decision outcomes. However, the psychological numbness account predicts psychological deactivation (including disengagement from attributional processes), which does not explain the parallel mediation processes that we found in study 6.

Figure 10. Study 6 Results (Mediation Model)



NOTE. *** $p < .001$.

Study 7: Effect of Human Decision Making versus Mere Human Observation

One could argue that participants in our previous studies reacted more positively to acceptance by humans due to social presence (Argo, Dahl, and Manchanda 2005; McFerran and Argo 2014); when an algorithm makes an acceptance decision, no social agent is aware of the outcome. By contrast, the social presence of the human decision-maker might lead participants to feel more positive about the outcome and thus react more positively toward the company.

Although it cannot explain several findings in the previous studies (e.g., the moderation in study 5), we conducted study 7 to directly test the alternative account of social presence by adding a new condition in which a human *monitored* (but did not interfere with) the algorithm's decisions. If social presence accounts for our effect, consumers should react similarly when a human makes the decision versus merely observes the favorable outcome. If our effect is due to distinct attributions under human versus algorithmic decision-makers, however, then reactions should be similar when an algorithm makes the decision with versus without a human monitoring the decision process.

Method. We randomly assigned 597 Mturk workers (M_{age} = 35.42, 318 females) to one of six conditions in a 3 (decision-maker type: algorithm-only vs. human vs. algorithm-with-human-monitoring) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design. The procedure of this study was similar to that of study 1a with the addition of the third decision-maker condition, in which the club coordinator ran and monitored the algorithm's evaluation of applications (see Appendix 1K). Participants completed the same attitude scale as in study 6 (α = .98).

Results. We found a significant main effect of the decision-maker type ($M_{algorithm\ only}$= 5.50, $SD_{algorithm\ only}$ = 2.98 vs. M_{human} = 5.76, SD_{human} = 3.17 vs. $M_{algorithm\ with\ human\ monitoring}$ = 5.17, $SD_{algorithm\ with\ human\ monitoring}$ = 2.83; $F(2, 591) = 4.52$, $p = .01$, $\eta_p^2 = .02$) and of decision outcome favorability ($M_{favorable}$ = 7.18, $SD_{favorable}$ = 2.67 vs. $M_{unfavorable}$ = 3.76, $SD_{unfavorable}$ = 2.24; $F(1, 591) = 295.05$, $p < .001$, $\eta_p^2 = .33$). The interaction effect was marginally significant ($F(2, 591) = 2.45$, $p = .087$, $\eta_p^2 = .01$; see Figure 11).[5]

In the favorable decision outcome condition, the simple effect of the decision-maker type was significant ($F(2, 591) = 5.67$, $p = .004$, $\eta_p^2 = .02$). Replicating our previous studies, attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm

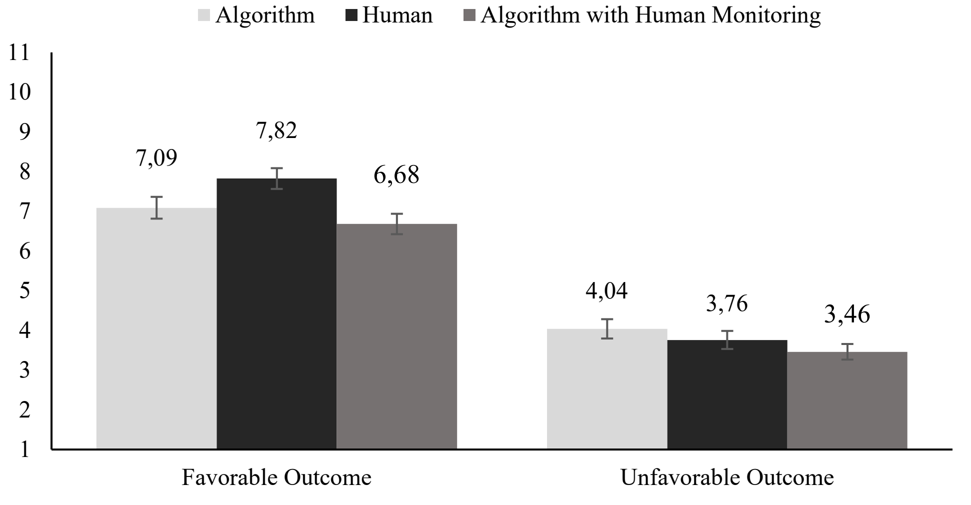
[5] To test our core hypothesis more directly, we conducted a planned contrast analysis in which we aggregated the algorithm-only and algorithm-with-human-monitoring conditions, which we hypothesized to show the same results. In this case, we observed a significant interaction effect ($F(1, 591) = 4.98$, $p < .05$, $\eta_p^2 = .01$).

than among participants whose applications were accepted by the club coordinator ($M_{algorithm\text{-}only}$ = 7.09, $SD_{algorithm\text{-}only}$ = 2.68 vs. M_{human} = 7.82, SD_{human} = 2.59; $F(1, 591) = 4.36$, $p = .04$, $\eta_p^2 = .01$). Moreover, we found a significant difference in attitudes between the human condition and algorithm-with-human-monitoring conditions; attitudes toward the country club were less positive in the latter condition (M_{human} = 7.82, SD_{human} = 2.59 vs. $M_{algorithm\text{-}with\text{-}human\text{-}monitoring}$ = 6.68, $SD_{algorithm\text{-}with\text{-}human\text{-}monitoring}$ = 2.65; $F(1, 591) = 11.13$, $p < .001$, $\eta_p^2 = .02$). There was no significant difference in attitudes between the algorithm-only and algorithm-with-human monitoring conditions ($M_{algorithm\text{-}only}$ = 7.09, $SD_{algorithm\ only}$ = 2.68 vs. $M_{algorithm\text{-}with\text{-}human\text{-}monitoring}$ = 6.68, $SD_{algorithm\text{-}with\text{-}human\text{-}monitoring}$ = 2.65; $F(1, 591) = 1.40$, $p = .24$). In the unfavorable decision outcome condition, attitudes toward the country club were not influenced by the decision-maker type ($F(2, 591) = 1.37$, $p = .26$).

Discussion. Consistent with our attribution account and inconsistent with the social presence account, we found that consumers react more positively when an acceptance decision is made by a human than by an algorithm, regardless of whether a human monitors the algorithm's decisions. At first glance, our findings may seem contradictory to those of study 9 in Longoni et al. (2019), in which individuals were more likely to use a medical algorithm if it was complemented by a human dermatologist (i.e., a dermatologist reviewed the algorithm's diagnosis and made a final decision). The studies, however, have a key difference: A human was actively engaged in the decision-making process in

Longoni et al.'s (2019) study, while a human merely observed the algorithm and could not alter its decisions in our study.

Figure 11. Study 7 Results



What Can Managers Do to Mitigate the Negative Effects of Algorithms?

We consistently observed that consumers react less positively when a favorable decision is made by an algorithm (vs. a human). Study 8 examined a potential solution: anthropomorphizing the algorithm. Extant work suggests that humanizing a non-human agent (e.g., referring to an object with a personal name) leads people to attribute human-like abilities to it (Crolic et al. 2021; Epley 2018). We proposed that humanizing an algorithm should more closely align consumers' perceptions of a human decision-maker and an algorithmic decision-maker, enabling the human-like algorithm to lead to more positive reactions than the non-human-like algorithm.

Study 8: Humanizing Algorithms to Mitigate Negative Consequences: Attitudes Toward the Company

Method. We randomly assigned 601 Prolific workers ($M_{age} = 33.52$, 316 females) to one of three conditions (decision-maker type: algorithm vs. human vs. human-like algorithm) in a between-participants design.

The procedure of study 8 was similar to that of study 1a. Participants were told they were applying for membership at a country club (see Appendix 1L); depending on the condition, the decision-maker was described as a country club algorithm (depicted as a robot), a country club coordinator named Sam (depicted as a woman), or a country club algorithm named Sam (depicted as a cartoonized version of the picture of the woman from the human condition). All participants were informed that their applications were accepted. We asked participants to indicate their attitudes toward the country club using the same items as in study 7 ($\alpha = .98$).

Pretest. We conducted a separate pretest to examine whether a human-like algorithm seems more human than an algorithm seems. We presented 100 Prolific workers ($M_{age} = 30.23$; 41 females) with the information from the algorithm and human-like algorithm conditions in the main study. We then asked participants, "To what extent do you think that [the country club algorithm / Sam] has some human-like qualities?" and "To what extent do you think [the country club algorithm / Sam] seems like a person?*"* (1 = not at all, 7 = very much; $r = .80$; adapted from Kim and McGill 2018). Results confirmed that our manipulation was successful: participants perceived the human-like algorithm to be more human than the algorithm was ($M_{human\text{-}like\text{-}algorithm}$= 3.92, $SD_{human\text{-}like\text{-}algorithm}$ = 1.56 vs. $M_{algorithm}$ = 2.65, $SD_{algorithm}$ = 1.29; $F(1, 598) = 19.86$, $p < .001$, $\eta_p^2 = .17$).

Results. In our main study, we conducted a one-way ANOVA on participants' attitudes toward the country club. Replicating our previous findings, the decision-maker type had a significant effect ($F(2, 598) = 4.69$, $p = .009$, $\eta_p^2 = .02$). Attitudes toward the club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm}$= 7.07, $SD_{algorithm}$ = 2.67 vs. M_{human} = 7.87, SD_{human} = 2.52; $F(1, 598) = 8.88$, $p = .003$, $\eta_p^2 = .01$). Importantly, humanizing the algorithm led to significantly more positive attitudes toward the country club ($M_{algorithm}$ = 7.07, $SD_{algorithm}$ = 2.67 vs. $M_{human\text{-}like\text{-}algorithm}$= 7.64, $SD_{human\text{-}like\text{-}algorithm}$ = 2.82; $F(1, 598) = 4.46$, $p = .04$, $\eta_p^2 = .01$) such that attitudes were similar whether the decision-maker was the human-like algorithm or the club coordinator ($M_{human\text{-}like\text{-}algorithm}$ = 7.64, $SD_{human\text{-}like\text{-}algorithm}$ = 2.82 vs. M_{human} = 7.87, SD_{human} = 2.52; $F < 1$, $p = .38$).

Discussion. Building on our prior studies' finding that consumers react less positively when a favorable decision is made by an algorithm (vs. a human), study 8 tested a potential solution: anthropomorphizing the algorithm. Attitudes toward the company were more positive when the favorable decision was made by a human-like (vs. a non-human-like) algorithm.

General Discussion

The current research reveals that consumers react differently to a company that uses algorithmic (vs. human) decision-makers as a function of decision outcome favorability: Consumers react less positively toward a company when they receive a favorable decision made by an algorithm than by a human; however, this difference is significantly mitigated when the decision outcome is unfavorable. The effect is driven by different attributions: consumers find it relatively more difficult to internalize a favorable decision made by an algorithm (vs. a human), while it is similarly easy to externalize an unfavorable decision made by either type of decision-maker. Finally, we demonstrate that humanizing the algorithm can mitigate the relatively negative reaction to an algorithmic (vs. a human) decision-maker in the setting of favorable decision outcomes.

Alternative Accounts

Several alternative accounts merit discussion. We review these accounts and discuss how our findings and study design rule them out. In addition, we have direct evidence, in the form of both mediation and moderation, that rules in attribution processes (studies 4–6).

First, one might argue that consumers care about a favorable outcome being witnessed by (rather than made by) another human and that it is this mere human presence that leads to more positive reactions to human decision-makers. Against such a social presence account, however, participants in study 7 reacted more positively only when a human (vs. an algorithm) made the favorable decision on them, but not when a human merely *observed* the algorithm and thus knew about the favorable decision outcome.

Second, our results might be explained by social cues. For instance, being accepted by a human might create a sense of social belonging, while being evaluated by an algorithm might engender feelings of disrespect. However, we observed the key interaction effect even in contexts in which social relationships are less salient (i.e., business loan application, market research participant panel). Moreover, if algorithmic (vs. human) evaluation creates feelings of disrespect, we should have found a main effect of the decision-maker type, but not necessarily the interaction effect between the decision-maker type and decision outcome favorability.

Third, consumers might pay less attention to unfavorable information about the self because they inherently avoid information that can hurt their self-esteem (Trope and Neter 1994). In this regard, consumers might be inattentive to *any* unfavorable information about the self, including the type of decision-maker that was involved in the unfavorable decision. However, we replicated our interaction effect even when we explicitly directed participants' attention to the decision-maker type (study 2), ruling out the inattention account. In addition, the inattention account does not explain the two opposing mediation processes for negative decisions in study 6.

Fourth, one could argue that psychological numbness explains the relative indifference to the decision-maker type for unfavorable decision outcomes. An experience of social exclusion (e.g., ostracism) can impair people's emotional sensitivity and cognitive function (Williams 2007), and even social rejections by non-human agents (e.g., robots) can lead to negative psychological consequences (Nash et al. 2018). If psychological numbness explains our effect, however, then it should be limited to contexts in which social relationships are salient—but our effect is significant in non-social contexts as well. Moreover, the psychological numbness account would predict that consumers who receive unfavorable decision outcomes should be less likely to engage in *any* cognitive processes including attributions, but in study 6, participants' reactions to unfavorable decisions were due to external attribution processes.

Fifth, one could argue that the perceived fairness of algorithmic versus human decision-makers explains our results. Consumers are known to perceive decisions made by algorithms (vs. humans) as less fair (Lee 2018). Differential perceptions of decision fairness should produce a main effect of the decision-maker type, but not necessarily the interaction effect that we observed consistently. Nonetheless, we conducted a follow-up study (see Appendix 1N) that measured the perceived fairness of the decision. We found a main effect of the decision-maker type: participants perceived the human to be fairer than the algorithm ($M_{human} = 4.12$, $SD_{human} = 1.55$ vs. $M_{algorithm} = 3.28$, $SD_{algorithm} = 1.57$; $F(1, 317) = 23.63$, $p < .001$, $\eta_p^2 = .07$). However, this effect was not moderated by decision outcome favorability ($F < 1$, $p = .58$), ruling out perceived fairness as a viable explanation for our effect.

Finally, one could be concerned about scale insensitivity as an explanation for the interaction between decision outcome and decision-maker type. Specifically, one could argue that there could be differences in consumers' reactions to unfavorable decision outcomes by different decision-maker types, but that our measures are not sensitive enough to capture these differences (e.g., because such reactions are in general quite negative). Study 2 rules out this concern. In study 2, we first elicited a response to the outcome (favorable or unfavorable) and then provided information about the decision-maker to probe how the information of the decision-maker type changes participants' attitudes towards the company. This procedure eliminated the strong main effect of decision outcome on the focal measure. We still observed that participants reacted to rejections by humans and algorithms similarly.

Theoretical Implications

The current research makes several theoretical contributions. Extending prior research on how consumers *decide* between algorithms and humans (Dietvorst et al. 2015; Longoni et al. 2019), the current research sheds light on how consumers' *reactions to a self-diagnostic decision* (i.e., decisions about the consumers themselves) are affected by the decision-maker type (human vs. algorithm). Second, our work identifies a theoretically and managerially relevant moderator (decision outcome favorability) that has been underexplored in the existing literature on algorithmic decision-making. Finally, the current paper extends the existing work on consumers' perceptions of the different decision-makers (e.g., Lee 2018) by examining how algorithmic (vs. human) decisions prompt different attributions as a function of decision outcome favorability. In doing so, our research marries the social psychology literature on attribution processes with the marketing literature on algorithmic decision-making.

Our research opens several avenues for future research. First, future research can examine consumers' perceptions of decisions that are made through human-algorithm collaboration. Consumers may react differently depending on the nature of the collaboration (e.g., who conducts the first round of screening versus makes a final decision). Second, companies use a variety of criteria to accept or reject consumers (e.g., high/low performance; passing/failing a threshold). In our studies, we did not specify why an application was accepted or rejected. We encourage researchers to investigate whether specific reasoning affects the interaction between the decision-maker type and decision outcome favorability. Third, even though big data has improved the quality of decisions made by both humans and algorithms, there are still concerns about the representativeness of data used by firms (Bolukbasi et al. 2016). Given that minority groups are often underrepresented in datasets (Sheikh 2006), the effect of the decision-maker type on consumers' reactions may differ for consumers from a minority versus majority group. Future research can incorporate consumer demographics to understand such differences. Fourth, our work focuses on consumers' attitudes toward the company, but more research is needed to understand how algorithmic decision-making impacts consumers' psychological security. For instance, future research can investigate how the decision-maker type affects consumers' perceived threat and anxiety (Mende et al. 2019). Fifth, future research can investigate whether consumers' reactions change depending on whether the decision outcome is communicated by a person or through a non-human medium (e.g., email). Although we manipulated only the decision-maker type and held all other communication about the decision outcome constant, future research can examine the effect of how decisions are communicated to consumers (e.g., Campbell 2007; price tag vs. store owner). Sixth, although the current research primarily focuses on consumers' attitudes toward the company, which is a managerially important consumer indicator, future research can extend our findings to other behavioral measures.

Lastly, it is interesting to consider under which conditions algorithmic (vs. human) decisions might be more likely to facilitate internal attributions. Although we observed a consistent pattern across different consumer contexts, responses, and procedures, it is possible that in some situations algorithmic acceptance might offer an especially salient cue of diagnosticity and facilitate internal attributions to a larger extent. In general, more research is needed to understand how our effects can be moderated by the nature of the evaluation context. For instance, if a decision process is based on a simple objective criterion (e.g., if one's GPA is above 80th percentile), a favorable decision might facilitate internal attributions regardless of whether the decision-maker is an algorithm or a human, mitigating the effect of the decision-maker type.

Managerial Implications

The current work has several managerial implications. First, our results offer insights—perhaps surprising to many managers—into how the adoption of algorithms for consumer-facing decisions may affect consumers' reactions toward the company. We found that some managers hesitate to automate consumer-facing decisions because they are concerned about exacerbating consumers' negative reactions to unfavorable decision outcomes (see in-depth interviews #2, #3, and #12 in Appendix 1C; Dietvorst et al. 2015; Luo et al. 2019). Our results, however, demonstrate that an algorithmic (vs. a human) decision-maker hurts consumers' reactions for *favorable* outcomes, not for unfavorable ones.

Second, in our interviews with managers, some managers expected that consumers would respond more positively when human and algorithmic decision-makers collaborate, and some mentioned that their companies are already using this strategy (see in-depth interviews #2 and #9 in Appendix 1C). Our results indicate that consumers may not necessarily respond more positively to companies if humans are merely observing the algorithms without active involvement in decision-making (study 7). By showing this, we offer managerial insights on how companies can design their evaluation processes. Additionally, we demonstrate that the effect of the decision-maker type is mitigated when the favorable decision outcome is not self-diagnostic (i.e., when the decision was based on a raffle; study 5). Managers can leverage these findings to improve consumers' reactions to companies that use algorithms for consumer-facing decisions.

Third, we explored a possible approach to mitigate the risk of less positive reactions following algorithmic acceptance: making the algorithm more human-like. In study 8, the addition of simple anthropomorphic cues eliminated the effect of the decision-maker type in the case of an acceptance decision. We also observed a similar pattern in field data from a financial services company. This data provides click-through-rates (CTR) on a link to the company's services after receiving financial feedback from human-like algorithms (vs. non-human-like algorithms, see Appendix 1M for details). Once consumers answered a questionnaire, the company provided feedback based on an algorithmic assessment of the consumer's financial health. Some consumers received feedback that was highly favorable (good financial health with just a check-up needed), mimicking the favorable outcome condition of study 8. Replicating the effect with a behavioral measure, consumers were more likely to seek information about the company's services when the favorable feedback came from a human-like (vs. a non-human-like) algorithm. These preliminary findings mimic those in study 8 and corroborate the conclusion that negative consequences of algorithmic decision-making may be averted by making algorithms more human-like (e.g., using a more conversational format, a human name, or a human-like photo).

Finally, we offer insights for policymakers. When the decision-maker type is not disclosed, consumers are likely to react similarly as they do to a human decision-maker (studies 3a–b), offering firms an incentive to avoid transparency, which is not in the interest of consumers. Our results align with recent movements calling practitioners to be more transparent about their use of algorithms (Rai 2020; Davenport et al. 2020) and laws in the US and EU that require companies to disclose whether they use algorithms in consumer-related tasks (Castelluccia and le Métayer 2019; Smith 2020).

CHAPTER 3

The Algorithm versus the Expert: High Subjective Knowledge in a Focal Domain Increases Consumers' Valuation of Algorithmic Recommendations

In the past, companies predominantly relied on human experts (i.e., people who are specialized in a specific domain and perform such tasks professionally, e.g., a knowledgeable agent) to provide their customers with product recommendations. Nowadays, an increasing number of companies offer recommendations generated by algorithms (i.e., computer systems programmed to follow a set of steps to perform a specific task; Castelo, Bos, and Lehman 2019). For instance, algorithms are used to recommend travel routes, jokes, clothing items, or beverages that consumers might like. Whereas some companies (e.g., Netflix) utilize only algorithms to generate taste-based recommendations, others (e.g., Stitch Fix) employ both recommender types simultaneously. Interestingly, managers rely on different strategies when communicating about the recommender—algorithm or human expert—to consumers: some companies (e.g., Wix) emphasize that their recommendations are generated by an algorithm, but others (e.g., Stitch Fix) downplay the algorithmic origin and instead emphasize a human connotation.

The fact that companies rely on different recommender types and/or adopt different communication strategies raises the question whether consumers value a recommendation more if it is said to be generated by an algorithm or by a human expert. In this research, we show that the answer to this question depends on consumers' subjective knowledge in the focal domain (e.g., whether they think they know a lot or little about the topic area in which they are seeking a recommendation). Building on the advice taking literature (e.g., Bonaccio and Dalal 2006), we predict an interaction effect between consumers' subjective knowledge and recommender type such that consumers with high subjective knowledge in a focal domain value a recommendation more when it is said to be generated by an algorithm (rather than by a human expert). We argue that this occurs because these consumers want to collaborate with the recommender and believe that they can engage in a more *meaningful collaboration* (i.e., a collaboration in which both parties have a common ground and jointly contribute to generate a recommendation) with an algorithm (vs. a human expert). Notably, we do not predict a greater valuation of algorithmic advice for consumers with low subjective knowledge in a focal domain. We contend that these consumers think they lack specific knowledge (Alba and Hutchinson 2000) and believe that they cannot engage in a meaningful collaboration regardless of the recommender type (algorithm vs. human expert). Thus, they are likely to favor outsourcing the recommendation task completely.

To test the proposed interaction effect between recommender type (i.e., algorithm vs. human expert) and consumers' subjective knowledge in a focal domain, we conducted seven studies online and in the field. Importantly, to assure robustness and generalization of the effect, we tested our hypotheses across three domains (i.e., beverages, travel routes, and workout activities). We both manipulated and measured our proposed moderator, subjective knowledge. Our results consistently reveal that consumers' subjective knowledge in a focal domain drives their valuation of recommendations said to be generated by an algorithm or a human expert. Specifically, when consumers think that they are knowledgeable in a focal domain, they expressed greater valuation for a recommendation presumably generated by an algorithm (vs. a human expert) because these consumers perceive algorithms (vs. human experts) to provide them with greater possibilities for meaningful collaboration. This greater valuation of algorithmic recommendations, however, was mitigated for consumers who do not think that they are knowledgeable in a focal domain.

This research makes several important contributions. First and foremost, our work adds to the growing research in marketing that explores consumers' valuation of algorithmic recommendations. Whereas early work documented algorithm aversion (i.e., greater preference for humans over algorithms; Onkal et al. 2009; Promberger and Baron 2006; Yeomans et al. 2019), recent work suggests algorithm appreciation (i.e., greater valuation of algorithms than humans; Logg, Minson, and Moore 2019) or highlights that consumers' valuation of algorithmic advice depends on contextual factors, such as characteristics of the task (Castelo et al. 2019), product attributes (Longoni and Cian 2020), and the decision outcome (Yalcin et al. 2021). We add to this research on contextual factors by taking a consumer perspective and highlighting consumers' subjective knowledge as another determining factor that can consistently and predictably shape consumers' reaction to algorithmic and human-based advice.

Second, we add to previous work in this domain by identifying a novel mechanism that underlies our base phenomenon: meaningful collaboration.

Process evidence in existing work has predominantly captured fundamental differences between algorithms and humans, including consumers' perception of what recommenders are typically like (e.g., Lee 2018) or what they lack (e.g., Longoni et al. 2019). Instead, our proposed process documents that consumers' beliefs about how they can interact with the recommender are influential in determining their valuations of advice from these recommenders; this emphasizes the importance of taking a consumer perspective and incorporating consumers' subjective knowledge in a specific domain when explaining their reactions to different recommender types.

Third, our research offers timely and actionable guidance for companies that incorporate recommendations by algorithms and/or human experts in executing their marketing strategy. Companies can leverage our conceptual insights and utilize customer information (proxies to subjective knowledge) to segment customers. This allows them to tailor their services and communication (dependent on the customer segment) to make recommendations more valuable for customers and, ultimately, more effective for the company. We will expand on this discussion in our General Discussion as we further highlight the substantive contributions of our work.

Theoretical Background

Algorithmic versus Human-Based Recommendations

Advancements in technology have enabled companies to utilize algorithms to provide recommendations in various domains, in addition to (or instead of) human experts. Algorithms have been generally defined as "a set of steps that a computer can follow to perform a task” (Castelo et al. 2019), such as generating personalized product recommendations. Given the prevalence of algorithmic recommendations in our daily lives, academics frequently compare consumers’ valuation of recommendations generated (or said to be generated) by algorithms and humans and historically have documented that individuals value algorithms and/or their output less. For instance, individuals trust medical recommendations from algorithms less than from doctors (Longoni et al. 2019; Promberger and Baron 2006) and are less likely to follow algorithmic (vs. human-based) forecasts for stock prices (Onkal et al. 2009). Similarly, individuals are reluctant to use algorithms when recommending jokes to others (Yeomans et al. 2019). However, in contrast to these findings, Logg et al. (2019) more recently showed that consumers may also value algorithmic advice more than advice from humans. Indeed, more contemporary research has suggested that neither “algorithm aversion” nor “algorithm appreciation” appropriately summarize consumers’ overall reaction but that it depends on contextual factors, such as characteristics of the task (objective vs. subjective; Castelo et al. 2019), characteristics of the product attributes (hedonic vs. utilitarian; Longoni and Cian 2020), and/or the favorability of the decision outcome (favorable vs. unfavorable; Yalcin et al. 2021). Table 1 summarizes the most relevant findings in this domain.

Table 1: Summary of the Existing Literature on Algorithmic Decision Making

Authors	Year	Main IV	Main DV	Main Finding	Trait measures
Bechwati and Xia	2003	Search engine vs. human aid	Perceived effort	Consumers perceive electronic decision aids to exert less effort compared to humans	
Bigman and Gray	2018	Computer vs. human	Perceived permissibility	When making moral decisions, it is less permissible for computers (vs. humans).	
Bonezzi and Ostinelli	2021	AI vs. human	Perceived bias	Algorithms (vs. humans) are less likely to be perceived as biased.	
Cadario et al.	2021	Algorithm vs. human	Subjective understanding of decision-making, preference	There is less illusory understanding for algorithmic (human-based) decisions. This makes people more reluctant to use algorithms.	
Castelo et al.	2019	Algorithm vs. human	Trust and preference	Consumers are less likely to rely on algorithms for subjective (vs. objective) tasks.	
Diab et al.	2011	Formula vs. interview	Perceived usefulness	Thorough discussions are viewed as more useful than a formula.	
Dietvorst and Bartels	2021	Algorithm vs. human	Likelihood of switching to another company	People are more likely to switch to another company when companies deploy algorithms in domains that are morally relevant.	
Dietvorst and Bharti	2020	Statistical model vs. self	Preference	Individuals prefer riskier methods for humans (vs. statistical models) in inherently uncertain domains.	
Dietvorst et al.	2015	Statistical model vs. self	Preference	Seeing an algorithm err decreases individuals' willingness to rely on it.	
Dietvorst et al.	2016	Statistical model vs. self	Preference	Individuals are more willing to rely on algorithmic advice when the algorithm is modifiable.	
Efendić et al.	2020	Algorithm vs. human	Perceived accuracy and trust	Slowly generated algorithmic (vs. human-based) predictions are perceived as less accurate and people are less willing to rely on them.	
Jago	2019	Algorithm vs. human	Perceived authenticity	Algorithms are less authentic than humans.	
Kim and Duhachek	2020	Artificial agent vs. human	Perceived appropriateness and compliance	When persuasive messages have low (vs. high) level construal features, messages by artificial (vs. human) agents are perceived as more appropriate and effective.	
Lee	2018	Algorithm vs. human	Trust and perceived fairness	People perceive algorithms to be less fair and trustworthy for tasks that require human (vs. mechanical) skills.	
Logg et al.	2019	Algorithm vs. human/self	Weight on advice	Individuals give more weight to advice by algorithms (vs. lay people).	Numeracy scale (Schwartz et al 1997): higher numeracy is correlated with greater reliance to algorithms.
Longoni and Cian	2020	AI vs. human	Preference	When hedonic (vs. utilitarian) attributes of a product are highlighted, consumers prefer human (vs. AI) recommenders.	
Longoni et al.	2019	AI vs. human	Preference	People choose to receive medical care from humans than AI.	Sense of uniqueness (Simsek and Yalcincetin 2010): people who consider themselves as more unique than others are more resistant to algorithms.
Newman et al.	2020	Algorithm vs. human	Perceived fairness	People perceive humans to be fairer than algorithms.	
Onkal et al.	2009	Statistical model vs. human	Weight on advice	Individuals give more weight to human-based (vs. algorithmic) advice.	Actual knowledge (stock prices): authors tested its main effect.
Promberger and Baron	2006	Computer vs. human	Acceptance of advice and trust	Individuals trust humans (vs. computers) more and are more likely to acceptance their advice.	
Senecal and Nantel	2004	Others vs. human expert vs. recommender system	Number of product choices	Using a recommender system as a label is more effective (i.e., more product choices) than using labels such as human experts or other consumers.	
Srinivasan and Sarial-Abi	2021	Algorithm vs. human	Brand evaluation	Consumers respond less negatively to a brand crisis when the error is caused by algorithms (vs. humans).	
Yalcin et al.	2022	Algorithm vs. human	Attitudes towards a company	Consumers react less positively when a favorable decision is made by algorithms (vs. humans). This difference is mitigated for unfavorable decisions.	
Yeomans et al.	2019	Algorithm vs. human	Preference	People want to receive joke recommendations from humans than algorithms.	

Essentially, the emerging work on contextual factors that moderate the relationship between recommender type and consumers' reactions focuses predominantly on characteristics of the task or the product at hand. However, little research has explored whether and how characteristics of the consumer (i.e., recommendation recipient) could moderate this relationship. This is somewhat surprising considering that advice taking research has repeatedly demonstrated that internal states of an advice recipient impact his/her receptiveness to advice from other humans (e.g., Bonaccio and Dalal 2006; Tost et al. 2012). Building on this literature, we suggest that a consumer's own belief about how much he/she knows in a domain may determine his/her valuation of algorithmic and human-based advice. In the following section, we first review existing work on subjective knowledge and its role in decision-making (in particular, advice taking) and then build our reasoning for why it impacts the valuation of algorithmic (vs. human-based) advice.

Consumers' Subjective Knowledge

Existing research distinguishes between objective (or actual) knowledge and subjective (or perceived) knowledge in a specific domain (e.g., Alba and Hutchinson 1987, 2000; Bandura 1977; Brucks 1985; Cadario et al. 2021; Hadar, Sood, and Fox 2013; Hadar and Sood 2014). Consumer research typically utilizes the term "objective knowledge" regarding accurate product-related information that consumers possess, whereas the term "subjective knowledge" captures consumers' own assessment of their knowledge or their meta-cognitive feeling of knowing (Alba and Hutchinson 1987, 2000; Hadar et al. 2013; Moorman et al. 2004). For instance, recognizing that red wine can be made from six different grapes represents objective knowledge whereas the belief that one is very knowledgeable about wines is an example of subjective knowledge (Hadar and Sood 2014).

Individuals often assess their subjective knowledge in a domain by drawing inferences from their own behaviors. They may rely on prior experiences (Ellen et al. 1991), including the frequency of engaging in related activities (Clarkson, Janiszewski, and Cinelli 2012) and experiential knowledge that stem from domain-specific experiences (Park, Mothersbaugh, and Feick 1994). Individuals' perception of how much they know in a domain influences their judgment and decision-making independently of actual knowledge (Fox and Weber 2002; Hadar et al. 2013; Reder and Ritter 1992). For instance, decision-makers may be more likely to invest in financial options that they feel knowledgeable about, even when they possess less actual knowledge about these options (Hadar et. al. 2013).

Consumers' Subjective Knowledge and the Valuation of Advice

Consumers' subjective knowledge in a focal domain directly impacts the extent to which they value information and seek out or accept advice in that domain. Generally, individuals with high subjective knowledge possess greater confidence in their own decision-making abilities (Park et al. 1994; Radecki and Jaccard 1995) and thus, are more likely to act on their own beliefs (Fernandes, Lynch, and Netemeyer 2014; Raju, Lonial, and Mangold 1995). For example, consumers with high subjective knowledge about a specific product are less interested in searching for product-related information as they perceive new information as redundant (Urbany, Dickson, and Wilkie 1989; Wood and Lynch 2002). Conversely, consumers with low subjective knowledge seek out product information more extensively (Urbany et al. 1989). In a similar vein, research on advice taking demonstrates that consumers' confidence in their own knowledge impacts reactions towards advice and/or an advisor (e.g., Yaniv and Kleinberger 2000), and influences their likelihood of accepting or rejecting advice (e.g., Bonaccio and Dalal 2006). Individuals find advice more valuable if the advisor is perceived as possessing more expertise relative to themselves; thus, when advisors have greater task-relevant knowledge or so-called ''expert power'' (French, Raven, Cartwright 1959; Bonaccio and Dalal 2006), individuals are more likely to rely on advice. Conversely, individuals are less likely to rely on advice if they (think they) possess knowledge.

Essentially, the literature reviewed here suggests that high subjective knowledge in a domain may decrease the tendency to incorporate external advice or "outsource" a decision task because consumers value their own viewpoints. However, we suggest that consumers with high subjective knowledge may be more susceptible to algorithmic (vs. human-based) advice because relying on algorithmic advice still enables them to feel involved in the decision process. Indeed, existing work in the advice taking literature shows that accepting advice from human advisors is typically perceived as fully outsourcing the responsibility for the decision (e.g., Bonacci and Dalal 2006; Harvey and Fischer 1997); thus, making consumers feel obliged to utilize the advice (Nadler 1991) or creating a sense of redundancy (Bhattacharya and Mukherjee 2013). Conversely, receiving advice from an algorithm is not necessarily associated with outsourcing the responsibility (Promberger and Baron 2006). This is presumably because humans are perceived to possess greater agency and intentionality than machines (e.g., Gray and Wegner 2012). Algorithms, however, lack agency and, thus, are frequently used as decision support systems.

Consequently, receiving advice from an algorithm will allow for more *meaningful collaboration* between the consumer and an algorithmic (vs. human) advisor because the algorithm is not perceived to be independent in defining the decision process. By meaningful collaboration,[6] we mean a two-sided process in which two parties jointly collaborate to find a solution (e.g., Couture and Sutherland 2006). This collaboration is meaningful as there is common ground (e.g., shared knowledge, strategies; Van Swol et al. 2018; Wood and Gray 1991), but also a greater possibility to acquire new information that algorithms might possess but consumers do not (e.g., Silver et al. 2018). Building on this, we suggest that consumers with high subjective knowledge value recommendations generated by an algorithm (as opposed to those by a human expert) more because they perceive that it allows them to meaningfully collaborate and be involved in the decision process. Notably, this prediction broadly mirrors research findings in different fields. For instance, research in organizational behavior documents that

[6] Whereas the advice taking literature sometimes referred to "collaboration" in the context of dyads (i.e., several advice recipients; Minson and Mueller 2012), our definition is different as our context does not involve several advice recipients.

managers accept and value algorithms as long as they themselves retain greater weight in the decision process (Haesevoets et al. 2021). Similarly, research on moral decision-making documents that individuals are more likely to accept machines to make moral decisions when they only possess an advisory role instead of taking over the decision process (Bigman and Gray 2018).

Our discussion so far has exclusively focused on consumers with high subjective knowledge. Conversely, consumers with low subjective knowledge lack specific knowledge and strategies to come up with a recommendation, find the overall process more difficult, and are likely to find it hard to collaborate in the process (e.g., Alba and Hutchinson 1987, 2000). For them, an advisor - regardless of whether it is an algorithm or a human expert - possesses expert power (e.g., French et al. 1959). Thus, compared to consumers with high subjective knowledge, these consumers are more likely to rely on external advice and outsource the whole decision process, regardless of the source of the advice (Bonaccio and Dalal 2006). As such, we hypothesize the greater valuation of algorithmic recommendations (that we predict for consumers with high subjective knowledge) to be mitigated for consumers with low subjective knowledge. More formally:

H1a: *Consumers with high subjective knowledge in a focal domain* are more likely to value recommendations generated by an algorithm (versus a human expert).

H1b: A greater valuation for recommendations generated by an algorithm (vs. a human expert) is attenuated for *consumers with low subjective knowledge in a focal domain*.

H2: The effect of recommender type (algorithm vs. human expert) on the valuation of recommendations for consumers with high subjective knowledge is mediated by the extent to which these consumers think they can engage in a meaningful collaboration with the recommender.

Overview of Studies

We conducted seven studies— in various domains (e.g., beverages, travel routes, fitness activities)—to test the impact of consumers' subjective knowledge in a focal domain on the valuation of recommendations said to be generated by an algorithm versus a human expert. In each study, participants were given a specific context (e.g., choosing a coffee flavor or planning a trip) and were told about a service that provides recommendations (e.g., tasty coffee flavors, scenic travel routes) to its users. To test the robustness of our effect across studies, we employed various contexts as well as operationalizations of our moderating variable: subjective knowledge. In studies 1a and 1b, we measured participants' subjective knowledge by assessing their perceived frequency of engaging in the focal activity (e.g., frequency of traveling), whereas in the remaining five studies we manipulated subjective knowledge in various ways. Specifically, participants were asked to choose beverages that they know a lot (vs. little) about (study 2), performed an essay writing task (Studies 3a, 4a, and 4b), or received a false feedback manipulation regarding their performance (study 3b). In doing so, we provide causal evidence for the impact of subjective knowledge and offer actionable guidelines for companies. Finally, in studies 4a and 4b, we focused on consumers with high subjective knowledge in a domain and tested our proposed process, meaningful collaboration, by means of mediation (study 4a) and moderation (study 4b). Detailed information about our scenarios and additional analyses to rule out alternative explanations can be found in the Appendix. Our Appendix also includes details on our measures, conditions, and data exclusions. In our studies, we aimed for at least 100 participants per cell for studies we conducted face-to-face[7] and utilized higher cell sizes for studies using online panels. Sample sizes were determined prior to data collection.

Studies 1a and 1b: Measuring Subjective Knowledge

In studies 1a and b, we measured participants' subjective knowledge in two different domains (i.e., tasty coffee-based drinks, scenic travel routes) by assessing their perceived frequency of engaging in the focal activity (e.g., frequency of traveling; adapted from Gai and Klesse 2019). We purposefully chose this measure because consumers' previous experiences in a specific domain impact their perception of how much knowledge they think they possess in this domain (e.g., Ellen et al. 1991).

Study 1a

Nowadays, companies increasingly deploy algorithms to generate personalized beverage recommendations, including recommendations for coffee (e.g., Craft Coffee). Motivated by these recent developments, we created a scenario in which we told participants about a new service, *Bean Me Up,* that offers tasty coffee recommendations.

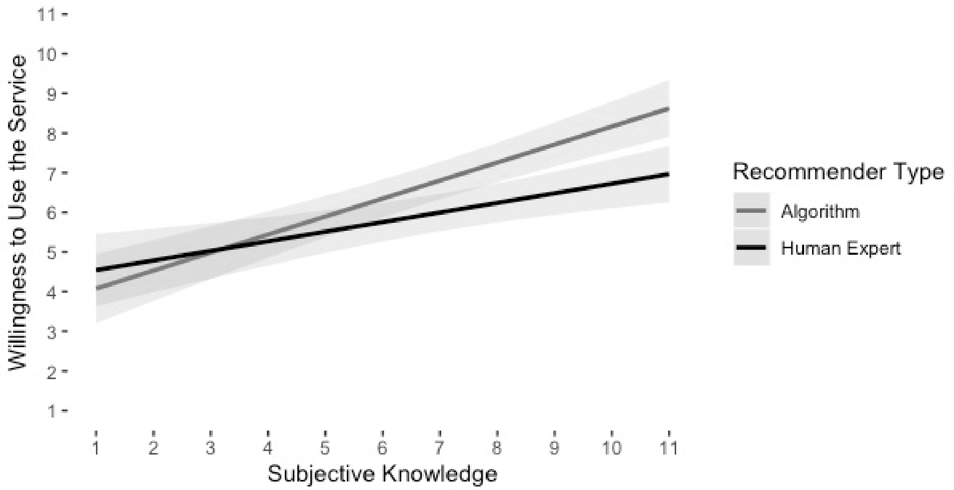
[7] Study 3a is an exception. It was conducted face-to-face and because of time limitations on the study duration, it was difficult to recruit more participants. We stopped data collection before reaching the target number, without looking at the data beforehand.

Participants and Procedure. Two hundred and sixty-four participants were recruited at the city center of a major European city (M_{age} = 32.85, 131 females, $N_{algorithm}$ = 128, N_{expert} = 136). First, we measured participants' subjective knowledge in the focal domain (i.e., coffee) by asking them to indicate how frequently they drink coffee (1 = I drink different coffee-based drinks very infrequently to 11 = I drink different coffee-based drinks very frequently). They then read about *Bean Me Up,* an easy-to-use website which offers recommendations with respect to tasty coffee-based drinks. Importantly, participants were randomly assigned to one of two recommenders: a coffee algorithm versus a coffee expert. Our main dependent variable was participants' willingness to use (WTU) the service (1 = not at all likely to 11 = very likely; see Appendix 2A for additional details).

Results. To test our proposed interaction effect between recommender type and consumers' subjective knowledge, we ran a linear regression with recommender type (algorithm = -1, human expert = 1), subjective knowledge (mean-centered), and their interaction as predictor variables and participants' WTU the service as the dependent variable. The analysis revealed a significant main effect of recommender type (β = -.13, $t(260)$ = -2.28, p = .02) and a significant effect of subjective knowledge (β = .42, $t(260)$ = 7.51, p < .001). As predicted, we also found a significant interaction effect between recommender type and subjective knowledge (β = -.13, $t(260)$ = -2.29, p = .02; see Figure 1). Floodlight analysis (Spiller et al. 2013) highlighted the region of significance for subjective knowledge as the values equal to or higher than 6.37 (algorithm >

human expert), whereas this positive effect of algorithms (vs. human experts) was insignificant for participants with low subjective knowledge.

Figure 1. Study 1a Results



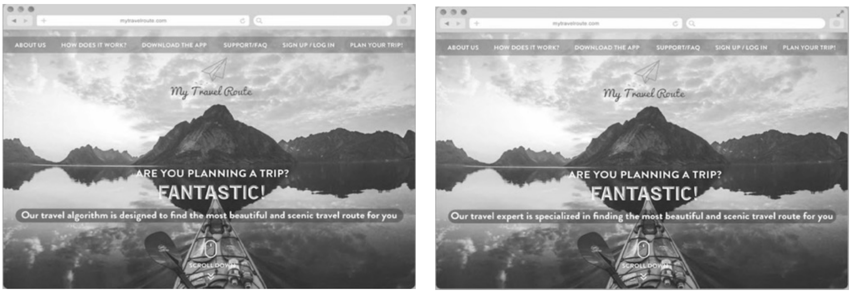
Study 1b

The aim of study 1b is to test the predicted interaction effect between recommender type and subjective knowledge in a different domain. Specifically, we chose the context of recommending scenic travel routes as algorithms are increasingly used to provide personalized travel recommendations (Cui, Luo, and Wang 2017).

Participants and Procedure. Three hundred students were recruited in the city center of a major European city (M_{age} = 22.27, 167 females, $N_{algorithm}$ = 150, N_{expert} = 150) and were asked to indicate their subjective knowledge in traveling. Again, we operationalized subjective knowledge in terms of participants' perceived frequency of traveling (1 = I travel very infrequently to 9 = I travel very frequently).

Participants were asked to imagine that they were planning a road trip through Canada. We purposefully referred to a specific country to assure that everyone had a similar travel route in mind. Participants then read about *MyTravelRoute* and depending on the condition that they were randomly assigned to, *MyTravelRoute* either utilized a travel algorithm or a travel expert to generate the most scenic travel route recommendations (see Figure 2). The remainder of the scenario was identical for both conditions

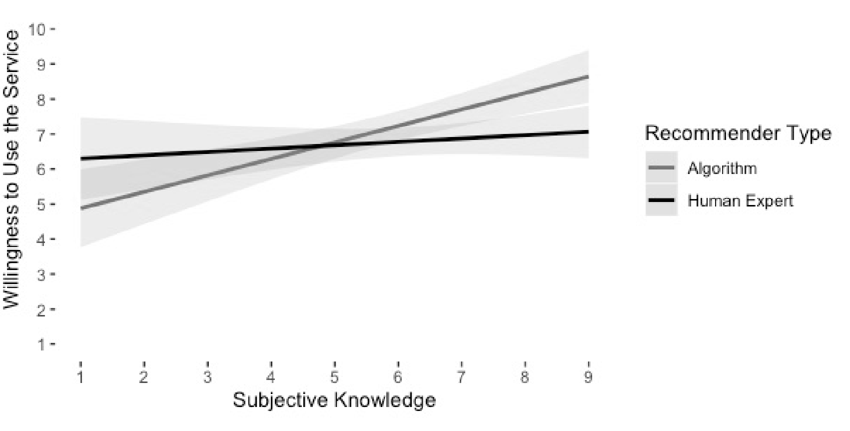
Figure 2. An Illustration of the Manipulation of the Recommender Type in study 1b



Our main dependent variable was participants' WTU the service (1 = not at all likely to 11 = very likely; see Appendix 2B for additional details). We also measured how much individuals would like to do a road trip through Canada ("I would very much like to do a road trip through Canada"; 1 = strongly disagree to 7 = strongly agree) as a potential covariate. This is because the valuation of the service might increase when people have specific interest in visiting this country (regardless of recommender type). Even though the main analysis was run without this covariate, the results were robust to the inclusion of it (please see Appendix 2B for the additional analysis with this covariate).

Results. To test for the proposed interaction effect between recommender type and consumers' subjective knowledge in traveling, we ran a linear regression with recommender type (algorithm = -1, human expert = 1), subjective knowledge (mean-centered), and their interaction on participants' WTU the service. The analysis revealed a non-significant main effect of recommender type ($\beta = -.09$, $t(296) = -1.58$, $p = .12$) and a significant effect of subjective knowledge ($\beta = .21$, $t(296) = 3.72$, $p < .001$). Importantly, we found a significant interaction effect between recommender type and subjective knowledge ($\beta = -.14$, $t(296) = -2.46$, $p = .01$; see Figure 3). As hypothesized, the floodlight analysis (Spiller et al. 2013) highlighted the region of significance for subjective knowledge as the values equal to or higher than 6.36 (algorithm > human expert). Additionally, this positive effect of algorithms (marginally) reversed as the values lower than 1.80 (human expert > algorithm).

Figure 3. Study 1b Results



Discussions of Studies 1a and 1b

The results of studies 1a and 1b consistently documented an interaction effect between recommender type and consumers' subjective knowledge in the focal domain (i.e., coffee, traveling) on participants' WTU a service. Importantly, floodlight analyses revealed that individuals with higher subjective knowledge value recommendations by algorithms more, whereas a positive effect of algorithms did not occur for individuals with lower subjective knowledge. For these consumers, we found that they either valued recommendations by human experts and algorithms similarly (study 1a) or valued recommendations by human experts (vs. algorithms) more (study 1b).

Importantly, we purposefully tested our main interaction effect using different domains (e.g., coffee-based drinks, travel routes) to establish generalizability of our effect. In addition, we conducted a follow-up lab study in which we utilized a behavioral outcome measure (i.e., signing up for a service). In this setting, we replicated our proposed interaction effect such that consumers with higher subjective knowledge were more likely to create an account for the service when it was described as using a travel algorithm (vs. travel expert) to generate recommendations. Please see Appendix 2C for further details about this follow-up study.

A potential limitation of our study 1, is the proxy measurement of subjective knowledge defined by the experience each participant had with the domain. While there is precedent for the logic behind this operationalization in the literature (e.g., Ellen et al. 1991), in the subsequent studies we manipulated subjective knowledge utilizing different operationalizations to provide a robust assessment of its impact in driving the pattern that we demonstrate.

Study 2: Consumers' High and Low Domain-Specific Subjective Knowledge

In our previous studies, we relied on between-participants designs to compare differences in valuation of a recommendation as a consequence of recommender type. In this study, we utilize a within-participants design to document that the same consumer values algorithmic recommendations differently depending on whether he/she possesses high or low subjective knowledge in a focal domain. Because many companies deploy algorithms to provide consumers with personalized recommendations for various beverages (e.g., wine: Bright Cellars; beer: ALEgorithms), we focus on beverages and ask participants to choose a beverage about which they feel knowledgeable as well as a beverage about which they do not feel knowledgeable.

Participants and Procedure. Two hundred Prolific users (M_{age} = 31.23, 114 females) participated in a 2-cell (subjective knowledge: high vs. low) within-participants design study.

Participants were told that they participate in a study about different beverages. To begin with, they were asked to select a beverage that they consume and think they know a lot about, choosing between coffee, tea, beer, wine, juice, and cocktail. Then, they were asked to select a beverage that they consume but think they know only little about, again choosing from the same set of options (see Appendix 2D for additional details). Afterward, all participants read that many companies use algorithms to provide personalized recommendations for their selected beverages. The algorithm was defined as "a sophisticated statistical software specialized in recommending the beverage of their choice". Then participants were asked to report how likely they would be to get a customized recommendation from this algorithm (1 = not at all likely to 9 = very likely) for each of the two beverages that they previously selected (i.e., the one that participants feel knowledgeable about and the one that they do not feel knowledgeable about).

Results and Discussion. We compared participants' self-reported likelihood to receive a recommendation for the beverage that they think they know a lot about and the beverage that they think they know little about. A paired t-test analysis showed that participants indicated to be more likely to get an algorithmic recommendation for the beverage they feel knowledgeable about (M = 6.42, SD = 2.10) compared to the beverage they do not feel knowledgeable about (M = 4.86, SD = 2.51; t(199) = 7.90, $p < .001$, $d = 1.12$).

Study 2 reveals an important insight: the extent to which the same consumer values algorithmic product recommendations depends on their subjective knowledge in a focal domain. Thus, the same consumer may value or devalue algorithmic recommendations depending on their subjective knowledge.

Studies 3a an 3b: Manipulating Subjective Knowledge

Companies (e.g., Yelp, Qualtrics) engage in strategies (e.g., providing performance feedback, badges) that could impact their consumers' subjective knowledge. Inspired by such practices, in studies 3a and 3b, we utilize two distinct manipulations to shift participants' subjective knowledge in a focal domain. In study 3a, we used a false feedback manipulation (e.g., Campbell 2015; Fishbach et al. 2010), and in study 3b, we adopted an essay writing task (e.g., Leung et al. 2018; Puntoni et al. 2011) to manipulate participants' subjective knowledge. Manipulating rather than measuring our moderator helps provide causal evidence for the role of subjective knowledge in the valuation of recommendations generated by algorithms versus human experts.

Study 3a

Participants and Procedure. We approached consumers at a shopping mall in a major Northern American city and asked whether they would participate in a short study about coffee-based drinks. If they agreed, we first asked them to list as many types of coffee-based drinks as they could. Participants were told that they could stop listing whenever they wanted. Six participants who listed fewer than three coffee-based drinks were not allowed to continue as our false-feedback manipulation (details follow below) would not have been believable for them.

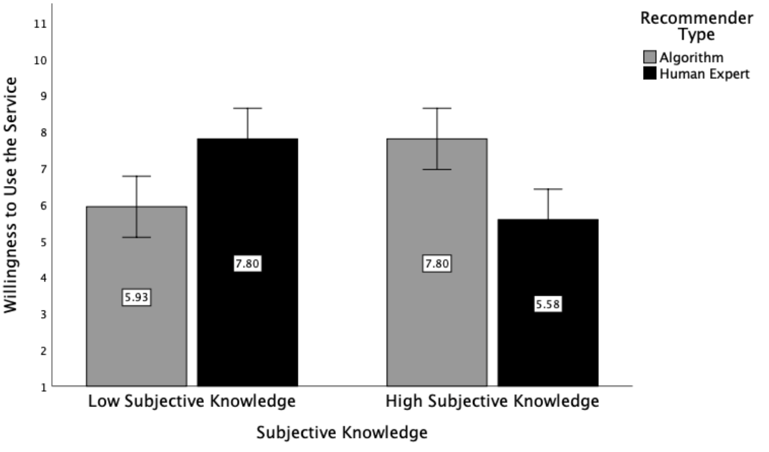
One hundred and eighty participants (M_{age} = 31.1, 94 females, $N_{alghigh}$ = 45, N_{alglow} = 45, $N_{experthigh}$ = 45, $N_{expertlow}$ = 45) completed our study. Regardless of the number of actual coffee-based drinks participants listed, they were randomly assigned to either a high or low subjective knowledge condition. Participants in the high subjective knowledge condition were told that other participants on average listed *two fewer* coffee-based drinks than they listed; hence their score was above average. This meant that they probably drink different types of coffee frequently and definitely have very good knowledge about a variety of coffee-based drinks. In contrast, participants in the low subjective knowledge condition were told that on average other participants listed *two more* coffee-based drinks than they listed, and their score was below average. This meant that they probably do not drink different types of coffee frequently and do not have very good knowledge about a variety of coffee-based drinks (see Appendix 2E for additional details).

After receiving their (false) performance feedback, participants were provided with information about a new start-up called *Bean Me Up*, an easy-to-use website which offers recommendations with respect to tasty coffee-based drinks. In line with our previous studies, we then manipulated whether the service utilized a coffee algorithm or a coffee expert to generate tasty coffee recommendations. Afterwards, participants indicated their WTU the service (1 = not at all likely to 11 = very likely) and responded to the following two-item manipulation check (a = .74): "Compared to an average person, how much do you think you know about coffee-based drinks?" (1 = not at all to 11 = very much) and "I was told that my knowledge about coffee-based drinks is ___" (1 = below an average person to 11 = above an average person). To make sure that participants were randomly distributed across conditions, we also measured the extent to which they like coffee (i.e., "How much do you like coffee-based drinks?"; 1 = not at all to 11 = very much) and how often they drink coffee in general ("How often do you drink coffee-based drinks?"; 1 = not at all often to 11 = very often). Additionally, we recorded the actual number of coffee-based drinks participants listed as a measure of objective knowledge. Finally, participants were thanked and told that the feedback they received was not reflective of their actual coffee knowledge.

Results. First, we checked whether our randomization was successful. A two-way ANOVA (recommender type x subjective knowledge) revealed no differences across conditions—neither a main nor an interaction effect— in terms of (1) the actual number of coffees participants listed, (2) the extent that they like coffee-based drinks and (3) how frequently they drink coffee in general (all F*'s* < 2.22, $p > .1$). Second, we assessed whether our manipulation of subjective knowledge was successful. A two-way ANOVA (recommender type x subjective knowledge) revealed a (marginally significant) main effect of recommender type ($F(1,176) = 2.95$, $p = .09$, $\eta_p^2 = .02$): participants in the algorithm condition reported (M = 6.50, SD = 2.74) more knowledge about coffee compared to participants in the human expert condition (M = 6.02, SD = 2.48). We also observed a main effect of the subjective knowledge manipulation ($F(1, 176) = 164.04$, $p < .001$, $\eta_p^2 = .48$) such that participants in the high subjective knowledge condition reported (M = 8.06, SD = 1.68) significantly more knowledge about coffee compared to participants in the low subjective knowledge condition (M = 4.46, SD = 2.09). Importantly, the results did not show a significant interaction effect between recommender type and subjective knowledge ($F < 1$, $p = .40$). These results suggest that we were able to successfully shift participants' subjective knowledge about different coffee-based drinks.

Moving to our main analysis, an ANOVA (recommender type x subjective knowledge) revealed neither a significant main effect of recommender type (F < 1, p = .68) nor of subjective knowledge (F < 1, p = .68), but a significant interaction effect between the two on participants' WTU the service ($F(1, 176) = 23.05$, $p < .001$, $\eta_p^2 = .12$; see Figure 5). As predicted, participants in the high subjective knowledge condition were more willing to use the service when it was described to use an algorithm (M = 7.80, SD = 2.87) versus a human expert (M = 5.58, SD = 3.04; $F(1, 176) = 13.62$, $p < .001$). This pattern reversed for participants in the low subjective knowledge condition as they valued the service more when it was described to utilize a human expert (M = 7.80, SD = 2.43) rather than an algorithm (M = 5.93, SD = 3.04; $F(1, 176) = 9.61$, $p = .002$).

Figure 5. Study 3a Results



Study 3b

Participants and Procedure. Six hundred and one Prolific users (M_{age} = 32.04, 393 females, $N_{alghigh}$ = 143, N_{alglow} = 159, $N_{experthigh}$ = 164, $N_{expertlow}$ = 135) participated in this study. We randomly assigned participants to one of four conditions in a 2 (subjective knowledge: high vs. low) x 2 (recommender type: algorithm vs. human expert) between-participants design.

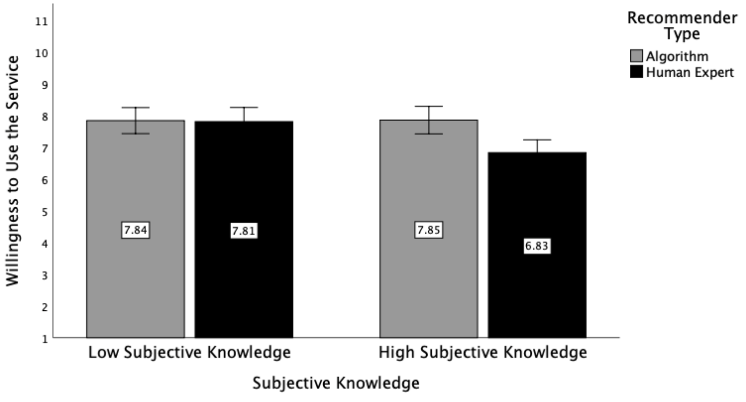
At the beginning of the study, we told participants that we would like to get to know more about their experiences with workout activities. Specifically, participants in the high subjective knowledge condition were asked to think and write about a specific workout activity that they engage in and feel very knowledgeable about. Conversely, participants in the low subjective knowledge condition were asked to think and write about a specific workout activity that they engage in but do not feel very knowledgeable about.

After this essay writing task, participants read about a new fitness platform called *Next Level*, an easy-to-use virtual platform which offers recommendations with respect to fun workout activities. Importantly, we then manipulated whether the service utilized a workout algorithm or a workout expert to generate fun workout recommendations. Afterwards, participants indicated their WTU the service (1 = not at all likely to 11 = very likely) and responded to the manipulation check (i.e., "After writing about the time I had reflected on, I feel knowledgeable about workout activities; 1 = strongly disagree to 9 = strongly agree; see Appendix 2F for additional details).

Results. First, we tested whether our essay writing manipulation successfully shifted participants' subjective knowledge about working out. As expected, a two-way ANOVA (recommender type x subjective knowledge) demonstrated a non-significant main effect of recommender type ($F(1, 597) = 1.51$, $p = .22$) and a non-significant interaction effect between the recommender type and subjective knowledge ($F(1, 597) < 1$, $p = .96$). More importantly, this analysis revealed that our manipulation was successful, and participants who wrote about an activity that they were good at reportedly felt more knowledgeable about ($M = 6.36$, $SD = 1.86$) than participants who wrote about an activity that they felt unknowledgeable about ($M = 4.68$, $SD = 1.94$; $F(1, 597) = 118.38$, $p < .001$, $\eta_p^2 = .17$).

Moving to our main analysis, an ANOVA (recommender type x subjective knowledge) revealed a significant main effect of recommender type so that participants reported greater WTU the service if the recommender was an algorithm ($M = 7.84$, $SD = 2.54$) as compared to a human expert ($M= 7.27$, $SD = 2.76$; $F(1, 597) = 5.95$, $p = .02$, $\eta_p^2 = .01$). We also observed a significant main effect of subjective knowledge so that the high subjective knowledge manipulation decreased WTU the service ($M = 7.31$, $SD = 2.92$) compared to the low subjective knowledge manipulation ($M= 7.82$, $SD = 2.36$; $F(1, 597) = 4.96$, $p = .03$, $\eta_p^2 = .01$). More importantly, we found a significant interaction effect ($F(1, 597) = 5.31$, $p = .02$, $\eta_p^2 = .01$; see Figure 4): as predicted, participants in the high subjective knowledge condition reported greater WTU the service when it was described to employ an algorithm ($M = 7.85$, $SD = 2.76$) versus a human expert ($M = 6.83$, $SD = 2.98$; $F(1, 597) = 11.52$, $p = .001$), whereas this pattern was not significant for participants in the low subjective knowledge condition: these participants valued the service similarly when it was described to utilize a human expert ($M = 7.81$, $SD = 2.37$) or an algorithm ($M = 7.84$, $SD = 2.35$; $F(1, 597) < 1$, $p = .93$).

Figure 4. Study 3b Results



Discussion of Studies 3a and 3b

Studies 3a and 3b replicated our interaction effect between recommender type and subjective knowledge when manipulating (rather than measuring) our moderating variable. Specifically, we showed the interaction effect by employing a false feedback manipulation (study 3a) and an essay writing task (study 3b). Importantly, in study 3a, our conditions did not differ in the extent to which participants liked coffee or how many coffee-based drinks they listed. Thus, differences in general interest or objective knowledge are unlikely to explain our results. Instead, merely shifting participants' subjective knowledge in the focal domain resulted in differences of the valuation of algorithmic versus human-based recommendations. This provides causal evidence for the role of subjective knowledge in the valuation of different recommender types.

Studies 4a and 4b: Process Evidence

Our studies so far have consistently documented the interactive effect between recommender type (i.e., algorithm vs. human expert) and consumers' subjective knowledge (high vs. low subjective knowledge) in a focal domain. Across contexts and operationalizations, consumers with high subjective knowledge were shown to value a recommendation more if it is said to be generated by an algorithm (vs. a human expert) whereas this effect was mitigated for consumers with low subjective knowledge, providing support for H1.

In the two remaining studies, we focused exclusively on consumers with high subjective knowledge in the focal domain and provided process evidence for why this effect occurs. Our theorization (H2) suggests that consumers with high subjective knowledge value algorithmic (vs. human-based) recommendations more because they believe they can engage in a more meaningful collaboration with an algorithm (vs. a human expert). Study 4a provided process evidence by means of mediation and study 4b offered process evidence through moderation. Both studies were pre-registered (study 4a: aspredicted.org/6FP_RZS, study 4b: aspredicted.org/P52_8MH).

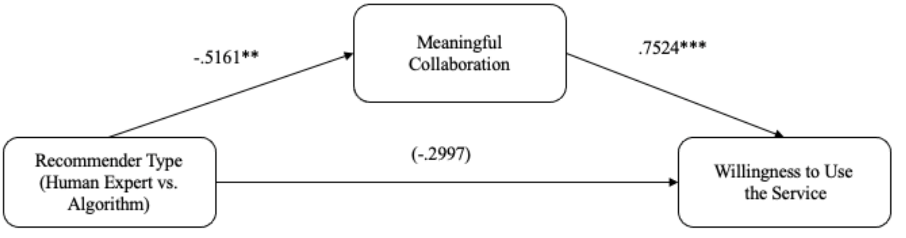
Study 4a

Participants and Procedure. Four hundred and ninety-nine Prolific users (M_{age} = 29.86, 309 females, $N_{algorithm}$ = 242, N_{expert} = 258) participated in this study. We randomly assigned participants to one of two conditions in a 2-cell (recommender type: algorithm vs. human expert) between-participants design.

Just like in study 3b, we first told participants that we would like to get to know more about their experiences with workout activities. Then all participants were instructed to think of and write about a specific workout activity that they engage in and feel very knowledgeable about. After this essay writing task, participants read about a new fitness platform called *Next Level*, an easy-to-use website which offers recommendations for fun workout activities. Importantly, we then manipulated whether the service utilized a workout algorithm or a workout expert to generate fun workout recommendations. Afterwards, participants indicated their WTU the service (1 = not at all likely to 11 = very likely) and responded to our mediator. Our mediator included the three following items that we aggregated into one joint measure: "The algorithm/expert would consult me as the algorithm/expert and I have similar knowledge with respect to fun workout activities", "The algorithm/expert relies on similar strategies to come up with a fun workout activity as I would", and "This algorithm/expert would collaborate with me because of our similar knowledge/strategies (a = .80; 1 = strongly disagree to 7 = strongly agree, see Appendix 2G for additional details). A factor analysis revealed that these three items loaded into a single factor.

Results. An ANOVA documented a significant effect of recommender type on participants' WTU the service ($F(1, 497) = 9.24$, $p = .002$, $\eta_p^2 = .02$) so that participants were more willing to use the service when it was described as utilizing a workout algorithm ($M = 8.17$, $SD = 2.39$) than a workout expert ($M = 7.48$, $SD = 2.67$). We then conducted the same ANOVA on our mediator and also found a significant effect of recommender type ($F(1, 497) = 23.33$, $p < .001$, $\eta_p^2 = .05$). As predicted, participants indicated that they could better collaborate with a workout algorithm ($M = 4.70$, $SD = 1.14$) compared to a workout expert ($M = 4.18$, $SD = 1.25$). Finally, a simple mediation analysis (Process Model 4, 10,000 bootstrapped samples; Hayes 2013) with WTU the service as the dependent variable, recommender type (0 = algorithm, 1 = human) as the independent variable, and meaningful collaboration as the mediator (see Figure 6) revealed a significant indirect effect (ab = -.3883 (.09), CI 95% [-.5701, -.2230]), whereas the direct effect was insignificant (beta = -.2997 (.22), CI 95% [-.7254, .1260).

Figure 6. Mediation Model from Study 4a



NOTE.—*$p < .05$; **$p < .01$; ***$p < .001$

Study 4b

In study 4b, we manipulated the process. In particular, if the greater valuation of algorithmic recommendations is driven by the perception that consumers can more meaningfully collaborate with an algorithm (vs. a human expert), we should see a mitigation of the effect if the algorithm is uncollaborative. We tested this prediction by adding a third condition in which the algorithm makes collaboration impossible and compared it to our focal two conditions, the regular algorithm condition as well as the human expert condition. We predicted the new algorithm condition (i.e., uncollaborative algorithm) would prompt a significantly lower valuation than the algorithm condition and would not be significantly different from the human expert condition.

Participants and Procedure. Nine hundred and seventy-five Prolific users (M_{age} = 29.71, 680 females, $N_{algorithm}$ = 331, N_{expert} = 314, $N_{uncollaborativealg}$ = 330) participated in this study. We randomly assigned participants to one of three conditions in a 3-cell (recommender type: algorithm vs. human expert vs. uncollaborative algorithm) between-participants design.

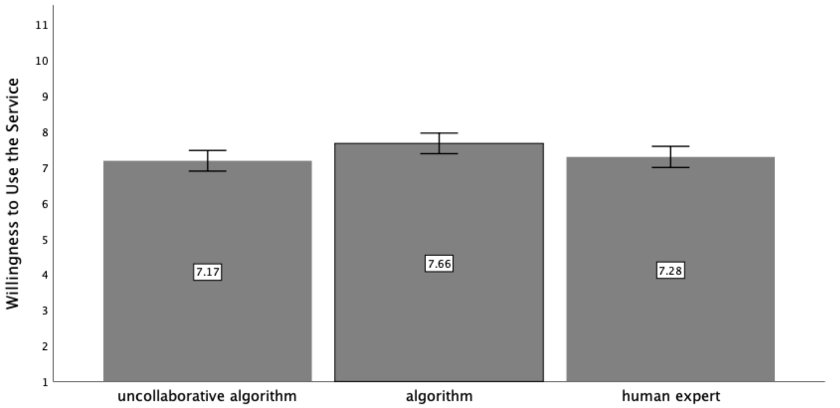
Similar to study 4a, all participants were asked to think of and write about a specific workout activity that they engage in and feel very knowledgeable about. They then read about *Next Level*, the virtual platform used in studies 3b and 4a. We randomly assigned participants to one of three conditions. Depending on condition, participants read that the service utilized a workout algorithm or a workout expert to generate fun workout recommendations (the description was identical to that used in study 3b and 4a). In the third condition, participants learned that they would not be able to collaborate with the algorithm because it possesses very different knowledge and relies on different strategies than them (see Appendix 2H for additional details). Afterwards, participants indicated their WTU the service (1 = not at all likely to 11 = very likely) and responded to our manipulation check, which was measured using the three-item mediation index from study 4a (a = .83).

Results. First, we conducted an ANOVA to explore whether we successfully manipulated the extent to which participants thought they could engage in a meaningful collaboration with the recommender: the results revealed a significant effect of recommender type on the extent to which participants perceived the recommender allowed for collaboration ($F(2, 972) = 52.00$, p <

.001, $\eta_p^2 = .097$). Specifically, participants perceived the uncollaborative algorithm (M = 3.57, SD = 1.64) as less likely to collaborate with them compared to the human expert (M = 4.19, SD = 1.30; mean difference = -.62, $p < .001$) and compared to the regular algorithm (M = 4.66, SD = 1.14; mean difference = -1.09, $p < .001$). The contrast between the human expert and the regular algorithm condition was also statistically significant (mean difference = -.47, $p < .001$).

Next, we ran a separate ANOVA to test the effect of recommender type on participants' WTU the service. This analysis revealed a significant effect of recommender type ($F(2, 972) = 3.01$, $p = .05$, $\eta_p^2 = .01$, see Figure 7). We replicated our main comparison: participants expressed greater WTU the service when the service was described as utilizing a workout algorithm (M = 7.66, SD = 2.74) than a workout expert (M = 7.28, SD = 2.61; mean difference = .38, $p = .07$); note that this time the effect was only marginally significant. Importantly, participants in the uncollaborative algorithm condition (M = 7.17, SD = 2.66) reported lower WTU the service compared to the algorithm condition (mean difference = -.49; $p = .02$). As predicted the uncollaborative algorithm condition was not statistically significantly different from the human expert condition (mean difference = -.11; $p = .61$).

Figure 7. Study 4b Results



Discussion of Studies 4a and 4b

In two pre-registered studies, we demonstrated that consumers with high subjective knowledge believe they can engage in a more meaningful collaboration with an algorithm (vs. a human expert); essentially, this perception of a more meaningful collaboration drove the greater valuation of algorithmic (vs. human-based) recommendations. Importantly, whereas study 4a provided process evidence by means of mediation, study 4b added to it by means of moderation. Including a third condition in which we described the algorithm as uncollaborative mitigated the positive effect of the algorithm because collaboration was no longer possible.

General Discussion

Nowadays, many companies utilize algorithms, in addition to, or instead of human experts to provide consumers with recommendations. When communicating the recommender type to consumers, managers employ different strategies: some companies emphasize that their recommendations are generated by an algorithm whereas others downplay the algorithmic origin and highlight a human connotation instead. These different strategies make it important to understand whether consumers would value the same recommendation equally depending on whether it is (said to be) generated by an algorithm or a human expert.

In this research, we took a consumer perspective and are, to the best of our knowledge, the first to highlight consumers' subjective knowledge in a focal domain as a factor that can consistently and predictably shift reactions to algorithmic recommendations. Across seven studies, three domains (i.e., beverages, travel routes, and fitness activities), and different operationalizations of subjective knowledge (measured and manipulated), we consistently documented that consumers valued algorithmic recommendations more when they perceive themselves to be knowledgeable in a focal domain. However, this positive effect was attenuated when consumers do not perceive themselves knowledgeable. In our final two studies, we offered process evidence for why consumers with high subjective knowledge value algorithmic recommendations more. Both studies highlighted the important role of meaningful collaboration: whereas study 4a showed that perceptions of meaningful collaboration mediated our effect, study 4b demonstrated that the greater valuation for algorithmic recommendations was mitigated when collaboration was no longer possible.

Theoretical and Practical Contributions

Academics have frequently investigated whether consumers value advice generated by algorithms or humans more. Early research in this domain predominantly suggests that consumers are averse to algorithmic advice (e.g., Dietvorst et al. 2014; Promberger and Baron 2006; Onkal et al. 2009), whereas more recent work documents that consumers appreciate it (Logg et al. 2019) or suggests that consumers' reaction may depend on contextual factors related to the task, product, or decision (Castelo et al. 2019; Longoni and Cian 2020; Yalcin et al. 2021). We contribute to this growing research stream by revealing a consumer-related factor that influences consumers' valuation of recommendations by algorithms: consumers' subjective knowledge in a focal domain. Essentially, our work utilizes a variety of different manipulations and designs (between-versus within-participants) to document that the same consumer may value or devalue algorithmic advice depending on the extent to which he/she feels (or is made to feel) knowledgeable in the focal domain. Thus, our research lends itself to the conclusion that labelling consumers, generally, as "averse" or "appreciative" of algorithms is too simple, because both may apply.

Second, our research contributes to existing work in algorithmic decision-making as we identify a novel mechanism behind consumers' valuation of algorithms. Past work in this research stream has mainly captured fundamental differences between algorithms and humans, such as consumers' perception of what recommenders are typically like (e.g., Lee 2018) or what they lack (e.g., Longoni et al. 2019). Our work instead documents a psychological mechanism (i.e., meaningful collaboration) that takes a consumer perspective to explain the valuation differential between algorithms and humans. Specifically, we reveal how consumers' beliefs about the extent to which they can engage in meaningful collaboration with the recommender impacts their valuations of these recommenders.

Finally, our work also has several timely and managerial contributions. Though an increasing number of companies have adopted algorithmic recommendation systems (e.g., Netflix, Spotify, Stitch Fix) in addition to or instead of human experts, companies utilize different strategies when communicating who or what generated the recommendations: some emphasize the algorithmic origin whereas others highlight a human connotation instead, assuming that consumers value human advice more. For instance, in a conversation one of the authors had with a leading e-commerce company, the marketing manager expressed concerns about highlighting the algorithmic origin of their recommendations as their target group might not value algorithms. This company and other companies can learn from our research that consumers' subjective knowledge in a domain plays a decisive role in whether consumers value algorithmic recommendations and, thus, should be considered by companies when designing their services (e.g., choosing the recommender type) and communicating them to consumers. Specifically, the e-commerce company may be correct that some consumers will not appreciate algorithmic recommendations but, importantly, our findings suggest that there most likely is a segment, i.e., those consumers with high subjective knowledge in the focal domain, which will value them.

Considering this, it is essential for companies to understand the extent to which consumers feel knowledgeable in the focal domain at hand. To assess consumers' subjective knowledge managers can rely on measures similar to the ones we utilized since companies frequently track their customers' behavior (e.g., frequency of purchasing). Alternatively, or in addition, companies could consider adopting strategies to shift consumers' subjective knowledge. In fact, many companies, such as Yelp or Qualtrics, already engage in strategies that potentially impact consumers' subjective knowledge, such as providing performance feedback or badges (e.g., rookie, pro) related to their behavior on the platform. The results of our studies 3a and 3b denote that it is possible to shift consumers' subjective knowledge by means of simple manipulations and that these shifts have direct consequences for their valuation of services regardless of their objective knowledge. Indeed, existing work on consumer knowledge indicates that subjective knowledge can be influenced through marketing practices (Hadar and Sood 2014), even when holding objective knowledge constant (Hadar et al. 2013; Heath and Tversky 1991).

Subjective Knowledge versus Related Constructs

We posit that it is consumers' subjective knowledge in a focal domain that interacts with recommender type. We purposefully utilized various measures and manipulations to provide solid evidence for this proposition and to exclude the possibility that related constructs are driving the effect. Nevertheless, one may argue that the interaction effect that we documented here is due to differences in *objective* (rather than subjective) knowledge. While subjective and objective knowledge are correlated (e.g., Brucks 1985; Duhan et al. 1997), we offer a few pieces of evidence suggesting that differences in subjective (rather than objective) knowledge are underlying the pattern of results that we document. Specifically, in studies 3a and 3b, we made our participants feel knowledgeable in the focal domain and show differences in the valuation of algorithmic recommendations simply because of this manipulation. Moreover, the design of study 3a, in which we asked participants to list as many coffee-flavored drinks that they know, provided us with insights on participants' objective knowledge (i.e., the actual number of coffee-flavored drinks they mentioned). Essentially, there was no difference in consumers' objective knowledge across conditions ($F < 1$, $p = .91$) and the interaction effect remained significant when controlling for participants' objective knowledge ($F(1, 173) = 24.41$, $p < .001$, $\eta_p^2 = .12$)[8]. Thus, we feel confident to conclude that the differences in valuation of algorithmic advice that we presented here are due to differences in subjective knowledge.

Second, one may speculate that consumers with high subjective knowledge in a domain are more involved and/or possess greater general interest in a focal domain; this makes sense because knowledge and involvement/interest can be correlated (Alba and Hutchinson 1987). Building on this, these differences in *involvement* (rather than in subjective knowledge) may have explained the pattern of our interaction effect. We have two pieces of evidence that refute this alternative account. First, in study 1b, we measured participants' general interest in the focal domain (i.e., "I would very much like to do a road trip through Canada"; 1 = strongly disagree to 7 = strongly agree). The results do not show any significant differences in interest across conditions ($F(1, 298) = 2.79$, $p = .10$)

[8] Note that there were two fewer participants in this analysis due to missing values on the covariate.

and our focal interaction effect remained significant when controlling for general interest/involvement (β = -.15, t(295) = -2.68, p = .008; see Appendix 2B for additional details). Moreover, in study 3a, in which we made participants feel knowledgeable (vs. unknowledgeable about coffee flavors), we measured their general interest in coffee (i.e., “How much do you like coffee-based drinks?”; 1 = not at all to 11 = very much). The results did not show any significant differences in interest across conditions ($F < 2.9$, $p = .14$) and our focal interaction effect remained significant when controlling for this measure ($F(1, 175) = 20.65$, $p < .001$; $\eta_p^2 = .11$).

Limitations and Suggestions for Future Research

Our work acknowledges the importance of taking consumer characteristics into account when examining the effect of recommender type on consumers’ valuation of recommendations (said to be) generated by algorithms versus human experts. Here, we focus on subjective knowledge and consistently demonstrate that high subjective knowledge increases the valuation of recommendations said to be generated by an algorithm. At first sight, this result may seem at odds with recent findings by Logg et al. (2019). Specifically, in study 4, the authors compared actual experts in geopolitical forecasting to lay people in their valuation of advice (measured in terms of weight of advice; WOA) generated by an algorithm or by humans and show that experts heavily discounted all advice sources. This seems contradictory to our finding that consumers with high subjective knowledge value algorithmic advice. Note though that our work differs from Logg et al. (2019) in several important aspects which make it difficult to directly compare the findings. First, instead of looking at actual differences in knowledge, we explore the role of subjective knowledge, which may be correlated with actual knowledge, but is a divergent construct (Hadar et al. 2013). Second, we focus on subjective domains in which there are no right or wrong recommendations but only recommendations that match or mismatch one's personal taste, whereas the context of forecasting can rather be understood as an objective domain with correct and incorrect judgments. Third, Logg et al. (2019) compare recommendations from algorithms to those from other people who are not necessarily experts (e.g., other lab participants), whereas our work explicitly parallels algorithms to human experts that specialized in a focal domain. Finally, whereas Logg et al. (2019) incorporate the trade-off between relying on one's own judgment and following the advice (WOA), our research measures the overall valuation of the recommendation without explicitly asking participants to consider their own input. We thus, call for future research to explore whether these differences (and if yes, which one(s) in particular) might function as (a) moderator(s).

Relatedly, Logg et al. (2019) document that lay people placed more weight on algorithmic (vs. human) advice. In our work, however, we found no evidence for greater valuation of algorithmic advice for consumers with low subjective knowledge. Again, one of the many differences between Logg et al. (2019) and our work may account for the variation in these findings. Yet, interestingly, across our studies, we sometimes found that consumers with low subjective knowledge value recommendations from both recommender types equally, whereas they sometimes value recommendations said to be generated by human experts more. At this point, we can only speculate about the factors that may have led to these differences. One of the most salient factors, may be the context of the study. For instance, in study 3a, using coffee-based drinks as the focal domain, we found that consumers with low subjective knowledge value a recommendation by a human expert (vs. an algorithm) more whereas study 3b, using workout activities as the focal domain, showed no difference in the valuation between both recommender types. Moreover, simply looking at our results over time, suggested that studies conducted pre-COVID-19 were more likely to document greater valuation of a recommendation generated by a human expert (vs. algorithm) for consumers with low subjective knowledge. However, studies during COVID-19 were more likely to result in equal valuations. Future research could focus on consumers with low subjective knowledge in a domain and further explore when they value advice from human expert more than advice from algorithms. Relatedly, it may be interesting for future research to explicitly compare consumers with high and low subjective knowledge in their motivations to follow advice from different recommender types. In our work, we document that consumers with high subjective knowledge possess the need to be involved in the process and collaborate even when they ask for recommendations. Consumers with low subjective knowledge might not share this motivation. Thus, their decision of receiving and following a recommendation may be more driven by whether they expect a good outcome (i.e., high quality). We deem it interesting to explore this avenue in future research.

In our work, we exclusively focused on how consumers' subjective knowledge impacts their own valuation of recommendations from different recommender types. An interesting extension of our work could be to investigate how individuals make inferences about a third person's valuation of different recommenders knowing that this person perceives him/herself as knowledgeable (vs. not) in a domain. This could be relevant because companies and/or employers frequently decide on the extent to which they incorporate algorithms (vs. human experts), for instance, in application processes, decision aids, performance interviews, and recommender systems that involve third persons. We conducted two brief studies (please see Appendix 2I), in which we presented participants with a fictitious character, called Sam. Depending on condition, he was described as perceiving him/herself as knowledgeable (versus not knowledgeable). Our results document that simply varying Sam's subjective knowledge impacted participants' decision on whether Sam would be more/less likely to choose an algorithm recommender such that the likelihood increased when Sam was described as knowledgeable. We leave it to future research to further explore how consumers make inferences about others when they are described as possessing high (vs. low) subjective knowledge.

Notably, while subjective knowledge is an important characteristic that has been well-studied in the advice taking literature, many other characteristics of the decision-maker remain unexplored. Future research might consider focusing on other characteristics of consumers (e.g., need for social interaction, tendency to engage in social comparison, and/or self-impression management tendencies) and investigate whether and how they impact consumers' reaction to different recommender types.

Finally, in our studies we focus exclusively on domains that are matters of taste (e.g., scenic routes). An interesting extension of our work could be to look at the effect of recommender type and consumers' subjective knowledge in domains that are not taste-related but rather objective in nature (e.g., shortest travel route). For instance, consider consumers that are looking for the shortest travel route (rather than the most scenic travel route; the context of our studies). Would consumers with different levels of subjective knowledge interact with different recommenders in the same way as we depict here? We leave it to future research to explore the role of consumers' subjective knowledge in particular for tasks that are more objective in nature.

As a concluding remark, even though Stitch Fix (a fashion retailer) uses a combination of algorithms and human experts to provide consumers with styling recommendations, they often highlight the human origin of their recommendation when communicating it to consumers. Our research suggests that one strategy does not fit all; consumers who perceive themselves as knowledgeable with respect to styling, might actually value a service more if they highlighted the algorithmic origin of their recommendation.

CHAPTER 4

Perceptions of Justice by Algorithms

Since the 1960s, scholars have been discussing the use of computers for analyzing and predicting judicial decisions (Elardo 1968; Lawlor 1963). They proposed that computer programs can not only find and analyze the law but also can predict decisions (Lawlor 1963). Even though computers have not yet reached widespread adoption in courts in the way these scholars envisioned, advancements in technology have recently started to enable the automated processing of large quantities of data as well as the handling of complex tasks (Parmar et al. 2014).

Artificial intelligence (AI) technology is rapidly spreading in our society (Granulo et al. 2019; Ostrom et al. 2015; Rust and Huang 2014). AI can provide personalized advice (Logg et al. 2019; Yeomans et al. 2019), interact with customers (Van Doorn et al. 2017), and drive vehicles autonomously (Lafrance 2015). In addition to their adoption in everyday life and businesses, AI has been increasingly used in government services (Feldstein 2019; Liu et al. 2019; Sun and Medaglia 2019; Mehr 2017). Today, computational and predictive technologies are already being used in medicine (Longoni et al. 2019), education (Tuomi et al. 2018), military (Cummings 2017), and justice systems (Fry 2018).

With the increasing use of algorithms and AI by law firms, courts have become more familiar with this technology. Law firms use algorithms and AI to read documents, prepare case files, and predict the win rate of court cases (Donahue 2018; Faggella 2020). It is safe to expect that the current state is just the beginning stage of AI application in courts. Recent reports indicate that AI can already forecast court decisions with great accuracy (Aletras et al. 2016; Katz et al. 2017; Sulea et al. 2017). In particular, algorithms have been shown to handle simple and standard cases (Mandri 2019), which consists of the vast majority of legal case load (Commission for the Evaluation of the Efficiency of Justice 2019; Reiling 2010; Silvestri 2014; Uzelac 2014). Unsurprisingly, new initiatives (e.g., CREA Project) are being developed that aim directly at resolving conflicts by AI. Limiting ourselves to the North Atlantics, an increasing number of governments (e.g., Estonia, England, the Netherlands) and international organizations (e.g., the Council of Europe) have been discussing and formulating policies related to the application of algorithmic decision-makers in courts (Castelluccia and Le Métayer 2019; Mandri 2019).

When the algorithmic judges are applied, many important legal questions will be raised. How will adoption of algorithms and AI influence the role of human judges? How will the adoption of algorithmic judges impact citizens' trust in the court system? How will adoption of algorithms that resolve disputes influence individuals' willingness to submit their legal cases to a court? What are the possible advantages and disadvantages of such algorithmic judges in the public's eye? We argue that any potential future decision on the adoption or the development of such algorithmic judges should take the perceptions and intentions of potential court users into account. To the best of our knowledge, however, there is no scientific research available on court users' perception of technological applications taking a decisive share in the adjudication.

In current work, we study individuals' perceptions towards algorithms deployed in judicial decision-making. As the public's trust in the justice administration is an important benchmark for a good government (Karpen 2010) and is often used as a reference point for the quality of the protection of the rule of law, we therefore investigate how interacting with algorithmic (vs. human) judges affects the extent that individuals trust them. We also test whether there are downstream consequences of changes in trust, such as individuals' intentions to submit their legal cases to the local court. Additionally, we test whether perceptions of trust are affected by the complexity of a legal case. Finally, we investigate individuals' awareness of potential advantages of algorithmic judges (i.e., speed, cost) over human judges.

Theoretical Background

Trust in Judges

Existing work reveals the public's trust in courts as an essential component of good governance (Jackson et al. 2011; Karpen 2010; Savela 2006), and citizens' trust in government organizations impacts their intentions (e.g., willingness to report a crime; Bennett and Wiegand 1994; Silver and Miller 2004). Given such importance of perceived trust (Canal et al. 2020), many governments and international institutions monitor and try to improve public trust (The Danish Court Administration 2015). Trust in institutions becomes even more important at a time when reports show that public trust has been declining due to economic distress, agitation and propaganda spread through social media, and demagogy politics (Hutchens 2018).

Previous work documents a strong connection between court users' evaluation of how they are treated and their trust in judges (Grootelaar and Van den Bos 2018; Lind 2018; Lind et al. 1993; Tyler et al. 2019; Van den Bos et al. 2014). In line with the previous literature, we propose that perceived trust towards (algorithmic or human) judges is an important factor that policymakers and governments should consider. Next, we identify essential factors of perceptions of trust in the existing research.

To earn and maintain public trust, courts should foremost fulfil their functions (Genn 2009; Mnookin and Kornhauser 1979; Resnik 2013). Two of the most important factors that affects citizens' trust in courts and the legal system is the extent that judicial officers are fair and unbiased (Rottman and Tyler 2014; Warren 2000). Judges are expected to perform all their duties in an unbiased and fair way, and to treat everyone equally (Martyn et al. 2017). Previous research also states that fairness and unbiasedness are strongly correlated and greatly impact perceptions of justice (Helberger et al. 2020; Lind at al. 1990). It is no surprise then that recent reports listed perceived fairness and impartiality to be influential in affecting the choice of court (BlackBox Research Pte 2016; IPSOS 2019; Lein at al. 2015).

In addition to these two factors, legal stability and predictability are also essential to what people mean by "the rule of law" (Genn 2009; Mnookin and Kornhauser 1979; Resnik 2013; Schwarzschild 2007). Predictability, for instance, has a moral valence as it ensures that cases will be treated equally based on an existing law (Lindquist and Cross 2012). When judges act unpredictably, it does not only damage individuals' trust in the legal system, but also creates a less stable legal environment for the development of economic and other human relations (Lindquist and Cross 2012).

Reviewing the literature on trust and procedural justice, we consider perceived trust as a combination of court user's perception of predictability, fairness, trustworthiness, and unbiasedness of a judicial decision-maker. Supporting the relevance of these dimensions, a recent survey found that fairness and predictability of the outcome, impartiality are found to be among the factors that influences the decision of going to a court the most (Themeli 2018).

Algorithmic versus Human Judges

Existing work has documented several systematic differences in individuals' perceptions of algorithmic versus human decision-making (Helberger et al. 2020; Yeomans et al. 2019). Looking at this stream of research, there are both upsides and downsides of algorithmic decision-makers. For instance, algorithms might be perceived as more consistent and objective than humans (Helberger et al. 2020; Lee 2018); however, individuals also think that algorithms (vs. humans) tend to ignore their unique characteristics (Longoni et al. 2019) and are less authentic (Jago 2019).

Considering individuals' trust towards algorithmic and human decision-makers, general finding in this line of research is that even though algorithms objectively outperform humans (Camerer 1981; Meehl 1954; Grove et al. 2000; Kaufmann and Wittmann 2016), individuals are often reluctant to rely on algorithms (Dawes et al. 1989; Dietvorst et al. 2015; Dzindolet et al. 2003;

Yeomans et al. 2019). For instance, individuals trust a human advisor (e.g., doctor) more than an algorithmic advisor (Longoni et al. 2019; Promberger and Baron 2006). In the field of online dispute resolution (ODR), recent work by Sela (2018) documents individuals' negative reactions towards online software mediators or arbitrators (Sela 2018). Regarding possible reasons of such aversion, previous work suggests that algorithm aversion could stem a variety of reasons including individuals' desire for control over outcomes (Dietvorst et al. 2018), or the perception that humans are easier to understand (Yeomans et al. 2019). Conversely, Helberger et al. (2020) find that people may consider automated decision-makers more fair than human decision-makers. This study suggests that emotions, the risk of manipulation, the need for a human touch, and the need to consider the context were important elements that influence how fair humans or automated decision-makers were considered. However, Helberger et al. (2020) indicate that other variables may play a role when comparing a human and automated decision-makers, which indicates the complexity of human algorithm interaction. In line with these findings, we hypothesize that individuals will trust algorithmic judges less compared to human judges. Additionally, we expect this lack of trust to have downstream consequences and lead to lower intentions to submit cases to a court.

Despite these predictions, there might still be perceived benefits in using algorithms as judges. We expect individuals to acknowledge some of the advantages of algorithmic judges. For instance, algorithms can be expected to complete the same task faster than humans due to their optimized procedures and high processing capabilities (Schneider et al. 2018; Soltanian-Zadeh et al. 2019). Moreover, adoption of technologies often leads to drastic reduction of operation cost as algorithms and machines do not require compensation (e.g., salary, pension fund, insurance; Meuter et al. 2000). Accordingly, we expect individuals to acknowledge these advantages and perceive algorithmic judges to be cheaper and faster than human judges.

Case Complexity

The concept of case complexity has taken on increased theoretical importance over the years (Campbell 1984; Campbell and Gingrich 1986). According to the existing work in this literature, complexity can come from many different sources (Campbell 1988; Earley 1985; Huber 1985): for instance, complexity can originate from psychological factors (e.g., identity relevance) or technical factors (e.g., number of rules to follow).

Going back to the literature on algorithmic decision-making, previous research suggests that the type of task at hand impacts individuals' attitudes towards the decision-maker (algorithms versus humans; Castelo et al. 2019). One classification that is often used is whether a task is emotional or cognitive in nature (Castelo et al. 2019; Waytz and Norton 2014). This stream of research indicates that non-human entities (e.g., organizations, robots) are perceived to be capable of thinking, but not feeling (Gray and Wegner 2012; Rai and Diermeier 2015). Accordingly, individuals are shown to express more favorable attitudes towards algorithms when a task is framed as requiring cognition compared to emotion (Lee 2018; Waytz and Norton 2014). Building on this work, we test whether individuals trust algorithmic and human judges differently depending on the nature of a legal case. Specifically, we propose that court users may perceive algorithmic judges especially more negatively (i.e., low perceived trust) when the legal case contains complexities that arise from psychological and emotional factors, compared to cases low in complexity or cases where complexity arises from technical issues.

Overview of Studies

Across two studies (N = 1,822), we examine how algorithmic (vs. human) judges affect trust. In our studies, participants read the description of a situation and are asked to complete a survey about their reactions. The materials were designed for a general audience and were written in non-technical language. We also used a fictional legal situation that is common in courts: a divorce case. We provided participants with the background of a legal case and randomly assigned them to either a human or an algorithmic judge. We also manipulated the type of case complexity (low vs. high emotional vs. high technical complexity): Participants in the low complexity condition were given a straightforward and simple case description, whereas we added details to complicate the case in the remaining conditions. Specifically, we either added technical (e.g., unequal shares of property) or emotional (e.g., psychological problems) details.

In each study, we measured participants' trust towards their assigned judge by aggregating four items (i.e., perceived trustworthiness, unbiasedness, fairness, and predictability). We also measured participants' willingness to submit the case to a local court. Finally, we measured perceived cost and speed of the judge. For the full list of measures and the scenario that were used in our experiments, see Appendix 3. All the data and study materials are available at https://tinyurl.com/24hr5bee. For the summary of study results and key statistics, please refer to Appendix 3D.

All participants were recruited using Mechanical Turk (Mturk), an online labor market operated by Amazon, the largest digital retailer. In the past few years, Mturk has become a leading source of human respondents for the behavioral sciences. Mturk has been shown to be a source of good data and has the advantage of enabling larger and more representative samples than many of the commonly used alternatives (e.g., student pools; Paolacci and Chandler 2014). To make sure that participants were paying attention to the experimental stimuli and to ensure quality data, we included an attention check in the experiment. Only participants who answered the attention check correctly were directed to the study.

Study 1

The main objective of study 1 is to test our main hypotheses that individuals trust algorithmic judges less than human judges and have lower intentions to submit their cases to the court. Additionally, this empirical study aims to test whether this perceived trust depends on the type of complexity (low complexity vs. high technical complexity vs. high emotional complexity) of the legal case.

Design and Participants

We recruited 608 American Mturkers ($M_{age} = 38.17$, 309 females). Study 1 employed a 2 (judge type: algorithm vs. human) x 3 (case complexity type: low complexity vs. high technical complexity vs. high emotional complexity) between-participants design. Participants were randomly assigned to one of the six experimental conditions.

Materials and Procedure

Participants were asked to imagine that they have been married for some years. As the love in their marriage has cooled down to almost zero, they and their partner agreed to separate and file for divorce. First, we manipulated the complexity of the divorce case. In the low complexity condition, participants were given an uncomplicated description of the divorce case (e.g., equal share of cost and property). In the high technical complexity condition, they were given a more complicated description in which the complexity arose from technical details (e.g., unequal shares of property, mortgage, inheritance). Finally, in the high emotional complexity condition, the complexity was due to emotional details (e.g., mental health problems of their partner). They were then given information about the judge that would take their divorce case. In the human judge condition, they were informed that cases like theirs are resolved by an experienced judge from the local court, whereas participants in the algorithmic judge condition were told of a new system, in place for some time, where cases like theirs are resolved by fully automated artificial intelligence and algorithms, that use the legislation and the relevant case law of their jurisdiction to resolve disputes.

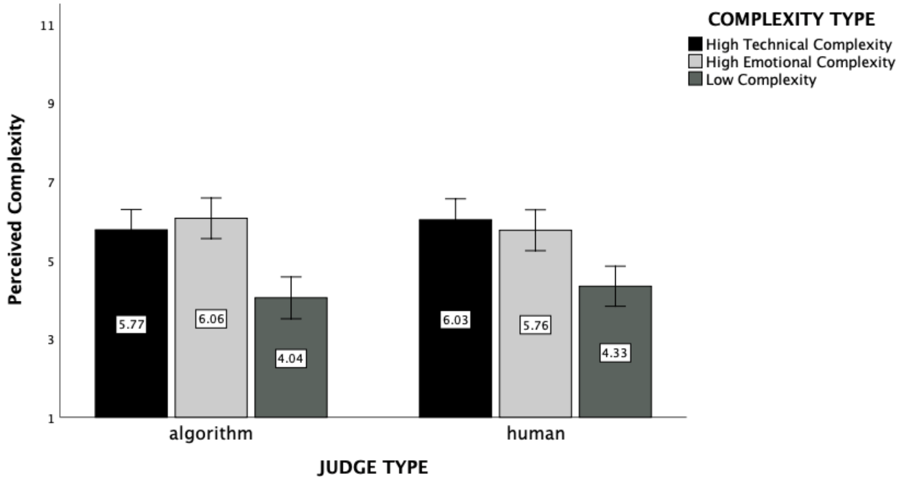
After reading the scenario, participants indicated their general trust towards the judge. As reviewed in the literature, we compiled a scale of four items to capture perceived trust (1 = *unfair / biased / not trustworthy / unpredictable* to 9 = *fair / unbiased / trustworthy / predictable*; α = .84). We also measured how likely individuals were to submit their case to the local court (i.e., "How likely would you be to submit your case that will be resolved by the artificial intelligence (vs. judge) to the local court?"; 1 = *not at all likely* to 11 = *very likely*). Participants then filled out our manipulation check on perceived complexity of the legal case on a 11-point scale (i.e., "When you think about the case that you read, how complicated do you think this divorce case is?", "How complicated do you think this divorce case is for artificial intelligence (vs. judge) to resolve?"; α = .76; 1 = *not at all complicated* to 11 = *very complicated*). Additionally, considering that speed and cost of a judge are factors that can influence attractiveness of a court (IPSOS 2019; Themeli 2018), we also measured perceived speed and cost of the judge (i.e., "Thinking about this divorce case and your future court experience, to what extent do you think that the artificial intelligence (vs. judge) will be ____; 1 = *slow/expensive* to 9 = *fast/cheap*). For ease of interpretation, in the analyses and graphs for all experiments below we reverse-coded the perceived cost item (1 = *cheap* to 9 = *expensive*), such that higher scores indicate higher perceived cost.

Results

Based on the measures discussed above, we computed indices by averaging the items used to measure each construct. These indices were then submitted to a General Linear Model where the two experimental factors and their interaction were entered as predictors.

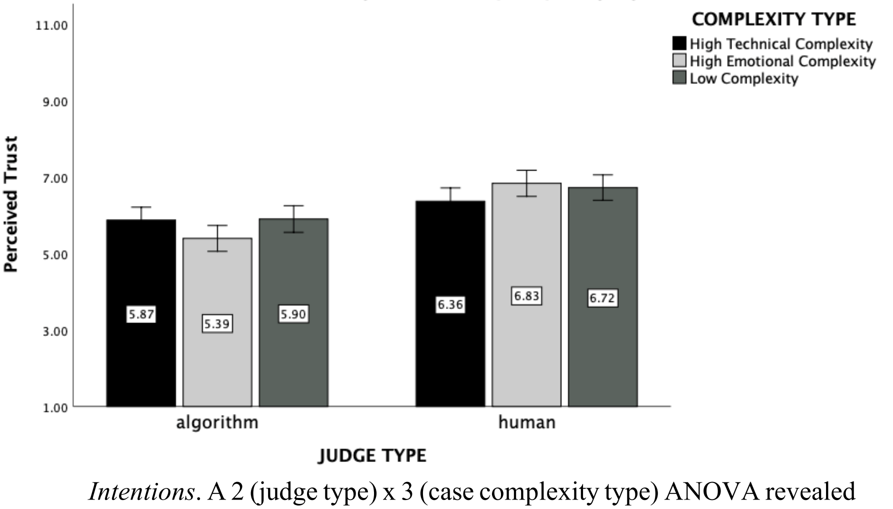
Manipulation Check. The main effect of case complexity was found to be statistically significant ($F(2, 602) = 28.92$, $p < .001$, $\eta_p^2 = .09$), and the contrast between high emotional complexity and high technical complexity cases were non-significant ($F < 1$, $p = .96$), meaning that the perceived complexity of the complex cases was the same, regardless of its cause (i.e., technicality, psychological factors). Importantly, this contrast analysis also revealed that both high complexity conditions were perceived to be more complex than the low complexity condition (mean differences < -1.73, $p < .001$), as expected. Moreover, we found neither a significant main effect of the judge type (i.e., artificial intelligence, human; $F < 1$, $p = .70$) nor an interaction effect between the judge and case complexity type ($F < 1$, $p = .44$).

Figure 1. Perceived Complexity as a Function of Judge and Case Complexity Type (study 1)



Perceived Trust. We found a significant main effect of the type of judge ($F(1, 602) = 42.00$, $p < .001$, $\eta_p^2 = .07$). Participants perceived the human judge to be more trustworthy ($M = 6.64$, $SD = 1.49$) than the algorithmic judge ($M = 5.71$, $SD = 1.98$). The main effect of case complexity was found non-significant ($F < 1$, $p = .43$). Importantly, the interaction effect between case complexity and judge type was significant ($F(2, 602) = 3.83$, $p = .02$, $\eta_p^2 = .01$, see Figure 2). Even though participants generally trusted the algorithmic judge less than the human judge, individuals' level of trust depended on the type of case complexity. Participants were found to trust the algorithm even less when the case included emotional complexities compared to the simple case (mean difference = .51, $p = .04$). This contrast, however, was non-significant for the technically complex case ($F < 1$, $p = .91$).

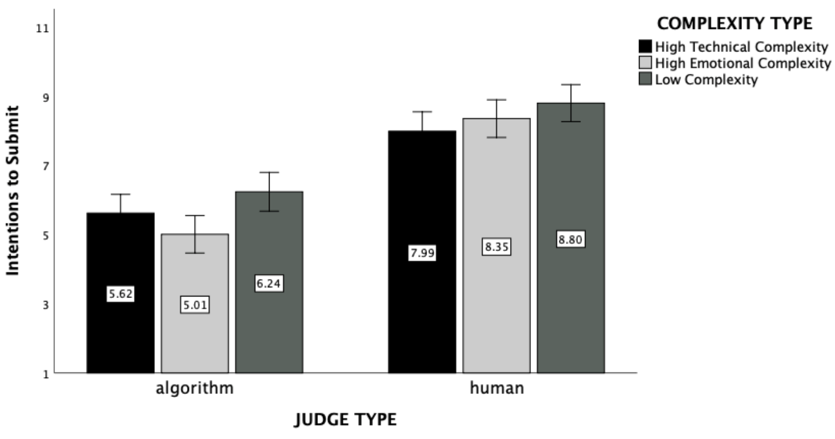
Figure 2. Perceived Trust as a Function of Judge and Case Complexity Type (study 1)



Intentions. A 2 (judge type) x 3 (case complexity type) ANOVA revealed a large main effect of judge type ($F(1, 602) = 152.30$, $p < .001$, $\eta_p^2 = .20$, see

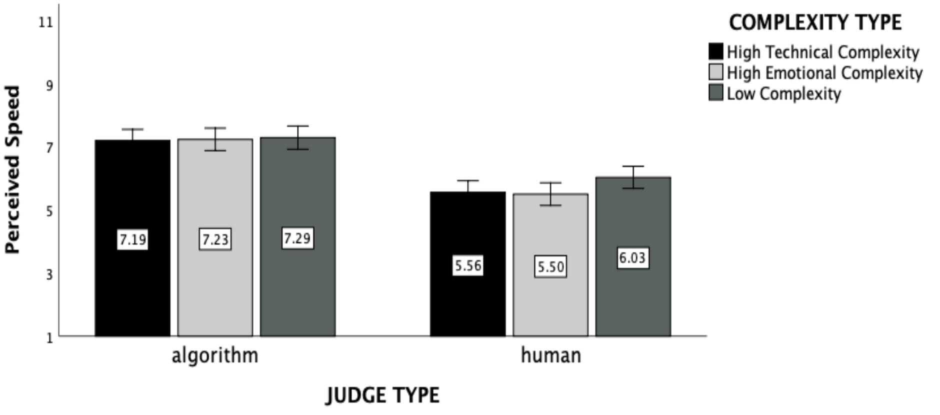
Figure 3). Participants were more willing to submit their cases to the local court when the judge was human (M = 8.39, SD = 2.11) than when it was an algorithm (M = 5.61, SD = 3.32). The main effect of complexity type was also found to be significant ($F(2, 602) = 5.47$, $p = .004$, $\eta_p^2 = .02$): Participants were more willing to submit their cases when the case they read about was low in complexity (M = 7.58, SD = 3.01) than high in emotional complexity (M = 6.67, SD = 3.32; mean difference = .84*,* $p = .002$) or high in technical complexity (M = 6.77, SD = 2.90; mean difference = .71, $p = .01$). Although directionally similar to the results for perceived trust, the interaction effect between judge and case complexity type was non-significant ($F(2, 602) = 1.78$, $p = .17$).

Figure 3. Intention to Submit the Case as a Function of Judge and Case Complexity Type (study 1)



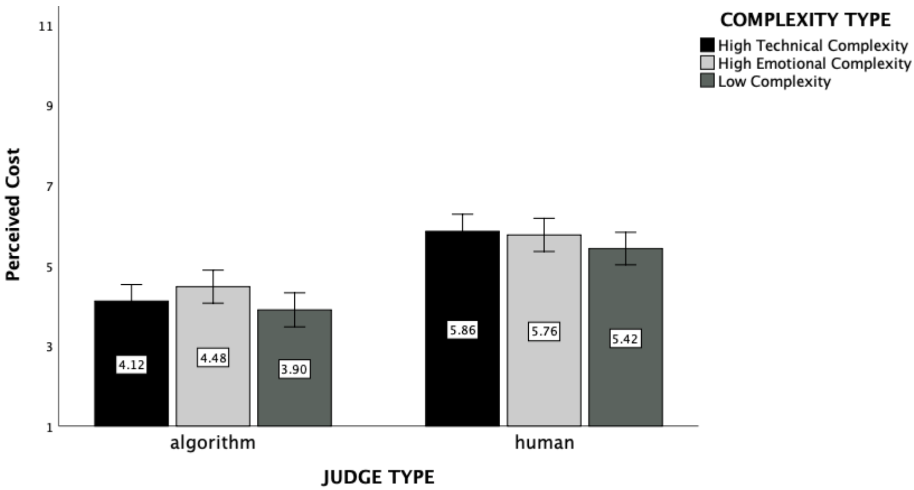
Perceived Speed. The analysis revealed a significant main effect of judge type ($F(1, 602) = 110.29$, $p < .001$, $\eta_p^2 = .16$, see Figure 4): Participants perceived the human judge to be slower (M = 5.70, SD = 1.82) than the algorithmic judge (M = 7.24, SD = 1.80). Additionally, neither the main effect of the case complexity (F(2, 602) = 1.70, p = .18) nor the interaction effect was found to be statistically significant (F(2, 602) = .97, p = .38).

Figure 4. Perceived Speed as a Function of Judge and Case Complexity Type (study 1)



Perceived Cost. The main effect of judge type was significant (F(1, 602) = 80.17, $p < .001$, $\eta_p^2 = .12$, see Figure 5). Participants perceived the algorithmic judge to be cheaper (M = 4.17, SD = 2.32) than the human judge (M = 5.68, SD = 1.84). Furthermore, the main effect of case complexity type was marginally significant (F(2, 602) = 2.60, p = .08, $\eta_p^2 = .01$): Cases with low complexities were perceived to be cheaper (M = 4.69, SD = 2.33) than the emotionally complex ones (M = 5.12, SD = 2.21, mean difference = -.46, p = .03). Finally, the interaction effect between judge and case complexity type was revealed to be non-significant (F < 1, p = .56).

Figure 5. Perceived Cost as a Function of Judge and Case Complexity Type (study 1)



Discussion

Results of study 1 provide support for the notion that individuals care about the specific judge (human vs. algorithm) that will adjudicate their case. In the context of a divorce procedure, we find that individuals have lower intentions to go to their local courts when they are informed that an algorithm will adjudicate. This is a large effect (d = 1.0). With regard to trust, we find a similar pattern: human judges are trusted more than algorithms. Note that our comparisons are made relatively (algorithm versus human), and not in absolute terms.

Furthermore, the analysis on perceived trust indicates that also that the type of case complexity matters as well. In particular, our results show that algorithmic judges are trusted even less when the complexity of the case derives from psychological factors (vs. low complexity vs. high technical complexity). Therefore, citizens might be relatively more open to algorithmic judges when they perceive high levels of technical complexity. Considering the perceived speed and cost, our findings validate the idea that individuals expect artificial intelligence to be faster and cheaper than humans. We find that this reluctance to go to court when the judge is not a human was not dependent on the type of case complexity (low vs. high emotional vs. high technical complexity). Apparently, the judge cue had such a strong impact on intentions that the information about the complexity of the case had no residual effect.

Overall, study 1 paints a rich picture of how court users think about the role of technology in the legal process and are likely to respond to the introduction of algorithms in the courtroom.

Study 2

Design and Participants

We recruited 1,214 American Mturkers (M_{age}= 38.1, 642 females) in study 2. We used study 1's design and randomly assigned participants to one of the six experimental conditions (judge type x case complexity type). Please see Appendix 3B for more details on the experimental stimuli, measures, and for details about randomization. study 2 was pre-registered (please refer to aspredicted.org/blind.php?x=ap82nz for the preregistration plan).

Materials and Procedure

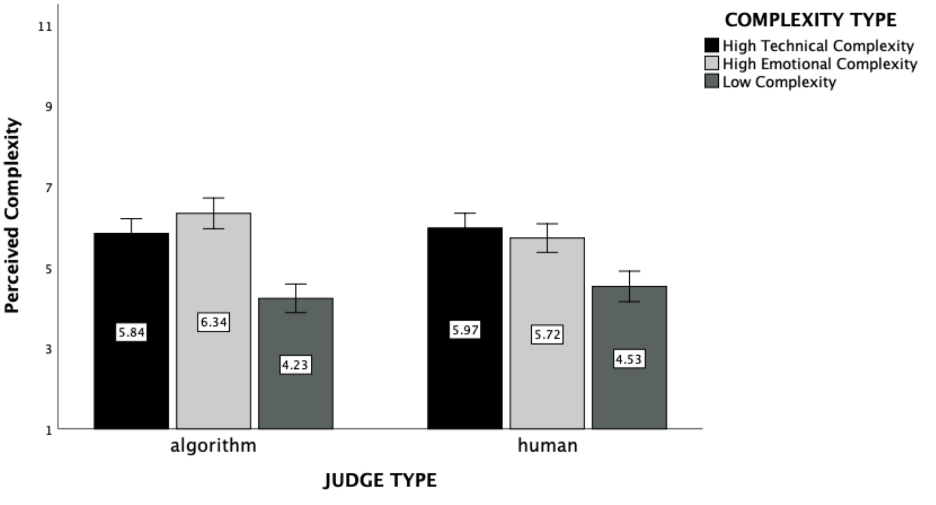
Study 2 used study 1's scenario: we again told participants to imagine that they and their partner agreed to separate. We then manipulated the complexity of the divorce case (low complexity vs. emotional vs. technical complexity) well as the type of judge that would take their case (algorithmic versus human judge).

We also utilized the same measures used in study 1. The only exception was that we used two items to measure intentions in study 2 (i.e., "How likely would you be to submit your case that will be resolved by the artificial intelligence (vs. judge) to the local court?", "In this situation, would you plan to submit your case that will be resolved by the artificial intelligence (vs. judge) to the local court?"; 1 = *not at all likely / no intention to submit* to 11 = *very likely / very strong intention to submit*; $\alpha = .91$).

Results

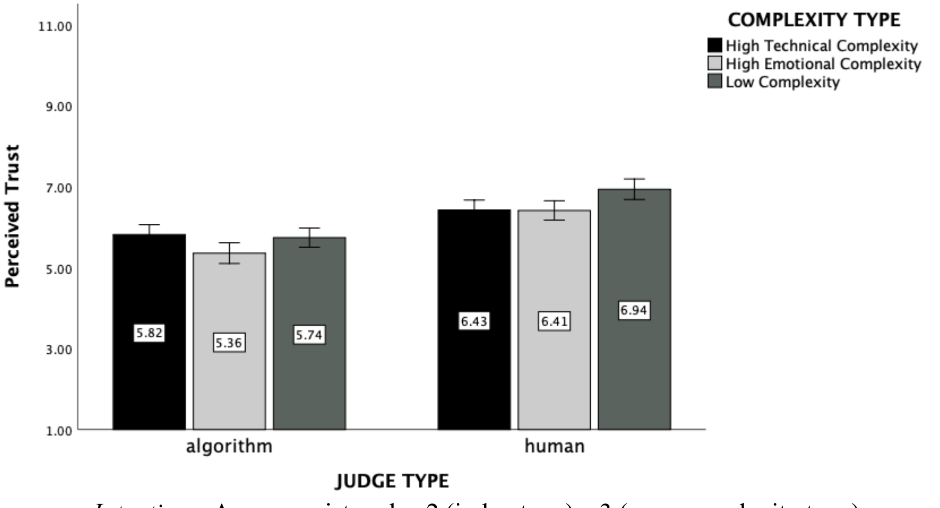
Manipulation Check. As expected, the main effect of case complexity was again statistically significant ($F(2, 1208) = 50.39$, $p < .001$, $\eta_p^2 = .08$), and the contrast between high emotional and high technical complexity case conditions was non-significant (mean difference = .12, $p = .50$), indicating that participants perceived the complexity of these cases the same regardless of its cause. Replicating study 1, the contrast analysis also revealed that both types of high complexity cases were perceived to be more complex than the low complexity one (mean difference > -1.65, $p < .001$). The main effect of type of the judge was found to be non-significant ($F(1, 1208) = .16$, $p = .69$). The interaction effect between the complexity and judge type, however, was significant this time ($F(2, 1208) = 3.48$, $p = .03$, $\eta_p^2 = .006$). This interaction effect indicates that perceived complexity of an emotionally complex divorce case was greater for a human judge compared to an algorithmic judge (mean difference = -.61, $p = .02$, see Figure 6), whereas the contrast between the two types of cases was statistically non-significant ($F < 1.3$, $p > .25$). Given that the materials were identical in the two studies and that the pattern of results in study 2 closely mimics those of study 1 (where we did not observe such an effect), this interaction on the manipulation check items is unlikely to explain the findings for the main dependent variables.

Figure 2. Perceived Complexity as a Function of Judge and Case Complexity Type (study 2).



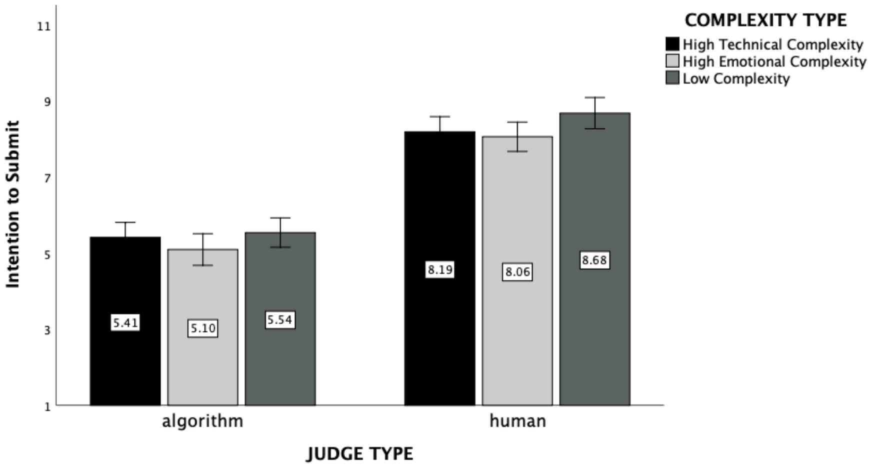
Perceived Trust. As pre-registered, we found a main effect of the judge type ($F(1, 1208) = 89.51$, $p < .001$, $\eta_p^2 = .07$): Participants perceived the human judge to be more trustworthy (M = 6.58, SD = 1.60) than the algorithmic judge (M = 5.65, SD = 1.91). Furthermore, the main effect of case complexity was also significant in this study ($F(2, 1208) = 6.72$; $p = .001$, $\eta_p^2 = .01$): Participants who read about the low complexity case perceived the judge as more trustworthy (M = 6.3, SD = 1.86) than participants who read about the emotionally (M = 5.93, SD = 1.85; mean difference = .45, $p < .001$) or technically complex cases (M = 6.12, SD = 1.74; mean difference = .21, $p = .08$). Importantly, the interaction effect between complexity and judge type was again significant ($F(2, 1208) = 3.12$, $p = .04$, $\eta_p^2 = .005$, see Figure 7). Similar to the results of study 1, participants trusted the algorithm even less when the case included emotional complexities compared to cases that were low in complexity (mean difference = -.38, $p = .03$) or technically complex (mean difference = -.46, $p = .01$). Interestingly, participants trusted the human judge more when the case was uncomplicated compared to cases that were high in emotional (mean difference = .52, $p = .003$) or technical complexity (mean difference = .51, $p = .004$).

Figure 7. Perceived Trust as a Function of Judge and Case Complexity Type (study 2)



Intentions. As pre-registered, a 2 (judge type) x 3 (case complexity type) ANOVA revealed an even stronger main effect of judge type ($F(1, 1208) = 331.40$, $p < .001$, $\eta_p^2 = .22$, see Figure 8). Replicating study 1's pattern, participants were more willing to submit their cases when the judge was human ($M = 8.3$, $SD = 2.34$) than an algorithm ($M = 5.36$, $SD = 3.25$). The main effect of case complexity was again statistically significant (F(2, 1208) = 3.61, p = .03, η_p^2 = .006): Participants were more willing to submit their cases when the case they read about was low in complexity (M = 7.01, SD = 3.2) than high in emotional complexity (M = 6.69, SD = 3.32; mean difference = .53, p = .008). This contrast was only directional when comparing the cases with low and high technical complexity (M = 6.8, SD = 3.04; mean difference = .31, p = .12). Finally, the interaction between judge type and case complexity was non-significant (F < 1, p = .66), indicating that interaction observed for trust did not spill over to intentions.

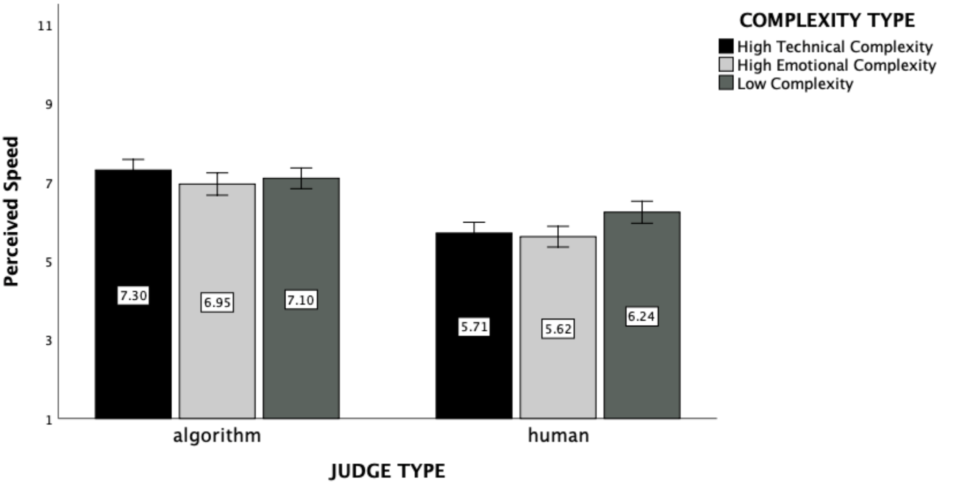
Figure 3. Intention to Submit the Case as a Function of Judge and Case Complexity Type (study 2)



Perceived Speed. Replicating study 1's results, a 2 (judge type) x 3 (case complexity type) ANOVA revealed a significant main effect of judge type (F(1, 1208) = 129.48, p < .001, η_p^2 = .10, see Figure 9). Participants again perceived the human judge to be slower (M = 5.84, SD = 1.93) than the algorithmic judge (M = 7.12, SD = 1.95). The main effect of case complexity was also significant

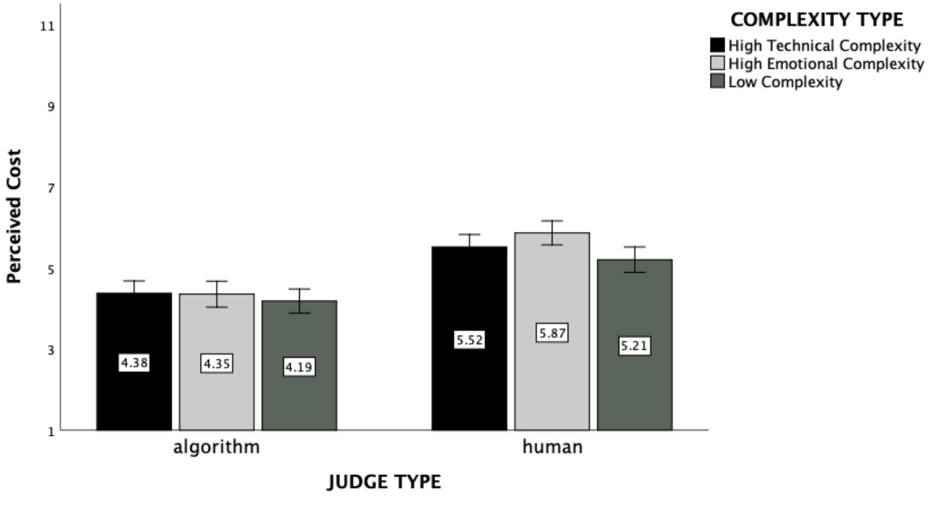
($F(2, 1208) = 3.99$, $p = .02$, $\eta_p^2 = .007$). In particular, cases that were low in complexity were considered to be processed faster (M = 6.69, SD = 1.95) than the ones that were emotionally complex (M = 6.23, SD = 2.05; $p = .005$). Finally, the interaction effect was significant ($F(2, 1208) = 3.77$, $p = .02$, $\eta_p^2 = .006$). Interpreting this interaction effect, human judge was perceived to be faster when the legal case was uncomplicated compared to emotionally (mean difference = .62, $p = .001$) or technically complex legal cases (mean difference = .53, $p = .007$), with no such difference in the case of the algorithmic judge (mean difference > -.21, $p > .27$).

Figure 9. Perceived Speed as a Function of Judge and Case Complexity Type (study 2)



Perceived Cost. Replicating study 1's results, the main effect of the judge type was statistically significant ($F(1, 1208) = 96.33$, $p < .001$, $\eta_p^2 = .07$, see Figure 10). Human judge was again perceived to be more expensive (M = 5.54, SD = 2.03) than the algorithmic judge (M = 4.30, SD = 2.32). Furthermore, the main effect of the case complexity was also significant (F(2, 1208) = 3.74, *p* = .02, η_p^2 = .006): Participants who read about the uncomplicated case rated the perceived cost to be significantly lower (M = 4.66, SD = 2.32) than the ones who read about emotionally (M = 5.17, SD = 2.21; mean difference = -.42, *p* = .007) or technically complex cases (M = 4.95, SD = 2.23; mean difference = -.25, *p* = .097). The interaction effect between judge and case complexity type was again non-significant (F(2, 1208) = 1.39, *p* = .25).

Figure 10. Perceived Cost as a Function of Judge and Case Complexity Type (study 2)



Discussion

The results of study 2 replicate the key main effects of judge type from study 1: Respondents reported less trust and lower intentions to submit a legal case to the local court when the judge was an algorithm than when it was a human. These main effects of judge type were again large in magnitude (intentions: *d* = 1.04; perceived trust: *d* = .53), corroborating generally negative views of respondents towards algorithmic judges. Moreover, we replicated the results for perceived speed and cost: The algorithmic judge was perceived to be faster and cheaper than the human judge. Finally, replicating study 1's findings, we observed an interaction between judge and case complexity type on perceived trust.

General Discussion

Every day, more and more computational and predictive technologies are being used within social institutions, including the justice system. There are many ongoing discussions about how to integrate AI in judicial decision-making and justice is one of the most frequently mentioned domains in which algorithms have a high potential to change the current practices (Araujo et al. 2018). We argue that it is important to understand how individuals perceive algorithmic judges when discussing the future application of AI in deciding court cases.

The current work studies individuals' trust towards algorithmic and human judges and explores their intentions to submit their cases to a local court. In two empirical studies with a combined sample of over 1,800 adult US residents, we provide strong support for the notion that individuals care about the specific judge (human vs. algorithm) that will adjudicate their case. Specifically, we demonstrate that even though potential court users acknowledge that algorithms might lead to quicker and cheaper processes, perceived trust and willingness to submit a case to court is negatively influenced by the use of algorithmic judge. Moreover, although human judges are in general trusted much more than algorithmic judges, both technical and emotional complexities reduce trust in human judges, whereas only emotional complexities reduce trust in algorithmic judges.

To provide robustness of our findings, we combined the data from all studies we ran in a single data file (three studies in total) and meta-analyzed the findings ($N = 3{,}039$, $M_{age} = 37.8$, 1,611 females). We again found for trust a significant main effect of judge type ($F(1, 3021) = 238.94$, $p < .001$, $\eta_p^2 = .07$, $d = .6$) and type of case complexity ($F(2, 3021) = 7.85$, $p < .001$, $\eta_p^2 = .005$). Importantly, in line with the results of studies 1 and 2, we found a significant interaction effect between judge and case complexity type on perceived trust ($F(2, 3021) = 4.34$, $p = .01$, $\eta_p^2 = .003$). Details of this internal meta-analysis can be found in the Appendix 3C.

Our work provides novel insights on the impact of algorithms on individuals' attitudes and decision-making. First, we document algorithm aversion in an important domain: Judicial decision-making. In many situations people need to go to court to protect their rights. The idea of facing an algorithmic judge may increase their frustration and influence their predisposition to use courts. Therefore, access to justice may suffer. Accordingly, despite the positive aspects of algorithms (i.e., speed and cost), policymakers should expect pushback from citizens against courts' adoption of algorithms in adjudication.

Our paper also adds to the growing literature on algorithmic decision-making (Helberger et al. 2020; Yeomans et al. 2019), we document its effect in a practical context, perceived trust of algorithmic and human judges. Additionally, existing research on algorithm aversion predominantly studies how individuals choose between using algorithms and humans (e.g., Dietvorst et al. 2015, 2018). We contribute to this line of research by investigating how individuals perceive algorithms and humans when they are on the receiving side of the decisions that would be made by such decision-makers. Finally, our paper adds to the existing work on algorithms as we investigate the impact of legal case complexity (emotional vs. technical complexity). In particular, results of our internal meta-analysis highlight that trust in algorithmic judges especially drops when a legal case involves emotional complexity (vs. technical vs. low complexity).

Limitations and Future Directions

Our studies have several limitations that deserve attention. First, all our respondents were US residents. Therefore, we would advise policymakers not to generalize our results to respondents residing in other countries as it is possible that differences across countries may influence the general trust in judges. For instance, in countries with low court trust and low esteem of justice institutions, algorithmic judges may be trusted more than in countries in which courts and the justice administration have a better reputation. Future research is needed to conduct the same research in other jurisdictions and to use court or justice trust indicators when comparing data between jurisdictions. Second, trust in algorithmic decisions might also be influenced by repeated interaction with an algorithmic judge. For instance, experienced court players may have different attitudes towards algorithmic judges as they practice. We recommend more research on the effect of repeated exposure to algorithmic judges.

Third, even though there are many differences between humans and algorithms, current work aims to study lay people's general perceptions of algorithms in judicial decision-making. Therefore, we prioritized achieving high internal validity and minimized differences between conditions by only manipulating the type of judge. Future research should investigate differences between algorithmic and human judges systematically. Additionally, our paper covers several different perceptions such as trust, speed, and cost. However, we do not investigate how and when these variables impact individuals' decisions to submit their legal cases to the court. More research is needed to further understand the dynamics between perceptions of algorithms and their impact on individuals' attitudes and behaviors.

Further research might also delve deeper into the potential differences between legal fields. Depending on the field of law and the type of case, there might be divergence in the legal knowledge and in the approach potential court users take. These differences can be explained by the fact that parties are assisted by legal professionals like attorneys, who exercise considerable power over their clients and control their litigation strategies (Themeli 2018). Moreover, differences in the nature of the parties (e.g., business vs. private individuals) might have an influence on the willingness to submit a case to an algorithmic judge.

Our research is comparable to that of Sela (2018). Both our studies indicate less appreciation for automated decision-making. However, the studies differ in the dispute resolution mechanism under investigation – court for us, ODR for Sela (2018); and the timing of the interview– ex ante for us, ex post for Sela (2018). Additionally, we investigate the role of different types of case complexities to provide policymakers with insights about what to expect when they adopt algorithmic judges.

In addition, our research may be comparable to Helberger et al. (2020). Both our studies investigate human perception of algorithm (*automated* for Helberger et al. 2020) decision-makers but reach different conclusions. This may be due to the following difference between both studies: Helberger et al. (2020) survey is broad and without reference to any sector, whereas our experiment focuses on court litigation; Helbeger et al. (2020) inquire on the perception of fairness (as used in legal literature), whereas for us fairness is one of the elements that constitute trust; Helbeger et al. (2020) base their study on a survey, ours is an experiment which uses complexity moderators in addition to manipulating human vs. algorithm; Helbeger et al. (2020) use a Dutch sample, whereas our sample is based in the US. Nevertheless, both our studies agree that the mechanism with which humans perceive algorithmic decision-makers is complex and sensitive to circumstances. Both our studies agree that more studies are needed in this direction.

Finally, we are also aware that the underlying values and concepts in this paper are very much legally imprinted. Our use of the categories simple and complex is closely related to what is accepted as such in the legal world. A civil litigation is legally simple when parties compromise on the outcome and the judge only has to sign at the bottom, after a marginal assessment of compatibility with minimum standards of law. In the psychological and technological frame of concepts and values, the categories simple and complex might refer to something totally different. Consequently, legally simple is not equal to easy to automate. To find out how those differences play out, a conversation is needed on the intricate conventions between the disciplines. Then it may turn out that the legally simple cases comprise a much larger variation in complexity than we envisage and that complex in the legal world does not correspond with complex in the technical world. We observe that behind a simple court case often a host of human complexities are hidden. We tried to mitigate the effects of our respective imprints, at least in part, by composing a multidisciplinary team for this first investigation. To bring our results further to concrete policy guidelines requires the inclusion of other experts into the conversation.

CHAPTER 5

Discussion and Conclusion

The goal of this dissertation is to provide comprehensive and nuanced theoretical and managerial insights into how consumers react to algorithmic and human decision-makers. Each chapter examines the role of a specific component of decision-making: the decision outcome (Chapter 2), decision recipient (Chapter 3), and decision complexity (Chapter 4).

Chapter 2 investigated how consumers react to different decision outcomes (i.e., favorable versus unfavorable) made by algorithms versus humans. In contrast to managers' predictions, ten studies revealed that consumers react less positively when a favorable decision is made by an algorithmic (vs. a human) decision-maker, whereas this difference is mitigated for an unfavorable decision. This interaction effect was also shown to be driven by distinct attribution processes: consumers find it easier to internalize a favorable decision outcome (e.g., an acceptance) that is made by a human (vs. an algorithm), whereas they find it easy to externalize an unfavorable decision outcome (e.g., a rejection) regardless of the decision-maker type.

Chapter 2 makes three theoretical contributions. First, extending prior research that focus on how consumers *decide* between algorithms and humans (e.g., Longoni et al. 2019), this chapter studies how consumer *react to* decisions about themselves that are framed to be made by algorithms and humans. Second, this chapter adds to the growing research on algorithmic decision making and introduces a theoretically and practically relevant moderator: decision outcome favorability. Third, by studying how algorithmic (vs. human) decisions prompt different attributions, this chapter bridges literature on attribution processes and on algorithmic decision-making. In addition to these theoretical contributions, the findings of Chapter 2 provide managers with important insights on consumer reactions towards algorithms and humans. First, considering the results of the managerial intuition survey and the in-depth interviews, Chapter 2's findings are managerially informative. Managers therefore can learn from our findings that an algorithmic (vs. a human) decision-maker hurts consumers' reactions for *favorable* decision outcomes, but not for unfavorable outcomes. Second, our results provide several practical insights, including on how managers can design evaluation processes or how companies can mitigate the negative effect of algorithmic acceptances. Finally, findings of Chapter 2 offer important insights also for policymakers as they highlight the dangerous consequences of not disclosing the algorithmic origin of decisions.

Chapter 3 aimed to understand which consumer traits or consumer-related variables can explain differences across consumers in their valuation of algorithmic advice. Specifically, this chapter explored the role of an important consumer characteristic—consumers' subjective knowledge in a specific domain. Seven studies demonstrated that consumers' subjective knowledge in a focal domain moderates their valuation of recommendations generated by algorithms (vs. human experts): consumers with high subjective knowledge value recommendations from algorithms (vs. human experts) more because they believe they can engage in more meaningful collaboration with an algorithm (vs. a human expert). This greater valuation of algorithmic recommendations, however, is found to be mitigated for consumers with low subjective knowledge in a focal domain.

Chapter 3 makes three main contributions. First, this chapter builds on the past work on how consumers value recommendations by algorithms and humans and introduces an important consumer-related contextual factor that shapes consumers' valuation for algorithmic (vs. human-based) recommendations: their own subjective knowledge in a focal domain. Second, this chapter identifies a novel psychological mechanism (i.e., meaningful collaboration) behind consumers' valuation of algorithms, and by doing so, contributes to past research on algorithmic decision-making. Third, findings in Chapter 3 offer important practical insights for managers. For instance, this chapter provides advice on how managers tailor their services, how they can communicate the algorithmic origin of their recommendations, and on identifying a promising consumer segment that value algorithmic (vs. human-based) recommendations.

Finally, Chapter 4 went beyond traditional marketing contexts and studied individuals' reactions towards algorithms and humans in judicial decision-making context. When investigating such reactions, this chapter tested the role of an important contextual factor: the type of complexity a judicial decision has (i.e., emotional vs. technical). Two experiments and an internal meta-analysis demonstrated that individuals' lower levels of trust and lower intentions to go to court when algorithms (vs. humans) adjudicate. Interestingly, these findings also revealed that trust for algorithms (vs. humans) is especially penalized when cases involve emotional complexities (vs. simple or technically complex cases).

Chapter 4 extends and complements the previous research on algorithmic decision-making in multiple ways. First, findings of this chapter reveal consumers' perceptions towards algorithms in a novel yet important domain: judicial decision-making. Second, this chapter extends the existing work by introducing a contextual factor that changes consumers' perceptions towards algorithms and humans: decision complexity. Furthermore, Chapter 4's findings have important implications for governments, policymakers, legal firms, and societies in general. For example, these findings indicate that despite some positive aspects of algorithms (i.e., perceived speed and cost), policymakers should expect strong pushback from citizens against courts' adoption of algorithms in adjudication.

Future Directions

Each chapter in this dissertation investigates the role of an important component of decision-making (i.e., the decision outcome, decision recipient, decision complexity), and discusses the fruitful questions they raise for future research. In this section, I will refrain from repeating these directions and instead pinpoint additional and complementary components of decision-making that open promising avenues for future research.

Decision process. Considering the widespread adoption of algorithms in businesses, it is hard to imagine a world in which we do not use algorithms. This calls for more research that move forward from *whether* to use algorithms to *how* to use algorithms when making decisions. Accordingly, future research can investigate the role of the decision process (i.e., series of steps taken to make a decision) on consumer reactions towards algorithms. Do consumers react differently when they utilize algorithms at earlier (e.g., generating options) or later stages (e.g., deciding on which option to choose) of decision-making? When making a decision, for what type of roles (e.g., exploring vs. exploiting) consumers would be willing to deploy algorithms? I encourage researchers to examine how algorithms can be integrated in decision processes.

Decision-maker type. The increased interest in algorithmic solutions in businesses is also reflected in an increasing number of articles that examine the psychological forces that shape consumer reactions to different types of decision-makers (i.e., the agent that makes the decision), including humans and algorithms. Looking at the practice, however, decision-maker type can be more nuanced than this comparison (i.e., humans versus algorithms) as there can be many different types of algorithms (e.g., machine-learning algorithm, artificial intelligence algorithms). Considering that companies are allowed to communicate their algorithms in different ways, do consumers react different types of algorithms in the same way? What can companies avoid or emphasize when communicating their algorithms with their customers? More research is needed to understand nuances between different types of algorithms.

Beyond the practical value of understanding consumer reactions to different types of algorithms, future research is needed to further examine the consequences of differences in valuation of different types of algorithms for the existing research. A careful look at the literature on algorithmic decision-making reveals that researchers have been operationalizing and referring different types of algorithms in various ways (e.g., statistical model, AI, computer programs) across papers or even within the same paper. Despite the interchangeable use of various labels, the existing work does not distinguish between such different types of algorithms conceptually or empirically. Moving forward in this literature, future research can adopt a more integrative understanding and explore the inferences consumers make about different labels we use. I aim to shed light on this component decision-making in an ongoing project (Yalcin et al. 2021). Together with prominent researchers in this research area, I am conducting a systematic synthesis of consumer responses to applications of algorithms via a meta-analysis of published and unpublished research. Such a meta-analytical approach is particularly suited to uncover the psychological antecedents of consumer reactions towards algorithms, and to provide valuable directions for future research.

Decision input. To ensure internal validity, the studies that are included in this dissertation did not disclose what type of decision-maker will make a decision (i.e., an algorithm vs. a human) before participants provided or imagine to be providing the information that will be used to make a decision (e.g., filling out the application form, answering the questions that would be used to determine their personalized recommendations). Looking at marketing practice, however, consumers might be aware of who will make a decision before they provide the information company asks for (i.e., decision input). For instance, companies like Netflix, Spotify, and Goodreads are known to adopt algorithmic recommenders: algorithms evaluate consumers' movie, music, or book preferences to decide on what recommendation to them. Moreover, many e-commerce retailers (e.g., Amazon) now utilize artificial customer service agents (e.g., chatbots) to interact with customers and to make decisions about their requests, such as order cancellation or product exchange. Existing work suggests that consumers have a different understanding of how algorithms and humans process information (e.g., Yeomans et al. 2019; Cadario et al. 2021). If this is the case, would consumers select different set of movies or songs when they are told that their recommendation will be generated by an algorithm (vs. a human)? Would consumers communicate their requests differently when an AI (vs. a human) agent will evaluate their refund request? I encourage researchers to further examine the role of decision input on consumers' experiences with companies.

To conclude, algorithms are everywhere, they are more capable than ever, and they are here to stay. We, as researchers, have an important role to play in helping companies, consumers, and policymakers understand the consequences of algorithm adoption. It is my hope that you – the reader – find this dissertation helpful in offering a nuanced perspective on how consumers react to algorithms.

CHAPTER 6

Appendices of Chapter 2, 3, and 4

Appendix 1: Additional Materials for Chapter 2

Appendix 1A: Additional Examples of Algorithmic Adoption

Decision Context		
Consumer-facing decisions	**Business-related decisions**	**Public services**
Loan applications **Earnest: https://www.earnest.com/refinance-student-loans** **Affirm: https://www.affirm.com/business/blog/alternative-underwriting** **Upstart: https://www.upstart.com/blog/upstart-ceo-dave-girouard-testifies-in-congress-about-ai-in-credit-underwriting** **Zestfinance: https://www.zest.ai**	• HireVue (https://www.hirevue.com) • Arya (https://goarya.com) • Monster: https://hiring.monster.com/employer-resources/uncategorized/the-future-of-ai-in-staffing/	**Judicial decisions** https://www.wired.com/story/can-ai-be-fair-judge-court-estonia-thinks-so/ **Probation decisions** *https://www.nytimes.com/2020/02/06/technology/predictive-algorithms-crime.html*

Financial product applications **Goldman Sachs:** **https://www.washingtonpost.com/business/2019/11/11/apple-card-algorithm-sparks-gender-bias-allegations-against-goldman-sachs/** **ING:** **https://www.ing.com/Newsroom/News/Using-AI-to-assess-credit-risk.htm**	• **Johnson & Johnson** • **JetBlue (https://www.shrm.org/hr-today/news/hr-magazine/0616/pages/using-algorithms-to-build-a-better-workforce.aspx)** • **Uber (https://www.wired.co.uk/article/uber-fired-algorithm)** •	Immigration & visa decisions **https://nationalpost.com/opinion/colby-cosh-rejected-by-a-robot-an-emerging-debate-over-ai-immigration**
Insurance applications: https://technative.io/the-future-of-ai-in-the-insurance-industry/ **Interpolis (car insurance):** **https://www.interpolis.nl/verzekeren/slimme-oplossingen/automodus** **Zelros: https://www.zelros.com/solutions/**	• Xerox: https://www.theatlantic.com/magazine/archive/2013/12/theyre-watching-you-at-work/354681/ • IBM Talent AI Watson: https://www.ibm.com/services/talent-management/talent-development	**Military decisions** *https://venturebeat.com/2019/11/08/the-u-s-military-algorithmic-warfare-and-big-tech/*
Telecommunication **Vodafone: https://www.vodafone.com/what-we-do/public-policy/policy-positions/artificial-intelligence-framework**	• Southwest Airlines: https://www.wsj.com/articles/southwest-airlines-automates-some-job-recruiting-tasks-as-air-travel-takes-off-11623103379?mod=djemCIO • Pymetrics: https://www.pymetrics.ai	**College admissions** *https://www.fastcompany.com/90342596/schools-are-quietly-turning-to-ai-to-help-pick-who-gets-in-what-could-go-wrong* https://www.washingtonpost.com/business/2019/10/14/colleges-quietly-rank-prospective-students-based-their-personal-data/
Membership applications **www.rayatheapp.com**		

Appendix 1B: Managerial Intuitions - Study Materials

Scenario and Measures

In many situations, companies can choose between having an employee or an algorithm review and decide on applications (e.g., loan application, credit card application, membership application, job applications). The decision-making process for both of these decision-makers is the same: they review documents (e.g., application forms), make a decision (e.g., acceptance, rejection), and notify applicants via email or letter.

Now, please imagine that you are a brand manager of a bank that utilizes algorithms and employees to review applications (e.g., membership applications, loan applications). The bank that you are working for can have either algorithms or employees review customers' applications and decide whether to accept or reject each application.

We are simply interested in your opinions about the potential impact of these decision-makers on customer reactions.

- Acceptance: Imagine the situation where the customers are being ACCEPTED. From a customer satisfaction and attitude-towards-the-bank perspective, would it be better if customers were told they were accepted by an EMPLOYEE or would it be better if customers were told they were accepted by an ALGORITHM? (-1 = getting accepted by an algorithm would be better than getting accepted by an employee, 0 = getting accepted by an algorithm would be equally good as getting accepted by an employee, 1 = getting accepted by an employee would be better than getting accepted by an algorithm)

- **Rejection**: Imagine the situation where the customers are being REJECTED. From a customer satisfaction and attitude-towards-the-bank perspective, would it be better if customers were told they were rejected by an EMPLOYEE or would it be better if customers were told they were rejected by an ALGORITHM? (-1 = getting rejected by an algorithm would be better than getting rejected by an employee, 0 = getting rejected by an algorithm would be equally good as getting rejected by an employee, 1= getting rejected by an employee would be better than getting rejected by an algorithm)
- **Experience:** How many years of working experience do you have?
- **Age**
- **Gender** (0 = male, 1 = female, 2 = other or prefer not to answer)

Appendix 1C: Overview of In-Depth Interviews

	Company	Experience	Types of tasks for which algorithms are used	Advantages and disadvantages of algorithmic vs. human decision-makers	Predicted customer reactions to being evaluated/reviewed by algorithms (A) vs. humans (H)
#1	Financial Services Company	Senior Portfolio & Business Developer	-Chatbot & customer service support -Customer segmentation: identifying risky customers based on the input provided by customers, and deciding on their premium -Evaluating and reviewing customer applications -Customized product recommendations -Pay-how-you-drive car insurance: "We use algorithms to determine customers' driving styles (e.g., acceleration, breaks) and give them a score & feedback. We offer customers discount on their premium if they are classified as good drivers. Customers' insurance requests can also be denied if their score is below our threshold."	**Advantages:** Algorithms are fairer and more objective; they can come up with a more objective score. -Algorithms are faster than humans. -Algorithms currently perform better than humans on many tasks. **Disadvantages:** Consumers sometimes find it harder to understand algorithmic processes and how an algorithm came up with decision/feedback. -Algorithms cannot achieve personal connection.	**Favorable decision outcomes (A < H):** Customers would be less happy to get favorable feedback from algorithms as it feels less like the decision directly came from the company. There is also less personal connection with algorithms; an algorithm can't be proud of you. **Unfavorable decision outcomes (A > H):** Customers would be less sad to get unfavorable feedback from algorithms. Rejections would be more impactful from a human.
#2	Data Science Center	Associate Executive Director	-Decision support system & forecasting: algorithms are used to predict demand and risk; humans monitor the algorithms. -Reviewing customers -Customer segmentation & targeting	**Advantages:** Algorithms can make processes more efficient, and they have huge potential to transform consumer experiences. -Algorithms are more objective and can avoid certain human biases. -Some people think algorithms are more secure than humans. **Disadvantages:** For complex or unique cases, algorithms currently perform worse than humans.	**Favorable decision outcomes (A < H)**: Customers would be happy if they are treated well, but they might feel even better with humans (vs. algorithms) as they might feel that they were taken seriously by the company. **Unfavorable decision outcomes (A < H):** When customers get unfavorable news, they might feel better when humans reject them as they might explain reasons and empathy.

				-Companies need to be careful about the biases their data or algorithm might have. -Many people see algorithms as a black box and find them less accountable than humans. -Algorithms lack human touch and connection.	
#3	Multinational Technology Company	Product Lead and Entrepreneur	-Providing market insights: Algorithms score market leads and identify businesses with high potential. The information is given to business owners.	**Advantages:** Algorithms are faster than humans and require less effort to complete the same task. **Disadvantages:** Algorithms cannot process feelings/emotions or things that are difficult to quantify (e.g., taste). -Algorithms are worse at recognizing unique cases or appreciating how special something is.	**Favorable decision outcomes (A < H)**: People would be less satisfied with an acceptance from algorithms (vs. humans) as algorithms can be fooled. **Unfavorable decision outcomes (A < H):** People would be angrier when they are rejected by algorithms as they might think that they were automatically discarded without being evaluated carefully.
#4	Data Science Center	Technology Evangelist + Employee at Medical Company	-Making medical decisions (e.g., whether there are cancerous cells)	**Advantages:** Algorithms can serve more people, faster. -Algorithms are less subjective than humans when making judgments. **Disadvantages:** Algorithms have less accountability. -People mainly see algorithms as a black box. -Algorithms might be biased if the data is biased.	**Favorable decision outcomes (A > H):** Customers would be more satisfied with algorithms as they are more unbiased. **Unfavorable decision outcomes (A < H):** If an algorithm makes the unfavorable judgment by itself, customers might not agree with the rejection and might want some recourse.
#5	Multinational Financial Services Company	Senior Vice President of Retail Credit Risk Analytics, Process Management and Underwriting	-Evaluating customer applications (e.g., credit cards, mortgage, business loans)	**Advantages:** Algorithms are faster and more cost-efficient. -Algorithms are more objective and consistent than humans. -Automatic decision-making increased drastically in the last 5 years	**Favorable decision outcomes (A > H):** Customers would be happier when algorithms accept them as the decision-making would be more efficient. **Unfavorable decision outcomes (A > H):** Customers would be relatively more satisfied

				and our overall NPS also increased, indicating that there are many advantages of algorithms from a customer experience perspective. **Disadvantages:** To ensure high quality and minimize biases, algorithms need close monitoring.	when a rejection comes from an algorithm as customers can get closure faster.
#6	Mobile Telecommunication Company	Head of Digital Innovation & Strategy	-Customer service support -Customized content & product recommendations: algorithms are used to provide customized offers or free products.	**Advantages:** Algorithms are more efficient and convenient. They are cheaper and faster. **Disadvantages:** It is very hard to find good data and develop high-quality algorithms.	**Favorable decision outcomes (A = H):** As long as customers get what they want, they would be equally happy with algorithms and humans. **Unfavorable decision outcomes (A > H):** We sometimes have to tell customers that they do not qualify for a new product (e.g., based on their credit check). I personally think customers might be more satisfied with digital channels as they might not need to face as many negative emotions.
#7	Asset Management Company	Lead Behavioral Scientist + Founder of a Marketing Insights Company	-Customer segmentation: using algorithms to determine how to communicate with customers based on their personalities and behaviors -Predicting customer engagement	**Advantages:** Algorithms are cheaper and more accurate than humans. -Algorithms do not judge you, while humans can be judgmental. **Disadvantages:** Algorithms might perform worse when there is a unique/exceptional case. -They might perform worse than humans when building customer trust and loyalty. -Consumers tend to be scared of algorithms.	**Favorable decision outcomes (A > H):** Humans might evoke warm feelings, but they can also have a hidden agenda (e.g., they just want to sell you something). That's why algorithms might be valued more as they are more objective and might be a more diagnostic signal that the consumer is on the right path. **Unfavorable decision outcomes (A > H):** Consumers just want to protect their egos, so their anger would be directed more toward a human than an algorithm.
#8	Online Financial Advisory Company	CEO	-Customer evaluation: evaluating customers' financial health based on the questions they answer	**Advantages:** Algorithms are faster. **Disadvantages:** Algorithms perform worse than humans on complex tasks (e.g., natural language processing).	**Favorable decision outcomes (A = H):** Customers react positively to favorable outcomes regardless of who generated the feedback.

			-Customer segmentation: clustering customers based on their behaviors and fears about investing	-Algorithms are worse than humans at social interactions.	**Unfavorable decision outcomes (A < H):** Customers would react more favorably to humans (vs. algorithms) as humans can empathize with and motivate them.
#9	Online Customer Experience Solutions Company	Data Scientist	-Customer segmentation: classifying customers based on behavioral/demographic data -Targeted advertising: customized targeted product recommendations (humans monitor the algorithms)	**Advantages:** Algorithms have more processing power to handle big data. **Disadvantages:** Algorithmic/data bias: people find it harder to understand the algorithmic processes.	**Favorable decision outcomes (A < H):** Customers would react more favorably to a favorable decision from a human due to personal connection. They would feel more special; the human might see something in them and believe in them. **Unfavorable decision outcomes (A > H):** Customers would blame the algorithm more if they are rejected by an algorithm (vs. a human).
#10	Multinational Mobile Telecommunication Company	Operational Intelligence Lead AI	-Customer service support: algorithms are used to review customer requests and offer solutions. -Evaluating and classifying customers (e.g., loyalty, churning) -Customized product recommendations: based on a "market basket analysis" algorithm, the firm sends personalized coupons and offers to customers.	**Advantages:** Algorithms are faster than humans. Our time-to-issue solution went down after switching to algorithms. They are also more cost-efficient. **Disadvantages:** Algorithms might be biased by geolocation or gender. -Algorithms deal with exceptions / unique cases poorly.	**Favorable decision outcomes (A = H):** As long as customers receive positive news, they should be happy. **Unfavorable decision outcomes (A < H):** When providing negative news, humans might be less frustrating as algorithms sometimes cannot give a good explanation, and they lack personal touch. At least with humans, there is also an acknowledgement that they cannot solve it.
#11	Mobile Telecommunication Company	Director Excellence Center - Customer Services	-Customer service support & chatbot -Forecasting & optimizing demand -Deciding whose requests to approve; employees can apply for new products/upgrades as a part of an internal channel.	**Advantages**: Algorithms are faster (decrease waiting time). -Algorithms have more knowledge, processing power, and memory (they do not forget). You are dependent on the knowledge someone has if it is human. **Disadvantages:** Algorithms perform worse than humans on many tasks (e.g., complex requests).	**Favorable decision outcomes (A < H)**: Humans are better at giving a sense of closure. **Unfavorable decision outcomes (A < H):** People do not trust algorithms and are quick to object when their request is denied by an algorithm.

			-Customized communication: when to send info, personalized offers	-An algorithm does not provide customers with a sense of closure. -Customers are less familiar with high-quality algorithms.	
#12	National Supermarket Chain	Web Commercial and Business Development Manager	-Customized product recommendations -Marketing & communication strategies: algorithms are deployed to decide when and how to contact customers. -Shopper segmentation: algorithms review and interpret behavioral data to classify customers (e.g., loyalty, ability to switch to online).	**Advantages**: Algorithms are cheaper. -They handle complicated data better, and they make higher-quality decisions in many domains. **Disadvantages:** Algorithmic bias -Algorithms do not have a personal touch; they cannot build personal connection with customers. -Using algorithms might make customers feel that we know everything about them. -People do not understand algorithms and perceive them as a black box.	**Favorable decision outcomes (H = A):** If algorithms are customized enough, there should not be any difference between the decision-makers. If it is not customized, then humans might be better as they can provide "personal interaction." **Unfavorable decision outcomes (A < H):** Algorithms would lead to worse satisfaction as customers might feel that they were not taken seriously by the company, and there is no personal human touch.
#13	E-commerce Company	Data Scientist	-Customized product recommendations, assortment, content, pricing, & ordering -Customer service & support	**Advantages:** Algorithms are very convenient and enable companies to handle big and complicated datasets. For instance, there are 75 M products on our website, and it is not possible for humans to handle this. -People do not have social awkwardness with algorithms, and there is no reason to follow social norms. **Disadvantages:** Algorithms can be perceived as scary if consumers do not know anything about technology (or sometimes know too much about technology). -Consumers might think that it is unfair to be reviewed by algorithms.	**Favorable decision outcomes (A = H):** People might be indifferent when the decision is positive as there is nothing to complain about. **Unfavorable decision outcomes (A < H):** Consumers would be angrier when a negative decision is made by an algorithm (vs. human).

				-Algorithms do not build personal connection with customers. -Algorithmic bias	
#14	E-commerce Company	Lead Data Scientist	-Product recommendations -Deciding when and how to contact customers -Making decisions about the price of a product -Customer segmentation & pricing	**Advantages:** Algorithms perform better on simple tasks. They are also much faster. **Disadvantages**: Algorithms are less flexible and are less likely to take situational factors into account. -Algorithms perform worse on complex tasks. -Algorithms cannot provide customer intimacy. -Algorithms cannot see beyond the data and read between the lines.	**Favorable decision outcomes (A = H):** As long as consumers get what they want, they should be indifferent. **Unfavorable decision outcomes (A < H):** Humans would lead to greater customer satisfaction as getting rejected by an algorithm is just unfair, and people would not understand what data was used to make the decision.

Appendix 1D: Scenario and Items Used in Study 1a and Additional Analysis

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, your job title), as well as a few questions about the reason you want to be a member.

Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, your job title), as well as a few questions about the reason you want to be a member.

In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by an IT company)] reviews each application and decides whose application to accept [reject].

You find out that the coordinator reviewed 100 applications and one of the people that the coordinator decided to accept [reject] is you. This is the final decision on your application and cannot be appealed.

On this website, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours.

Measures

- Attitude scale: What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

- Open-ended question: Any comments?

Additional Analysis

In study 1a, one participant did not complete the demographic variables. Although in subsequent studies, we included participants who completed all measures to our analysis, we included this one person to our main analysis to be consistent with our pre-registration. To test the robustness of our findings, we also analyzed the data after excluding this participant (N = 992 Mturk workers).

We conducted a 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA on the attitudes toward the country club. This analysis revealed a significant main effect of the decision-maker type ($M_{algorithm} = 5.15$, $SD_{algorithm} = 3.09$ vs. $M_{human} = 5.38$, $SD_{human} = 3.29$; $F(1, 988) = 5.23$, $p = .02$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable} = 7.48$, $SD_{favorable} = 2.61$ vs. $M_{unfavorable} = 3.07$, $SD_{unfavorable} = 1.96$; $F(1, 988) = 922.10$, $p < .001$, $\eta_p^2 = .48$). Consistent with study 1a's findings, we again found a significant interaction effect ($F(1, 998) = 8.78$, $p = .003$, $\eta_p^2 = .01$). Specifically, attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm}$ = 7.11, $SD_{algorithm}$ = 2.58 vs. M_{human} = 7.88, SD_{human} = 2.58; $F(1, 988) = 13.70$ $p <$ .001, η_p^2 = .014). By contrast, the effect of the decision-maker type was significantly attenuated for participants whose applications were rejected ($M_{algorithm}$ = 3.12, $SD_{algorithm}$ = 2.11 vs. M_{human} = 3.02, SD_{human} = 1.82; $F < 1$, $p = .63$).

Appendix 1E: Scenario and Items Used in Study 1b

Scenario

Imagine that you are an entrepreneur and you came up with a business idea. You decided to apply for a business loan to start your company.

The bank that you are applying requires potential customers to fill out an application form. The application form includes several demographics questions (e.g., age, gender), questions about yourself (e.g., your occupation, your salary), a few questions about the reason you want to get a loan and about your business idea. The average acceptance rate of this bank is 8%.

Now imagine that you filled out the application form and submitted it to bank's website. You answered the demographics questions (e.g., age, gender), the questions about yourself (e.g., your occupation, your salary), questions about the reason you want to get a loan. You also gave details about your business idea and why it is a good investment opportunity.

In this bank, a loan officer (an employee who is specialized in this area) [a loan algorithm (that is designed by the IT department)] reviews each application and decides whose applications to approve [deny]. You recently find out that the loan officer reviewed 100 loan applications and one of the applications that the loan officer [algorithm] decided to approve [deny] is yours.

The loan officer [algorithm] reviewed 100 business loan applications and one of the applications that the loan officer decided to approve [deny] is yours.

Measures

- Attitude scale: What is your general opinion about this bank? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- Word-of-Mouth Intention: On a scale from 0-10, how likely are you to recommend this bank to a friend or colleague? (0 = not at all likely, 10 = extremely likely)

- Age

- Gender (0 = male, 1 = female, 2 = other / prefer not to answer)

- Open-ended question: Any comments?

<u>Appendix 1F: Scenario and Items Used in Study 2</u>

Scenario and Measures

Welcome! This survey is conducted by Johnson Customer Insight. At Johnson Customer Insight, we aim to create a high quality special participant pool. We dedicated today to recruit eligible participants! Today, we will evaluate applications for our special participant pool.

This survey is a short application form to assess your eligibility for our future surveys in which you can get a generous compensation as well as extra bonus payments (on average 20 cents). By taking this survey, you will be considered to submit your application for the Johnson Customer Insight's special participant pool.

As a part of this application, you will asked to answer questions (e.g., cognitive abilities, Prolific history) that are predictive of your diligence and attractiveness as a research participant. After then, there will be a short waiting period while a decision is made about whether to invite you to the special participant pool or not.

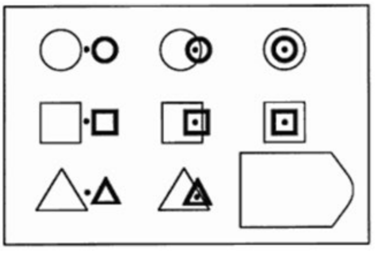
Finally, we will inform you about whether your application is accepted or rejected and you will answer a few follow-up questions.

Application Form

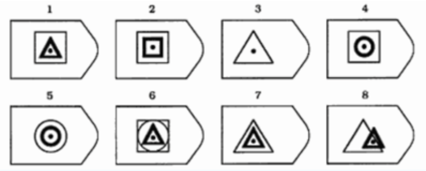
Welcome to our application form! In this form, you will be asked to fill out questions about your cognitive abilities and your previous experience with Prolific surveys, and write a short essay.

Note that your answers to these questions will be considered as your application for our special participant pool and to participate.

PART 1: In the first part of the survey, we would like to ask you to complete a question assessing your cognitive abilities. Please click on next and answer this question carefully.



- Look at the shapes in the boxes above. Do you see how they are related to each other? Please find the answer that goes in the empty box so the shapes in the bottom row will relate to each other in the same way as the shapes in the top row.



○ 1 ○ 2 ○ 3 ○ 4

○ 5 ○ 6 ○ 7 ○ 8

PART 2: In this part of the survey, we would like to ask you to complete several questions about your Prolific history. Please click on next and answer these questions carefully.

- What do you think is the approximate total number of studies you completed so far?

(1 = 0-50, 2 = 51-100, 3 = 101-200, 4 = 201-300, 5 = 301-500, 6 = 501-700, 7 = 700 +)

- What do you think your current approval rate is?

(1 = 0-30%, 2= 31-50%, 3 = 51-70%, 4 = 71-80%, 5 = 81-90%, 6 = 91-95%, 7 = 96-100%)

- Please write a short essay about why you are a good research participant and should be considered to be a panel of our special high quality participant pool (min character: 50).

- **Age**

- **Gender** (0 = male, 1 = female, 2 = other / prefer not to answer)

- Education level: What is the highest level of education you have completed?

(1= less than high school degree, 2 = High school graduate (high school diploma or equivalent including GED), 3 = Some college but no degree, 4 = Associate degree in college (2-year), 5 = Bachelor's degree in college (4-year), 6 = Master's degree, 7 = Doctoral degree, 8 = Professional degree (JD, MD)

Prolific user ID: ${prolific_id/ChoiceTextEntryValue}

Case number: #674${rand://int/100:300}

Thank you for your responses! Your application is now submitted and is being considered to be your application for our special participant pool.

We dedicated today to recruit eligible participants! Right now, your application is being evaluated. Please wait until your evaluation is completed. Note that this evaluation process might take up to about 3 minutes.

Prolific user ID: ${prolific_id/ChoiceTextEntryValue}

Case number: #674${rand://int/100:300}

Congratulations, you are accepted! Given this result, you will be added to our special participant pool and informed about our future surveys with bonus compensations [Unfortunately, you are rejected. Given this result, you will not be added to our special participant pool and will not be informed about our future surveys with bonus compensations].

Please click on the next button below to get further information and answer some follow-up questions.

- Initial rating: We constantly strive to improve our service standards. We would like to get your feedback on Johnson Customer Insight. What is your overall evaluation of Johnson Customer Insight? (10-point star rating).

At Johnson Customer Insight, a team of coordinators (an employee who is specialized in this area) [an algorithm (a computer program that is designed by our IT team) evaluates application forms, and decides whom to accept or reject. This means that your application was reviewed and accepted [rejected] by one of these coordinators [this algorithm].

- Change in attitude: On the previous page, we informed you about who made the decision to accept[reject] your application. We would like to understand how this information influences applicants' feelings about Johnson Customer Insight and their opinions of our evaluation process. How do you feel about Johnson Customer Insight now? (1 = less positive, 7 = more positive).

Debriefing form

Thank you for completing our survey. We highly appreciate your input! Note that all responses will be treated as confidential, and in no case will responses from individual participants be identified. Rather, all data will be pooled and published in aggregate form only. If you have any questions related to this study, please contact [RESEARCHER NAME (researcher email address)].

The organization described as part of this survey is not active; we used the information for research purposes. As a token of our appreciation, everyone, regardless of their communicated result, will be paid 10 cent bonus compensation, and there won't be any future surveys. This study examines whether people show different reactions when they receive positive news from different types of decision-makers. We also would like to kindly remind you that the type of decision-maker you saw was randomly determined. We would like to kindly ask you not to share the actual purpose of this study with others as we are still collecting data. On behalf of our team, we wish you a great day.

Appendix 1G: Scenario and Items Used in Studies 3a and 3b

Study 3A: Country Club Application

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member.

Algorithm and human conditions: In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by an IT company)] reviews each application and decides whose application to accept. You recently find out that the coordinator [the algorithm] reviewed 100 applications and one of the people that the coordinator [the algorithm] decided to accept is you. As a reminder, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours.

Unspecified decision-maker condition: In this country club, applications are reviewed to decide whose application to accept. You recently find out that 100 applications were reviewed and one of the people that is accepted is you. As a reminder, the applications were reviewed, including yours.

Measures

- Attitude scale: What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- Active member (0 = no, 1 = yes)

- Age

- Gender (0 = male, 1 = female)

Study 3B: Bank Loan Application

Scenario

Imagine that you are applying for a loan. A bank requires potential customers to fill out an application form. The application form includes several demographics questions (e.g., age, gender), questions about yourself (e.g., your occupation, your salary), as well as a few questions about the reason you want to get a loan.

Now imagine that you filled out the application form and submitted it to bank's website. You answered the demographics questions (e.g., age, gender), the questions about yourself (e.g., your occupation, your salary), as well as a few questions about the reason you want to get a loan.

Algorithm and human conditions: In this bank, the loan officer (an employee who is specialized in this area) [the loan algorithm (that is designed by an IT company)] reviews each application and decides whose application to accept. You recently find out that the loan officer [algorithm] reviewed 100 applications and one of the people that the loan officer [algorithm] decided to accept is you. As a reminder, the loan officer (an employee who is specialized in this area) [the loan algorithm (that is developed by the IT department)] reviewed the applications, including yours.

Unspecified decision-maker condition: In this bank, applications are reviewed to decide whose application to accept. You recently find out that 100 applications were reviewed and one of the people that is accepted is you. As a reminder, the applications were reviewed, including yours.

Measures

- Attitude scale: What is your general opinion about this bank? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- Age

- Gender (0 = male, 1 = female)

- Open-ended question: Any comments?

<u>Appendix 1H: Scenario and Items Used in Study 4 and Additional Analysis with Inattentive Participants</u>

Scenario and Measures

- Attention check: What color is sky? This question is designed to ensure that people are at high attention throughout or not. This question seems deceptively easy if you're just skimming, but we insert instructions like "make sure to select orange for this answer so that we know you are paying attention" in the middle of the copy of the question. Try it for yourself (1 = Orange, 0 = Blue)

Imagine that you decide to sign up to a country club. The country club that you are considering is Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. Note that this country club has an acceptance rate of 10%.

Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by an IT company)] reviews each application and decides whose application to accept [reject]. You recently find out that the coordinator [the algorithm] reviewed 100 applications and one of the people that the coordinator [the algorithm] decided to accept is you.

On this website, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours.

- **Attitude scale:** What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

Multiple factors might have influenced the decision on your application. For instance, they can be attributed to something about yourself (e.g., your behaviors, personal qualities) as well as something not related to you, such as the way of decision-maker evaluating or interpreting your application. Now please think about the acceptance [rejection] decision you received. Please read the following questions carefully and indicate the extent to which you think the decision is made based on your personal qualities or behaviors.

- **Internal attribution scale:** "To what extent do you feel this decision reflects something about yourself?", "To what extent do you feel this decision can be attributed to something about yourself?", "To what extent do you feel this decision is due to your personal qualities or behaviors?" (1 = not at all, 11 = very much)

- **Age**

- **Gender** (0 = male, 1 = female, 2 = prefer not to answer)

- **Open-ended question:** Any comments?

Additional Analysis with Inattentive Participants

To test the robustness of our findings, we analyzed the data including participants who failed the attention check (N = 600 Prolific workers). First, we conducted a 2 (decision-maker type) x 2 (decision outcome favorability) ANOVA on the attitudes toward the company. We found a significant main effect of the decision-maker type ($M_{algorithm} = 4.97$, $SD_{algorithm} = 2.93$ vs. $M_{human} = 5.84$, $SD_{human} = 3.09$; $F(1, 596) = 8.34$, $p = .004$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable} = 6.94$, $SD_{favorable} = 2.92$ vs. $M_{unfavorable} = 3.88$, $SD_{unfavorable} = 2.30$; $F(1, 596) = 197.07$, $p < .001$, $\eta_p^2 = .25$). Most importantly, we replicated the interaction effect ($F(1, 596) = 2.91$, $p =.088$, $\eta_p^2 = .005$): attitudes toward the country club were less positive among participants whose applications were accepted by the algorithm than among participants whose applications were accepted by the club coordinator ($M_{algorithm} = 6.40$, $SD_{algorithm} = 2.92$ vs. $M_{human} = 7.38$, $SD_{human} = 2.86$; $F(1, 596) = 10.53$, $p = .001$, $\eta_p^2 = .02$). By contrast, the effect of the decision-maker type was significantly attenuated for participants whose applications were rejected ($M_{algorithm} = 3.76$, $SD_{algorithm} = 2.33$ vs. $M_{human} = 4.01$, $SD_{human} = 2.26$; $F < 1$, $p = .40$).

We conducted an analogous ANOVA on attribution. We found a significant main effect of the decision-maker type ($M_{algorithm} = 6.54$, $SD_{algorithm} = 2.78$ vs. $M_{human} = 7.23$, $SD_{human} = 2.68$; $F(1, 596) = 7.39$, $p = .007$, $\eta_p^2 = .01$) and of decision outcome favorability ($M_{favorable} = 7.54$, $SD_{favorable} = 2.45$ vs. $M_{unfavorable} = 6.23$, $SD_{unfavorable} = 2.88$; $F(1, 596) = 33.75$, $p < .001$, $\eta_p^2 = .05$). Importantly, we found a significant interaction effect ($F(1, 596) = 10.91$, $p = .001$, $\eta_p^2 = .02$): the internal attribution was weaker when the acceptance decision was made by the algorithm than when it was made by the club coordinator ($M_{algorithm} = 6.83$, $SD_{algorithm} = 2.51$ vs. $M_{human} = 8.13$, $SD_{human} = 2.24$; $F(1, 596) = 18.10$, $p < .001$, $\eta_p^2 = .03$). The effect of the decision-maker type on the internal attribution was significantly attenuated when participants' applications were rejected ($M_{algorithm} = 6.29$, $SD_{algorithm} = 2.98$ vs. $M_{human} = 6.17$, $SD_{human} = 2.76$; $F < 1$, $p = .68$).

Finally, we conducted a moderated mediation analysis (Process Model 8, 10,000 bootstrapped sample; Hayes 2013) with attitude as the dependent variable, decision-maker type (-1 = algorithm, 1 = human) as the independent variable, decision outcome favorability (-1 = unfavorable, 1 = favorable) as the moderator, and internal attribution as the mediator. Replicating our findings in the main analysis, we found a significant moderated mediation effect (moderated mediation index = .16, 95% CI [.0585, .2790]). For a favorable decision outcome, the indirect effect of the decision-maker type through internal attribution was significant (B = .15, 95% CI [.0726, .2286]), suggesting that the less positive reaction to the company after receiving a decision from an algorithm (vs. a human) was driven by the weaker internal attribution of the favorable decision. For an unfavorable decision outcome, however, the indirect effect was not significant (B = -.01, 95% CI [-.0917, .0602]).

<u>Appendix I: Scenario and Items Used in Study 5 and Additional Analysis with Inattentive Participants</u>

Scenario and Measures

- Attention check: What color is sky? This question is designed to ensure that people are at high attention throughout or not. This question seems deceptively easy if you're just skimming, but we insert instructions like "make sure to select orange for this answer so that we know you are paying attention" in the middle of the copy of the question. Try it for yourself (1 = Orange, 0 = Blue).

Imagine that you decide to sign up to a business networking club. The networking club that you are considering is NetworkLink Business Club.

NetWorkLink

NetWorkLink is an exclusive business networking community for professionals with management experience, and its members can enjoy numerous social networking activities and career-related workshops as well as meeting other professionals.

This networking club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member.

Now imagine that you filled out the application form and submitted it to the network club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member.

In this networking club, the club coordinator (an employee who is specialized in this area) [the club algorithm (that is designed by the IT department)] is in charge of the application process and 100 applications were submitted this year.

Evaluation condition: After the initial screening, the coordinator [the algorithm] evaluates each of 100 applications and decides whose applications to accept based on his [its] evaluations. You recently find out that your application is evaluated by the coordinator [algorithm] and one of the people who got accepted (based on his [its] evaluations) is you.

On this website, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] evaluated the applications (including yours) and accepted applications based on his [its] evaluations.

Raffle condition: After the initial screening, the coordinator [algorithm] randomly selects names from 100 applications and decides whose applications to accept based on this raffle. You recently find out that your name is randomly drawn by the coordinator [algorithm] and one of the people who got accepted (based on the raffle) is you.

On this website, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] randomly selected names and accepted applicants based on a raffle.

- Attitude scale: What is your general opinion about Networklink Business Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

Multiple factors might have influenced the decision on your application. For instance, they can be attributed to something about yourself (e.g., your behaviors, personal qualities) as well as something not related to you, such as the way of decision-maker evaluating or interpreting your application. Now please think about the acceptance decision you received. Please read the following questions carefully and indicate the extent to which you think the decision is made based on your personal qualities or behaviors.

- Internal attribution scale: "To what extent do you feel this decision reflects something about yourself?", "To what extent do you feel this decision can be attributed to something about yourself?", "To what extent do you feel this decision is due to your personal qualities or behaviors?" (1 = not at all, 11 = very much)

- Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

- Open-ended question: Any comments?

Additional Analysis with Inattentive Participants

To test the robustness of our findings, we analyzed the data including participants who failed the attention check (N = 501 Prolific workers). First, we conducted a 2 (decision-maker type) x 2 (decision method) ANOVA on participants' attitudes toward the company. We found no main effect of the decision-maker type ($M_{algorithm} = 6.41$, $SD_{algorithm} = 2.60$ vs. $M_{human} = 6.58$, $SD_{human} = 2.76$; $F(1,497) = 2.08$, $p = .15$) but a significant main effect of the decision method ($M_{evaluation} = 7.29$, $SD_{evaluation} = 2.39$ vs. $M_{raffle} = 5.70$, $SD_{raffle} = 2.71$; $F(1, 497) = 50.33$, $p < .001$, $\eta_p^2 = .09$). Importantly, we found a significant interaction effect ($F(1, 497) = 3.78$, $p = .05$, $\eta_p^2 = .01$): when the acceptance decision was based on an evaluation of the applications, attitudes toward the networking community were less positive among participants who were accepted by the algorithm than among participants who were accepted by the club coordinator $M_{algorithm} = 6.94$, $SD_{algorithm} = 2.34$ vs. $M_{human} = 7.72$, $SD_{human} = 2.41$; $F(1, 497) = 5.74$, $p = .02$, $\eta_p^2 = .01$). However, the effect of the decision-maker type was attenuated for participants who were selected based on a raffle ($M_{algorithm} = 5.76$, $SD_{algorithm} = 2.76$ vs. $M_{human} = 5.65$, $SD_{human} = 2.68$; $F < 1$, $p = .72$).

Next, we conducted an analogous ANOVA on attribution. We found a significant main effect of the decision-maker type ($M_{human} = 6.04$, $SD_{human} = 3.21$ vs. $M_{algorithm} = 5.64$, $SD_{algorithm} = 3.01$; $F(1, 497) = 9.59$ $p = .002$, $\eta_p^2 = .02$) and of the decision method ($M_{evaluation} = 7.44$, $SD_{evaluation} = 2.25$ vs. $M_{raffle} = 4.24$, $SD_{raffle} = 3.04$; $F(1, 497) = 190.35$, $p < .001$, η_p^2

$= .28$). Importantly, we again found a significant interaction effect ($F(1, 497) = 5.01$, $p = .03$, $\eta_p^2 = .01$). When the decision was based on an evaluation of the applications, the internal attribution of the acceptance was weaker among participants who were selected by the algorithm than among participants who were selected by the club coordinator ($M_{algorithm} = 6.87$, $SD_{algorithm} = 2.34$ vs. $M_{human} = 8.14$, $SD_{human} = 1.94$; $F(1, 497) = 14.24$, $p < .001$, $\eta_p^2 = .03$). However, the effect of decision-maker type on internal attribution was significantly attenuated for participants who were selected based on a raffle ($M_{algorithm} = 4.13$, $SD_{algorithm} = 3.06$ vs. $M_{human} = 4.33$, $SD_{human} = 3.03$; $F < 1$, $p = .54$).

Finally, we conducted a moderated mediation analysis (Process Model 8, 10,000 bootstrapped samples; Hayes 2013) with participants' attitudes toward the company as the dependent variable, the decision-maker type (-1 = algorithm, 1 = human) as the independent variable, and decision method (-1 = raffle, 1 = evaluation) as the moderator, and internal attribution as the mediator. We found a significant moderated mediation effect (moderated mediation index = .22, 95% CI [.0343, .4358]): when the decision was self-diagnostic (such that the decision was based on evaluation and thus participants were motivated and able to internally attribute the favorable outcome), the indirect effect through internal attribution was significant (B = .27, 95% CI [.1480, .3994]), suggesting that the more positive reaction to the company after receiving a decision from the algorithm (vs. human) was driven by the stronger internal attribution of the favorable decision. When the decision was not self-diagnostic (such that the decision was based on a raffle and thus participants were not able to internally attribute the favorable outcome), however, the indirect effect was not significant (B = .0431, 95% CI [-.1195, .2057]).

Appendix 1J: Scenario and Items Used in Study 6

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by an IT company)] reviews each application and decides whose application to reject.

You recently find out that the coordinator [algorithm] reviewed 100 applications and one of the people that the coordinator [algorithm] decided to reject is you.

Measures

- Perceived objectivity of the decision-maker: To what extent do you think this club coordinator [algorithm] [made an unbiased assessment of your application/ made an unemotional assessment of your application/ assessed your application rationally]? (1 = not at all, 11 = very much)

- Uniqueness consideration scale: To what extent do you think this club coordinator [algorithm] [recognized the uniqueness of your application/ considered the unique aspects of your application/ tailored the decision to your unique case]? (1 = not at all, 11 = very much)

- Attitude scale: On this website, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours. What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

- Open-ended question: Any comments?

<u>Appendix 1K: Scenario and Items Used in Study 7</u>

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member.

Human and algorithm conditions: In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by an IT company)] reviews each application and decides whose application to accept [reject]. You recently find out that the coordinator [algorithm] reviewed 100 applications and one of the people that the coordinator [algorithm] decided to accept [reject] is you.

As a reminder, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours.

Human monitoring algorithm condition: In this country club, the country club coordinator (an employee who is specialized in this area) runs the country club algorithm (that is designed by an IT company) and monitors the review process when the algorithm reviews each application and decides whose application to accept [reject]. You recently find out that the algorithm reviewed 100 applications and one of the people that the algorithm decided to accept [reject] is you.

As a reminder, the algorithm (that is developed by the IT department) reviewed the applications, including yours and the coordinator (an employee who is specialized in this area) monitored the review process.

Measures

- **Attitude scale:** What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

- **Active member** (0 = no, 1 = yes)

- **Age**

- **Gender** (0 = male, 1 = female)

-**Open-ended question:** Any comments?

<u>Appendix 1L: Scenario and Items Used in Study 8</u>

Pretest

Scenario and Measures

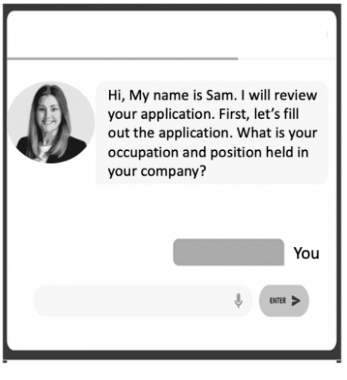
Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), demographics questions (e.g., age, gender, the neighborhood you live in), as well as a few questions about the reason you want to be a member.

Algorithm condition: In this country club, the country club algorithm reviews each application and decides whose application to accept. The image below is an example of how the application progress works. Now, we have a few questions about what you think about the country club algorithm.

Human-like algorithm condition: In this country club, Sam (the country club algorithm) reviews each application and decides whose application to accept. The image below is an example of how the application progress works. Now, we have a few questions about what you think about Sam.



- Humanization index: To what extent do you think that the country club algorithm [Sam] has some humanlike qualities?, To what extent do you think the country club algorithm [Sam] seems like a person? (1 = not at all, 7 = very much).

- Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer / other)

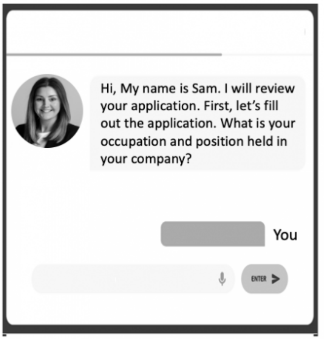
Main Experiment

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

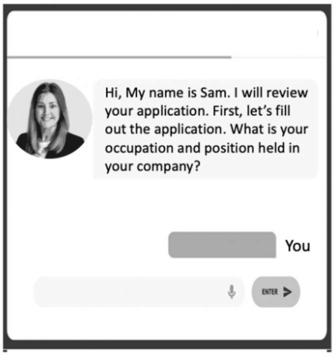
This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), demographics questions (e.g., age, gender, the neighborhood you live in), as well as a few questions about the reason you want to be a member.

Human condition: In this country club, Sam (the country club coordinator) reviews each application and decides whose application to accept. The image below is an example of how the application progress works.



Algorithm condition: In this country club, the country club algorithm reviews each application and decides whose application to accept. The image below is an example of how the application progress works.

Human-like algorithm condition: In this country club, Sam (the country club algorithm) reviews each application and decides whose application to accept. The image below is an example of how the application progress works.



Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), the demographics questions (e.g., your age, the neighborhood you live in), as well as the questions about the reason you want to be a member.

Human condition: You recently find out that Sam reviewed 100 applications and one of the people that Sam decided to accept is you.

Algorithm condition: You recently find out that the club algorithm reviewed 100 applications and one of the people that it decided to accept is you.

Human-like algorithm condition: You recently find out that Sam reviewed 100 applications and one of the people that Sam decided to accept is you.

Measures

- Attitude scale: What is your general opinion about Violethall Country Club? (1 = dislike a great deal / very negative / not favorable at all, 11 = like a great deal / very positive / very favorable)

-Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer / other)

Appendix 1M: Further Information About the Secondary Field Data and Additional Analyses

We obtained a secondary field dataset from a company that leverages algorithms to assess consumers' financial situations and help them improve their financial health. The data was collected for about two weeks among Mexican consumers, with all materials in Spanish.

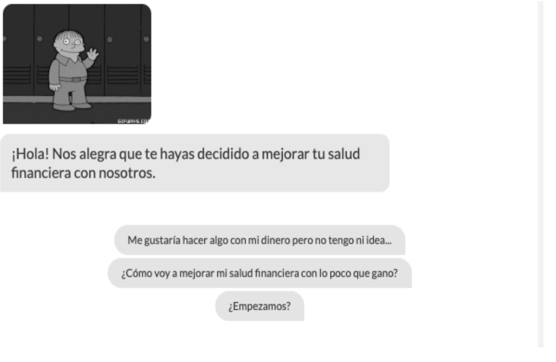
Method

The company used two different algorithmic interfaces in the campaign: a human-like chat format in which the interactive interface used emotionally expressive cues such as emojis (see Figure 1) and a standard form format in which consumers answered questions without interacting with the algorithm. Once a consumer answered all the questions, the company provided a diagnosis of the consumer's financial health. The company offered one of three diagnoses: highly favorable (good financial health with just a routine check-up recommended), moderately favorable (good financial health with a consultation needed to stay healthy), and highly unfavorable (bad financial health with an intervention needed). After getting the feedback, consumers could click on a link to learn more about the company's services for improving their financial health. Our dependent variable was the click-through rate (CTR), a measure of consumers' willingness to initiate a relationship with the company and a behavioral consequence of a positive evaluation of the company.

Appendix 1M. Table 1. Click-Through Rate (Number of Clicks / Number of Impressions) By Algorithm Type and Decision Outcome Favorability

	Highly Favorable Diagnosis	Moderately Favorable Diagnosis	Highly Unfavorable Diagnosis
Human-like Algorithm	230/251	224/241	66/73
Non-human-like Algorithm	63/141	75/154	32/49
Total N = 690/909	293/392	299/395	98/122

Appendix 1M Figure 1. Illustration of the Human-like Algorithmic Interface



Results

A total of 909 consumers completed the financial assessment, received feedback, and were presented with the link for information about the company's services.[9]

To examine the external validity of study 8, we first focused on consumers who received highly favorable feedback (N = 392). Specifically, we compared the CTR between the human-like and non-human-like conditions, which resemble the human-like-algorithm and algorithm conditions, respectively, in study 8. Replicating the findings of study 8,

[9] Although the company randomly assigned consumers to one of the two interfaces, we observed more impressions in the human-like (vs. non-human-like) algorithm treatment, which is partly explained by different attrition rates (non-human-like algorithm: 43.67% vs. human-like algorithm: 58.90%; $\chi^2 = 41.74$, df = 1, $p < .001$).

consumers were more likely to seek information about the company's services when the favorable assessment of their financial health was made by a human-like algorithm than by a non-human-like algorithm ($M_{human\text{-}like\text{-}algorithm}$ = 91.6% vs. $M_{algorithm}$ = 44.7%; χ^2 = 105.44, df = 1, p < .001).

Although we have demonstrated that the decision-maker type—specifically, an algorithm vs. a human—affects consumers' reactions as a function of decision outcome favorability (favorable vs. unfavorable), it remains an empirical question whether this interaction effect extends to different types of algorithms (i.e., human-like vs. non-human-like). To test this, we regressed the CTR on diagnosis outcome favorability (-1 = highly unfavorable, 1 = highly favorable), the algorithm type (-1 = non-human-like, 1 = human-like), and their interaction. Note that we used these two comparison conditions (highly favorable vs. highly unfavorable) in our analysis as it directly resembles to the levels of our decision outcome favorability factor. We observed a significant effect of the algorithm type (B = 1.05, z = 7.36, p < .001), which was qualified by a marginal interaction effect (B = .25, z = 1.74, p = .08): the CTR was higher among consumers who received a highly favorable diagnosis from a human-like algorithm than among consumers who received a highly favorable diagnosis from a non-human-like algorithm ($M_{human\text{-}like\text{-}algorithm}$ = 91.6% vs. $M_{algorithm}$ = 44.7%; B = 1.30, z = 9.18, p < .001). The algorithm type had a smaller (though still significant) effect among consumers who received a highly unfavorable diagnosis ($M_{human\text{-}like\text{-}algorithm}$ = 90.4% vs. $M_{algorithm}$ = 65.3%; B = .81, z = 3.23, p = .001).

In addition, we conducted a supplementary analysis including the third diagnosis type, moderately favorable. We combined the consumers who received a favorable diagnosis (highly or moderately favorable) and compared them with the consumers who received a highly unfavorable diagnosis. A regression revealed a significant effect of the algorithm type

(B = 1.06, z = 7.83, p < .001), which was qualified by a marginal interaction effect (B = .25, z = 1.85, p = .06): the CTR was higher among consumers who received a favorable diagnosis from a human-like algorithm than among consumers who received a favorable diagnosis from a non-human-like algorithm ($M_{human\text{-}like\text{-}algorithm}$ = 92.3% vs. $M_{algorithm}$ = 46.8%; B = 1.30, z = 12.71, p < .001). The algorithm type had a smaller (though still significant) effect among consumers who received a highly unfavorable diagnosis ($M_{human\text{-}like\text{-}algorithm}$ = 90.4% vs. $M_{algorithm}$ = 65.3%; B = .81, z = 3.23, p = .001).

Appendix 1N: Study Materials and Analysis of the Follow-Up Study (Fairness)

Scenario

Imagine that you decide to sign up to a country club. The country club that you are considering is an exclusive and selective social network: Violethall Country Club.

VIOLETHALL COUNTRY CLUB

This exclusive country club requires potential members to fill out an application form. The application form includes a photo of you (in which your face is visibly seen), several demographics questions (e.g., age, gender, the neighborhood you live in), questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member. Now imagine that you filled out the application form and submitted it to the country club's website. You took a photo in which your face is visibly seen, you answered the demographics questions (e.g., your age, the neighborhood you live in), the questions about yourself (e.g., your occupation, the position you hold in a company, your other social network memberships), as well as a few questions about the reason you want to be a member.

In this country club, the country club coordinator (an employee who is specialized in this area) [the country club algorithm (that is designed by the IT department)] reviews each application and decides whose application to accept [reject]. You recently find out that the coordinator [algorithm] reviewed 100 applications and one of the people that the coordinator [algorithm] decided to accept [reject] is you.

As a reminder, the coordinator (an employee who is specialized in this area) [the algorithm (that is developed by the IT department)] reviewed the applications, including yours.

Measures

- Perceived fairness: How fair do you think this decision made on your application for Violethall Country Club is? (1 = not at all, 7 = very much)

- Active member: Are you currently an active member of a country club/private social network? (1 = yes, 0 = no)

- Age

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

- Open-ended question: Any comments?

Method and Results

We randomly assigned 321 Prolific workers (M_{age} = 33.47, 190 females) to one of four conditions in a 2 (decision-maker type: algorithm vs. human) x 2 (decision outcome favorability: favorable vs. unfavorable) between-participants design. Participants read that they were to apply for membership at a country club, Violethall Country Club. Depending on the condition, we told participants that their application was accepted or rejected either by an algorithm (i.e., country club algorithm) or by a human (i.e., country club coordinator). Next, participants assessed perceived fairness of the decision ("How fair do you think this decision made on your application for Violethall Country Club is?"; 1 = not at all, 7 = very much).

A 2 (decision-maker type) x 2 (decision outcome favorability) revealed a significant main effect of the decision-maker type ($M_{algorithm} = 3.28$, $SD_{algorithm} = 1.57$ vs. $M_{human} = 4.12$, $SD_{human} = 1.55$; $F(1, 317) = 23.63$, $p < .001$, $\eta_p^2 = .07$) and of decision outcome favorability ($M_{favorable} = 4.10$, $SD_{favorable} = 1.48$ vs. $M_{unfavorable} = 3.29$, $SD_{unfavorable} = 1.64$; $F(1, 317) = 21.73$, $p < .001$, $\eta_p^2 = .06$). There was no significant interaction between decision-maker type and decision outcome favorability ($F(1, 317) < 1$, $p = .58$).

Appendix 1O: Analysis of the Exploratory Measures Used in Our Studies

Study	**Exploratory Measure**	**Results**
Study 3a	Are you currently an active member of a country club/private social network? (0 = no, 1 = yes)	Participants with different membership status (active vs. not) were randomly assigned to conditions (*p* > .367).
Study 7	Are you currently an active member of a country club/private social network? (0 = no, 1 = yes)	Participants with different membership status (active vs. not) were randomly assigned to conditions (*p* > .193).
Follow-up fairness study	Are you currently an active member of a country club/private social network? (0 = no, 1 = yes)	Participants with different membership status (active vs. not) were randomly assigned to conditions (*p* > .279).

Appendix 2: Additional Materials for Chapter 3

Appendix 2A: Materials and Additional Analyses for Study 1a

Scenario

Welcome to our study! This survey is being conducted by a group of researchers and has been approved by the Internal Review Board. This study is strictly anonymous. Please answer all questions as accurately and as honestly as possible. When filling out the survey, do not forget to only select one answer option (circle) per question.

When choosing a new coffee-based drink to try out, there are many flavors, roasts, sensations to consider. The possibilities can be overwhelming, and it is hard to decide on a tasty coffee-based drink. We would like to introduce to you a new start-up called Bean Me Up.

BEAN ME UP

Bean Me Up provides an easy-to-use platform which offers customized recommendations with respect to coffee-based drinks. The start-up company aims to find the tastiest and the most enjoyable coffee-based drinks for customers.

A coffee algorithm [expert] helps users find the tastiest coffee drinks. This algorithm is a computer model that is designed to find the tastiest and most enjoyable coffee-based drink for customers [This expert is an experienced coffee drinker who is specialized in finding the tastiest and most enjoyable coffee-based drink for customers]. To come up with a tasty coffee-based drink, this algorithm [expert] requires users to answer a couple of questions. Some of these questions are listed below:

- What sensation do you like on your palate? (please describe vividly)

- What flavors are you most drawn to?

- Can you provide any details that you find relevant for your coffee preferences?

Based on the answers to these questions, the coffee algorithm [expert] will come up with a tasty coffee-based drink recommendation for you.

Measures

- Subjective Knowledge: First, we would like to ask you how frequently you consume different coffee-based drinks (1 = I drink different coffee-based drinks very infrequently to 11 = I drink different coffee-based drinks very frequently)

- Willingness to Use the Service (WTU): Please read the question below and then select the response that applies to you the most. How likely would you be to use this service to receive a recommendation for the tastiest and most enjoyable coffee-based drink from a coffee algorithm[expert]? (1 = not at all likely to 11 = very likely)

- Type of benefits: When consumers employ recommendation services, there are typically two main objectives at play: (i) they want to understand the process of why and how a recommender recommends a specific option to them and (ii) they want the recommender to provide them with knowledge that they might not possess. Importantly, these objectives are not equally important, but consumers typically give more weight to one or the other. Now think about the service you read about and the coffee expert it utilizes to provide tasty coffee recommendations. Before you answer the next question, please make sure that you understand the difference between these two types of benefits. Please consider whether the service you read about is better at providing you with process-related benefits (left side of the scale) or outcome-related benefits (right side of the scale; 1 = process-related benefits to 11 = outcome-related benefits)

- **Age** (open-ended)

- **Gender** (0 = male, 1 = female, 2 = prefer not to answer)

Additional Analysis

- Testing for an alternative account (type of benefit): One might argue that participants can perceive different types of benefits (process vs. outcome) depending on their subjective knowledge in a focal domain and the recommender type. Study 1a included a measure to test this possibility. We ran a linear regression with recommender type (algorithm = -1, human expert = 1), participants' subjective knowledge (mean-centered), their interaction as predictor variables, and type of benefit as the dependent variable. This analysis revealed a non-significant main effect of recommender type ($\beta = .08$, $t(260) = 1.23$, $p = .22$), and a significant main effect of subjective knowledge ($\beta = .13$, $t(260) = 2.19$, $p = .03$) such that participants with high subjective knowledge reported that the service is better at providing them with outcome (vs. process) related benefits. Importantly, we did not find a significant interaction effect ($\beta = .04$, $t(260) = .59$, $p = .56$), which refutes the alternative explanation that differences in perceived benefits could explain our results.

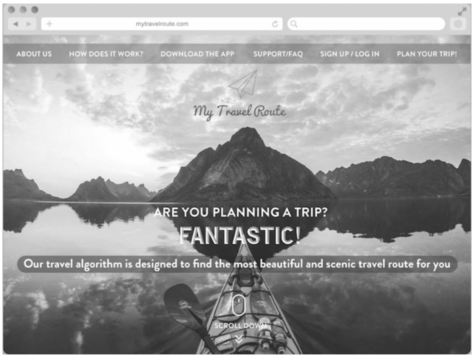
Appendix 2B: Materials and Additional Analyses for Study 1b

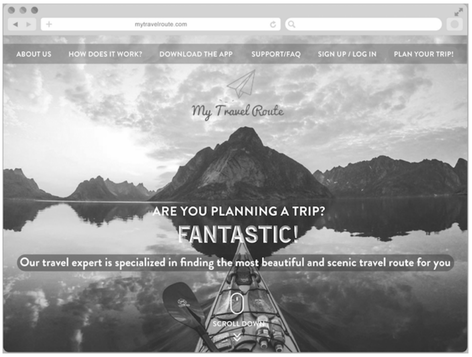
Scenario and Measures

Welcome to our study! This survey is being conducted by a group of researchers and has been approved by the Internal Review Board. This study is strictly anonymous. Please answer all questions as accurately and as honestly as possible. When filling out the survey, please only select one answer option (circle) per question.

Please imagine that you are planning a trip to Canada. When planning a trip to another country, there are many different cities, sights and highlights to visit and see. Therefore, the possibilities can be overwhelming, and it is hard to decide on a travel route. Considering your travel plans to Canada, you could use some help planning your trip. We would like to introduce to you a new start-up called *MyTravelRoute*.

This start-up company provides an easy-to-use website which offers customized recommendations with respect to travel route plans. A travel algorithm [expert] helps users find the most beautiful travel route. The algorithm is designed to find the most beautiful and scenic route for customers [The expert is specialized in finding the most beautiful and scenic route for customers]. For instance, in your specific case, this algorithm comes up with the most beautiful and scenic travel route through Canada. Below is an illustration of the user interface of the website.





To come up with a travel route, this algorithm [expert] requires users to answer a couple of questions. Users need to provide answers to these questions to be able to use this service. For instance, when choosing to visit Canada, users have to answer questions like the ones listed below:

- What is the maximum & minimum number of cities you want to visit?

- What is the spirit that you want your trip to have?

- Can you provide any details that you find relevant for your trip?

Measures

- Subjective Knowledge: This study is about traveling. Even though your possibility to travel at the moment is affected by COVID-19, please imagine a time when you could freely travel as you wish (e.g., before the COVID-19 crisis), and indicate how frequently you travel (under normal circumstances; 1 = not at all frequently to 9 = very frequently)

- Willingness to Use the Service (WTU): How likely would you be to use this service to receive a recommendation for the most beautiful and scenic route from a travel algorithm [expert]? (1 = not at all likely to 11 = very likely)

- Type of benefits: When consumers employ recommendation services, there are typically two main objectives at play: (i) they want to understand the process of why and how a recommender recommends a specific option to them and (ii) they want the recommender to provide them with knowledge that they might not possess. Importantly, these objectives are not equally important, but consumers typically give more weight to one or the other. Now think about the service you read about and the coffee expert it utilizes to provide tasty coffee recommendations. Before you answer the next question, please make sure that you understand the difference between these two types of benefits. Please consider whether the service you read about is better at providing you with process-related benefits (left side of the scale) or outcome-related benefits (right side of the scale; 1 = process-related benefits to 11 = outcome-related benefits).

- **Covariate:** I would very much like to do a road trip through Canada (1 = strongly disagree to 7 = strongly agree)

- **Visiting Canada:** I have visited Canada multiple times before (1 = strongly disagree to 7 = strongly agree)

- **Difficulty in imagining:** It was very difficult for me to imagine a time when I could travel freely (e.g., before COVID-19; 1 = strongly disagree to 7 = strongly agree).-

- Age (open-ended)

- **Gender** (0 = male, 1 = female, 2 = prefer not to answer)

Additional Analyses

- Results of the linear regression with the covariate: Our main analysis was run without a covariate. To make sure that our results are not affected by how much participants would like to visit Canada (as this could increase their WTU the service regardless of the recommender type), we conducted another a linear regression with recommender type (algorithm = -1, human expert = 1), subjective knowledge (mean-centered), and their interaction as predictor variables, how much participants would like to visit Canada as covariate, and WTU the service as the dependent variable. This analysis revealed a marginally significant main effect of recommender type (β = -.10, t(295) = -1.83, p = .07), a significant main effect of subjective knowledge (β = .19, t(295) = 3.36, p = .001), and a significant main effect of the covariate (β = .15, t(295) = 2.71, p = .007). In line with the results that we report in the manuscript, we found a significant interaction effect between recommender type and subjective knowledge (β = -.15, t(295) = -2.60, p = .01).

- Testing for an alternative account (type of benefit): As in study 1a, we included a measure to test whether there is an interaction effect between recommender type and subjective knowledge on the type of benefits that participants expect from the service. A linear regression with recommender type (algorithm = -1, human expert = 1), subjective knowledge (mean-centered), their interaction as predictor variables, and type of benefit as the dependent variable revealed a significant main effect of recommender type (β = .12, t(296) = 2.21, p = .03) and of subjective knowledge (β = .19, t(296) = 3.32, p = .001).

Interestingly, the interaction effect between recommender type and subjective knowledge was also significant (β = -.16, t(296) = -2.78, p = .006) this time. Looking at participants with low subjective knowledge showed greater valuation for process-based benefits when provided by human experts (vs. algorithms) whereas this positive valuation was mitigated for participants with high subjective knowledge. Note that this pattern of the interaction effect only emerged in this study but not in study 1a. Further, note that the significant effect was driven by participants with low subjective knowledge whereas there was no effect for participants with high subjective knowledge; thus, this alternative account cannot explain the effect that we document for participants with high subjective knowledge. We leave it to future research to investigate why participants with low subjective knowledge in a focal domain particularly value process-related benefits when the recommender is a human expert.

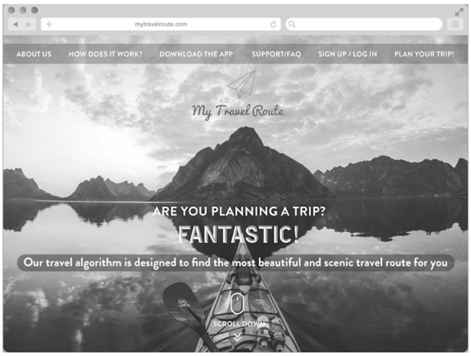
-None of the exploratory measures we included in this study changed the results or the pattern we reported.

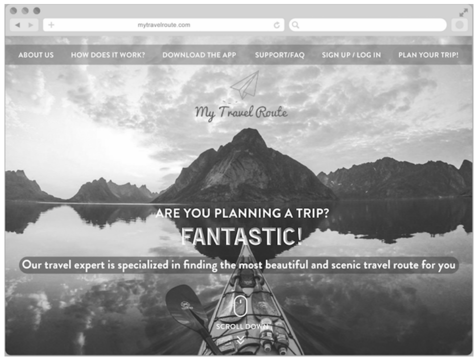
Appendix 2C: Materials and Results of the Follow-Up Study

Scenario

This study focuses on traveling. Please imagine that you are planning a trip to the United States. When planning a trip to another country, there are many different cities, states, sights and highlights to visit and see. Therefore, the possibilities can be overwhelming and it is hard to decide on a travel route. Considering your upcoming travel plans, you could use some help planning your trip to the United States. We would like to introduce to you a new start-up called *MyTravelRoute*.

This start-up company provides an easy-to-use website which offers customized recommendations with respect to travel route plans. A travel algorithm [expert] helps users find the most beautiful travel route. The algorithm is designed to find [the expert is specialized in finding the most beautiful and scenic route for his customers]. For instance, in your specific case, this algorithm [expert] comes up with the most beautiful and scenic travel route through the United States. On the next page, you will see the user interface of the website.





To come up with a travel route, this algorithm (recommendation system) [expert] requires its users to answer a couple of questions. Users need to provide answers to these questions to be able to use this service. For instance, when choosing to visit the United States, users have to answer questions like the ones listed below.

- What is the maximum & minimum number of states/cities you want to visit?
- What is the spirit that you want your trip to have?
- Can you provide any details that you find relevant for your trip?

Based on the answers to these questions, the algorithm [expert] will come up with the most beautiful and scenic route for you.

Measures

- Behavioral DV: "In cooperation with the start-up *MyTravelRoute*, we would like to offer you the possibility to get further information on this service. You can now sign up to get further information by filling out your email address. Please note that your contact address will be kept confidential. You can continue with the next page if you do not want to get further information on this service."

- Secondary DV (WTU): "How likely would you be to use this service, which uses a travel expert to recommend the most beautiful and scenic travel route?" (1 = not at all likely to 11 = very likely)

- Perceived capability: "To what extent do you think that the travel algorithm [expert] has enough information to find the most beautiful and scenic travel route for you? (1 = not at all to 7 = very much)

- Perceived customization: a = .67; 1 = strongly disagree to 7 = strongly agree

- "The travel route recommendation that I get will be targeted towards me"
- "The travel route recommendation that I get will be made for me"
- "This recommender would give the same recommendation also to others" (reverse-coded)

- **Subjective knowledge:** "How frequently do you travel?" (1 = I do not travel at all to 11 = I travel all the time)

- **Covariate:** "I would very much like to do a road trip through the United States." (1 = strongly disagree to 7 = strongly agree)

- **Age** (open-ended)

- **Gender** (0 = male, 1 = female)

Participants and Procedure

One hundred and eighty-one undergraduates (M_{age} = 20.61, 83 females) participated in a lab experiment at a major European university in exchange for extra course credits. Participants were provided with information about *MyTravelRoute* and randomly assigned to the algorithm or human expert condition. Unlike previous studies, we informed participants that we are collaborating with *MyTravelRoute* and that they had the opportunity to receive further information on the service by signing up with their email addresses. Our main dependent variable was whether participants signed up for the service. As a secondary outcome measure, we asked participants to indicate their WTU such service (1 = not at all likely to 11 = very likely). Finally, they filled out how frequently they travel (1 = I do not travel at all to 9 = I travel all the time). Note that our recommender type manipulation did not significantly influence this measure (p = .29).

Results

Seven participants were excluded from the analysis since they did not follow the instructions and/or computer-related problems occurred, leaving us with 174 participants. We ran a logistic regression with recommender type (algorithm = -1, human expert = 1), subjective knowledge (mean-centered), their interaction, and how much participants would like to visit the United States as (i.e., covariate) as predictor variables and signing up for the service (0 = did not provide an email address, 1 = provided an email address) as the dependent measure. We neither observed a significant main effect of recommender type (b = -.06, Wald test = .14, p = .71, odd ratio = .94) nor a main effect of subjective knowledge (b = -.06, Wald test = .17, p = .68, odd ratio = .94) but a significant interaction effect between recommender type and subjective knowledge (b = -.34, Wald test = 5.61, p = .02, odd ratio = .71). Floodlight analysis highlighted the region of significance for subjective knowledge as the values equal to or lower than 4.17 (human expert > algorithm) and equal to or higher than 7.66 (algorithm > human expert). Finally, we replicated the interaction effect when utilizing participants' WTU as the dependent variable ($\beta = -.17$, $t(169) = -2.34$, $p = .02$) and the floodlight analysis highlighted the region of significance for subjective knowledge as the values equal to or lower than 2.78 (human expert > algorithm) and equal to or higher than 7.33 (algorithm > human expert). Note that including the seven participants that were excluded from the analyses did not change the pattern of our focal interaction effect for neither the behavioral measure ($p = .05$) nor WTU ($p = .03$).

None of the exploratory measures we included in this study changed the results or the pattern we reported.

<u>Appendix 2D: Materials for Study 2</u>

Scenario and Measures

In this study, we would like to know about your experiences with different types of beverages. Please read the questions carefully.

- High Subjective Knowledge: Below, you see various types of beverages. We would like to know which beverage you consume and know a lot about. If you consume and know a lot about several of these beverages, please select the one that you know about the most (1 = coffee, 2 = tea, 3 = beer, 4 = wine, 5 = juice, 6 = cocktail).

- Low Subjective Knowledge: Now, we would like to know which beverage you consume but know only little about. If there are several beverages that you consume and know little about, please select the one about which you know the least (1 = coffee, 2 = tea, 3 = beer, 4 = wine, 5 = juice, 6 = cocktail).

We asked you to select a beverage that you consume and know a lot about and you picked [insert selected beverage]. Now, we would like to learn more about your opinions about this beverage. Nowadays, companies use algorithms (i.e., sophisticated statistical softwares that are specialized in recommending [insert selected beverage]) to provide their customers with recommendations. To get a recommendation, customers answer several questions. The algorithm then analyzes these answers and comes up with a personalized recommendation for the customer.

- WTU_High: How likely would you be to get a [insert selected beverage]) recommendation from this algorithm? (1 = not at all likely to 9 = very likely)

Now we are moving to the beverage that you indicated that you know little about. We asked you a beverage that you consume but know little about and you picked [insert selected beverage]. Now, we would like to learn more about your opinions about this beverage. Nowadays, companies use algorithms (i.e., sophisticated statistical softwares that are specialized in recommending [insert selected beverage]) to provide their customers with recommendations. To get a recommendation, customers answer several questions. The algorithm then analyzes these answers, and comes up with a personalized recommendation for the customer.

- WTU_Low: How likely would you be to get a [insert selected beverage]) recommendation from this algorithm? (1 = not at all likely to 9 = very likely)

- **Age** (open-ended)

- **Gender** (0 = male, 1 = female, 2 = other or prefer not to answer)

<u>Appendix 2E: Materials and Additional Analyses for Study 3a</u>

False Feedback Manipulation

- High Subjective Knowledge: People on average lists N-2 coffee drinks. This means your score is actually very good! You probably drink different types of coffee frequently and definitely have very good knowledge about a variety of coffee drinks that exist.

- Low Subjective Knowledge: People on average lists N+2 coffee drinks. This means your score is actually below average! You probably do not drink different types of coffee frequently and do not have very good knowledge about a variety of coffee drinks that exist.

Scenario

Welcome to our study! This survey is being conducted by a group of researchers and has been approved by the Internal Review Board. This study is strictly anonymous. Please answer all questions as accurately and as honestly as possible. When choosing a coffee drink, there are many flavors, roasts, sensations to consider. The possibilities can be overwhelming, and it is hard to decide on a tasty coffee drink. We would like to introduce to you a new start-up called *Bean Me Up*.

BEAN ME UP

This start-up company provides an easy-to-use website which offers customized recommendations with respect to tasty coffee drinks. A coffee algorithm [expert] helps users find the tastiest coffee drinks. The algorithm is designed to find [expert is specialized in finding] the tastiest and most enjoyable coffee drink for customers.

To come up with a tasty coffee drink, this algorithm [expert]requires the users to answer a couple of questions. Users need to provide answers to these questions to be able to use this service. Some of these questions are listed below:

- What sensation do you like on your palate? (please describe vividly)
- What flavors are you most drawn to?
- Can you provide any details that you find relevant for your coffee preferences?

Based on the answers to these questions, the algorithm [expert] will come up with a tasty coffee drink recommendation for you.

Measures

- WTU: "Please read the question below and then select the response that applies to you the most. How likely would you be to use this service, which uses a coffee algorithm [expert] to recommend the tastiest and most enjoyable coffee drink for customers?" (1 = not at all likely to 11 = very likely)

- General liking of coffee: "How much do you like coffee-based drinks?" (1 = not at all to 11 = very much)

- General frequency of drinking coffee: "How often do you drink coffee-based drinks?" (1 = not at all often to 11 = very often)

- Manipulation check: "Compared to an average person, how much do you think you know about coffee-based drinks?" (1 = not at all to 11 = very much), "I was told that my knowledge about coffee-based drinks is ___” (1 = below an average person to 11 = above an average person)

- **Age** (open-ended)

- **Gender** (0 = male, 1 = female, 2 = prefer not to say)

None of the exploratory measures we included in this study changed the results or the pattern we reported.

Appendix 2F: Materials and Additional Analyses for Study 3b

Scenario and Measures

- **Attention check:** For the success of this study, it is of utmost importance that you read all instructions carefully. Thus, we may check whether you actually pay attention. In this study, there will be a series of questionnaires. It is important that you pay attention to all the questions, otherwise we cannot interpret your answers. To make sure that you read the instructions, please write the word "blue" in the box below, and please ignore the question at the end of this paragraph. Thank you very much for your cooperation. In which country do you live? (open-ended)

This study consists of two parts: Part I and Part II. Now, please click on next (>>>) to start Part I.

This study is about workout activities. With workout activities, we mean a range of activities that people engage in to work out. These activities can be performed indoors (e.g., at home) or outdoors (e.g, at a park). Some examples include but are not limited to running, weight lifting, pilates, push-ups, squats.

Now, we would like to get to know more about your experience with workout activities (e.g., strength-training, cardio activities, push-ups, squats). Please think about a specific workout activity that you engage in and feel very knowledgeable about [do not feel knowledgeable about]. Write the name of this workout activity below. Note: the workout activity that you choose does not have to be one of the examples; feel free to pick any workout activity as long as you engage in and feel knowledgeable about [do not feel knowledgeable about].

- Selected activity: Please type ONLY the name of the workout activity in the text box below.

We asked you to name a workout activity that you feel very knowledgeable about [that you do not feel knowledgeable about] and your answer was [insert mentioned activity]. Now, we would like to get to know more about your experience with this workout activity.

Please think about a specific time that you were engaging in this particular workout activity and felt very good about your knowledge about it [did not feel good about your knowledge about it]. For instance, this might be a time that you considered yourself to be good at this activity] you considered yourself not to be good at this activity]. Take the next 30 seconds to reflect on how knowledgeable you felt at that time. Try to relive that moment as much as you can and carry those reflections with you to this moment. Note that you will be asked to write the details of your reflections on the next page.

- Essay writing: Please spend the next three minutes writing about this workout activity and the time that you felt knowledgeable [unknowledgeable] about it. Please try to relive that moment as much as you can and be detailed in your elaboration. You will be able to continue with the survey after three minutes have passed.

Thank you for your answer! You are now moving to Part II of the study on workout activities. Please click on next (>>>) to start Part II.

When choosing a workout activity, there are many factors to consider. One important factor is how much fun the workout activity is as it affects to what extent you stick to your plan.

When choosing fun workout activities that you can perform, the possibilities can be overwhelming, and it is hard to find activities that you find fun and exciting. We would like to introduce you to a new virtual workout platform called *Next Level.*

NEXT LEVEL

This service provides an easy-to-use virtual platform which offers customized recommendations for fun workout activities. A workout algorithm [expert] helps users find workout activities that are not boring. On the next page, you will get more information about the workout algorithm [expert].

First, users are asked to choose a workout category from a list of different workout categories (e.g., cardio, flexibility-enhancing activities, muscle-strengthening activities). Then, the workout algorithm [expert] requires users to answer a couple of questions to come up with a fun workout recommendation for them. Users need to provide answers to these questions to be able to use this service. Some of these questions are listed below:

- What are your workout goals?
- What is the level of intensity you enjoy? (e.g., low, high)
- What do you like about being active?
- Can you provide any other details regarding your preferences when working out?

Based on the answers to these questions, the algorithm [expert] will come up with a fun workout recommendation for each user.

- WTU: How likely would you be to use this virtual platform to receive a recommendation for fun workout activities from a workout algorithm [expert]? (1 = not at all likely to 11 = very likely)

- Uniqueness Considerations: Please read the statements below and indicate the extent to which you agree/disagree with them (1 = strongly disagree to 7 = strongly agree).

- I think this recommender would recognize the uniqueness of my case.
- I think this recommender would consider my unique circumstances.
- I think this recommender would tailor the recommendation to my unique case.

- Manipulation Check: After writing about the time I had reflected on, I feel knowledgeable about workout activities (1 = strongly disagree to 9 = strongly agree).

- Difficulty in reflecting: It was difficult for me to reflect on a workout activity that I am knowledgeable [unknowledgeable] about (1 = strongly disagree to 7 = strongly agree).

- Age (open-ended)

- Gender (0 = male, 1 = female, 2 = prefer not to say)

Additional Analyses

- In our main analysis, we did not exclude participants. Note that our results and the pattern we reported held when the main analysis was run without participants who failed the attention check (N = 374) or the participants who failed the attention and comprehension checks (N = 310).

- Note: In this study significantly more people in the expert condition (as compared to the algorithm condition) failed the comprehension check (pearson chi-square: 21, $p < .001$), whereas the likelihood of failing the comprehension check was independent of condition in some other studies.

-**Uniqueness Considerations:** To test whether our results are explained by perceived uniqueness considerations of the recommender type, we included a measure in this study (see above). We ran a 2 (recommender type) x 2 (subjective knowledge) ANOVA. This analysis revealed neither a significant main effect of recommender type ($F(1, 597) = .51$, p

= .47), nor a significant main effect of subjective knowledge ($F(1, 597) = .65$, $p = .42$). Additionally, we did not find a significant interaction effect ($F(1, 597) = .40$, $p = .53$), ruling out the possibility that uniqueness considerations of the decision-maker explains our results.

- None of the exploratory measures we included in this study changed the results or the pattern we reported.

Appendix 2G: Materials and Additional Analyses for Study 4a

Scenario and Measures

- Attention check: For the success of this study, it is of utmost importance that you read all instructions carefully. Thus, we may check whether you actually pay attention. In this study, there will be a series of questionnaires. It is important that you pay attention to all the questions, otherwise we cannot interpret your answers. To make sure that you read the instructions, please write the word "green" in the box below, and please ignore the question at the end of this paragraph. Thank you very much for your cooperation. In which country do you live? (open-ended)

This study consists of two parts: Part I and Part II. Now, please click on next (>>>) to start Part I.

This study is about workout activities. With workout activities, we mean a range of activities that people engage in to work out. These activities can be performed indoors (e.g., at home) or outdoors (e.g, at a park). Some examples include but are not limited to running, weight lifting, pilates, push-ups, squats.

Now, we would like to get to know more about your experience with workout activities (e.g., strength-training, cardio activities, push-ups, squats). Please think about a specific workout activity that you engage in and feel very knowledgeable about. Write the name of this workout activity below. Note: the workout activity that you choose does not have to be one of the examples; feel free to pick any workout activity as long as you engage in and feel knowledgeable about.

- **Selected activity:** Please type ONLY the name of the workout activity in the text box below.

We asked you to name a workout activity that you feel very knowledgeable about and your answer was [insert mentioned activity]. Now, we would like to get to know more about your experience with this workout activity.

Please think about a specific time that you were engaging in this particular workout activity and felt very good about your knowledge about it. For instance, this might be a time that you considered yourself to be good at this activity. Take the next 20 seconds to reflect on how knowledgeable you felt at that time. <u>Try to relive that moment as much as you can and carry those reflections with you to this moment</u>. Note that you will be asked to write the details of your reflections on the next page.

- **Essay writing:** Please spend the next two minutes writing about this workout activity and the time that you felt knowledgeable about it. Please try to relive that moment as much as you can and be detailed in your elaboration. You will be able to continue with the survey after two minutes have passed.

Thank you for your answer! You are now moving to Part II of the study on workout activities. Please click on next (>>>) to start Part II.

When choosing a workout activity, there are many factors to consider. One important factor is how much fun the workout activity is as it affects to what extent you stick to your plan. When choosing fun workout activities that you can perform, the possibilities can be overwhelming, and it is hard to find activities that you find fun and exciting. We would like to introduce you to a new virtual workout platform called *Next Level.*

NEXT LEVEL

This platform uses an algorithm to provide their customers with workout recommendations. This algorithm is a sophisticated statistical software that is designed to recommend workout activities [This expert is a workout enthusiast who is specialized in recommending workout activities]. To get a recommendation, customers answer several questions. The algorithm [expert] then analyzes these answers and comes up with a personalized recommendation for the customer.

- WTU: How likely would you be to use this virtual platform to receive a recommendation for fun workout activities from a workout algorithm [expert]? (1 = not at all likely to 11 = very likely)

- Meaningful Collaboration Index (Mediator): Please take a moment to think of the algorithm [expert] who will recommend a fun workout activity to you and then indicate the extent to which you agree/disagree with each of the following statements (1 = strongly disagree to 7 = strongly agree).

- The algorithm [expert] would consult me as the algorithm [expert] and I have similar knowledge with respect to fun workout activities.
- The algorithm [expert] relies on similar strategies to come up with a fun workout activity as I would.
- This algorithm [expert] would collaborate with me because of our similar knowledge/strategies.

- **Subjective Knowledge Check**: After writing about the time, I had reflected on, I feel ____ about workout activities (1 = very unknowledgeable to 9 = very knowledgeable).

- **Perceived Risk**: How risky do you think it is to use this service (for instance, because you might receive a bad recommendation or one that does not match your taste)? (1 = not risky at all to 11 = very risky)

- **Age** (open-ended)

- **Gender** (0 = male, 1 = female, 2 = prefer not to say)

Additional Analyses

- In our main analysis, we did not exclude participants. Note that our results and the pattern we reported held when the main analysis was run without participants who failed the attention check (N = 288) or the participants who failed the attention and comprehension checks (N = 261).

- Note: In this study significantly more people in the expert condition (as compared to the algorithm condition) failed the comprehension check (pearson chi-square = 5.76, p = .02) whereas the likelihood of failing the comprehension check was independent of condition in other studies.

- **Testing for an alternative account (perceived risk)**: One could argue that consumers with high subjective knowledge might value algorithmic recommendations more because they may think that algorithms offer safer (or riskier) options. To test for this alternative account, we measured participants' perception of how safe (vs. risky) the recommendation will be in study 4b (see details on measure above). The result of an ANOVA indicated that there was no significant difference between the algorithm and human expert condition in terms of perceived risk ($F < 1$, $p = .46$), hence ruling out this alternative account.

- None of the exploratory measures we included in this study changed the results or the pattern we reported.

Appendix 2H: Materials and Additional Analyses for Study 4b

Scenario and Measures

- Attention check: For the success of this study, it is of utmost importance that you read all instructions carefully. Thus, we may check whether you actually pay attention. In this study, there will be a series of questionnaires. It is important that you pay attention to all the questions, otherwise we cannot interpret your answers. To make sure that you read the instructions, please write the word "green" in the box below, and please ignore the question at the end of this paragraph. Thank you very much for your cooperation. In which country do you live? (open-ended)

This study consists of two parts: Part I and Part II. Now, please click on next (>>>) to start Part I.

This study is about workout activities. With workout activities, we mean a range of activities that people engage in to work out. These activities can be performed indoors (e.g., at home) or outdoors (e.g, at a park). Some examples include but are not limited to running, weight lifting, pilates, push-ups, squats.

Now, we would like to get to know more about your experience with workout activities (e.g., strength-training, cardio activities, push-ups, squats). Please think about a specific workout activity that you engage in and feel very knowledgeable about. Write the name of this workout activity below. Note: the workout activity that you choose does not have to be one of the examples; feel free to pick any workout activity as long as you engage in and feel knowledgeable about.

- Selected activity: Please type ONLY the name of the workout activity in the text box below.

We asked you to name a workout activity that you feel very knowledgeable about and your answer was [insert mentioned activity]. Now, we would like to get to know more about your experience with this workout activity.

Please think about a specific time that you were engaging in this particular workout activity and felt very good about your knowledge about it. For instance, this might be a time that you considered yourself to be good at this activity. Take the next 20 seconds to reflect on how knowledgeable you felt at that time. Try to relive that moment as much as you can and carry those reflections with you to this moment. Note that you will be asked to write the details of your reflections on the next page.

- Essay writing: Please spend the next two minutes writing about this workout activity and the time that you felt knowledgeable about it. Please try to relive that moment as much as you can and be detailed in your elaboration. You will be able to continue with the survey after two minutes have passed.

Thank you for your answer! You are now moving to Part II of the study on workout activities. Please click on next (>>>) to start Part II.

When choosing a workout activity, there are many factors to consider. One important factor is how much fun the workout activity is as it affects to what extent you stick to your plan. When choosing fun workout activities that you can perform, the possibilities can be overwhelming, and it is hard to find activities that you find fun and exciting. We would like to introduce you to a new virtual workout platform called *Next Level.*

Algorithm condition: We would like to introduce you to a new virtual platform that provides its users with personalized recommendations with respect to workout activities. This platform uses an algorithm to provide their customers with workout recommendations. This algorithm is a sophisticated statistical software that is designed to recommend workout activities.

Human expert condition: We would like to introduce you to a new virtual platform that provides its users with personalized recommendations with respect to workout activities. This platform uses an expert to provide their customers with workout recommendations. This expert is a workout enthusiast who is specialized in recommending workout activities.

Uncollaborative algorithm condition: We would like to introduce you to a new virtual platform that provides its users with personalized recommendations with respect to workout activities.

This platform uses an algorithm to provide their customers with workout recommendations. This algorithm is a sophisticated statistical software that is designed to recommend workout activities. You might think that you can collaborate with this algorithm and jointly find a recommendation for a workout activity. However, the algorithm relies on very different knowledge and strategies than you. This makes collaboration difficult, but outsources the recommendation task fully to the algorithm. To get a recommendation, customers answer several questions. The algorithm then analyzes these answers and comes up with a personalized recommendation for the customer.

- Meaningful Collaboration Index (Manipulation Check): Please take a moment to think of the algorithm [expert] who will recommend a fun workout activity to you and then indicate the extent to which you agree/disagree with each of the following statements (1 = strongly disagree to 7 = strongly agree).

- The algorithm [expert] would consult me as the algorithm [expert] and I have similar knowledge with respect to fun workout activities.
- The algorithm [expert] relies on similar strategies to come up with a fun workout activity as I would.
- This algorithm [expert] would collaborate with me because of our similar knowledge/strategies.

- WTU: How likely would you be to use this virtual platform to receive a recommendation for fun workout activities from a workout algorithm [expert]? (1 = not at all likely to 11 = very likely)

- Subjective Knowledge Check: After writing about the time, I had reflected on, I feel ____ about workout activities (1 = very unknowledgeable to 9 = very knowledgeable).

- Age (open-ended)

- Gender (0 = male, 1 = female, 2 = prefer not to say)

Additional Analyses

- In our main analysis, we did not exclude participants. Note that our results and the pattern we reported held when the main analysis was run without participants who failed the attention check (N = 622) or the participants who failed the attention and comprehension checks (N = 576).

- Participants did not fail the comprehension check significantly differently depending on their assigned condition (pearson chi-square = 1.71, p = .43).

Appendix I: Materials for the Studies in General Discussion

GD Study 1

Scenario

In this study, you will read a scenario about Sam, and answer questions about it. Please read the scenario carefully. It is very important for us that you read the scenario carefully. Please pay extra attention to the instructions in this study!!

Sam wants to find fun workout activities that he can engage in at home. Although Sam considers himself very knowledgeable with respect to different workout activities [As Sam does not consider himself knowledgeable with respect to different workout activities at all], he would like to receive recommendations for workout activities that he can engage in from home.

Sam found a service that offers personalized recommendations online via a virtual platform: *Next Level.* This service provides an easy-to-use virtual platform which offers personalized recommendations for workout activities. This service has two options. Users can receive recommendations from a workout algorithm (a sophisticated statistical model) or from a workout enthusiast (a workout expert).

Importantly, regardless of the recommender, the users go through the same process:

1) They log in to the virtual platform.

2) They choose the recommender (workout algorithm or workout enthusiast).

3) They answer a set of questions (identical regardless of the recommender they chose) to provide input for what kind of activities they want & details of their request. They then submit their answers to the platform.

4) The recommender comes up with a fun workout recommendation for each user. Note that there is no further interaction between the user and the recommender. There is no add-on service elements to the recommendation based on the recommender.

5) The user can now decide whether to follow the recommendation they receive.

As a reminder, Sam feels very knowledgeable [unknowledgeable] about workout activities. To use the service and get a workout recommendation, he can pick either a workout algorithm or a workout enthusiast.

Measures

- Comprehension check #1: We introduced you to Sam. According to the information you received about Sam, is Sam knowledgeable or unknowledgeable about workout activities? (1 = Sam is knowledgeable, 2 = Sam is unknowledgeable, 3 = I do not know / I do not remember)

- Comprehension check #2: We introduced you a service: Next Level. Which recommender(s) does this service offer? (0 = both a workout enthusiast and a workout algorithm, 1 = only a workout enthusiast, 2 = only a workout algorithm, 3 = I do not remember)

- Recommender preference: To use this service, Sam has to pick the recommender that he wants to receive a workout recommendation from. Which recommender do you think Sam would pick to get a workout recommendation given that he feels very knowledgeable[unknowledgeable] about workout activities? (1 = definitely the workout algorithm to 9 = definitely the workout enthusiast)

- Thought protocol: You indicated which recommender Sam would pick. Please elaborate on why Sam would pick this particular recommender over the recommender you did not pick. We are particularly interested in what Sam can get from this particular recommender that he could not get from the unchosen one. Said differently, what is the main reason why you think that Sam would go with the recommender you picked. Please be detailed. Please write at least 100 characters (open-ended)

- General knowledge: Please indicate how knowledgeable you perceive yourself about workout activities in general. Please make your judgment unrelated to the scenario you read about Sam but rely on your general perception when it comes to your knowledge about workout activities (1 = not knowledgeable at all to 7 = very knowledgeable).

- **Ease in imagining the scenario:** It was easy for me to imagine the scenario I read about Sam (1 = strongly disagree to 7 = strongly agree)

- Age (open-ended)

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

Additional Analyses

- In our main analysis, we did not exclude participants. Note that our results and the pattern we reported held when the main analysis was run without participants who failed comprehension checks (N = 195).

- Participants did not fail the comprehension checks significantly differently depending on their assigned condition (comprehension check #1: Pearson chi-square = 3.2, p = .08; comprehension check #2: Pearson chi-square = .29, p = .59).

- None of the exploratory measures we included in this study changed the results or the pattern we reported.

GD Study 2

Scenario

In this study, you will read a scenario about Sam, and answer questions about it. Please read the scenario carefully. It is very important for us that you read the scenario carefully. Please pay extra attention to the instructions in this study!!

Sam wants to find tasty recipes that he can cook by himself. Although Sam considers himself very knowledgeable with respect to cooking [As Sam does not consider himself knowledgeable with respect to cooking at all], he would like to receive recommendations for tasty recipes that he can prepare at home.

Sam found a service that offers personalized recommendations online via a virtual platform: *What's Cooking*. This service provides an easy-to-use virtual platform which offers personalized recommendations for tasty recipes. This service has two options. Users can receive recommendations from a cooking algorithm (a sophisticated statistical model) or from a cooking enthusiast (a cooking expert).

Importantly, regardless of the recommender, the users go through the same process:

1) They log in to the virtual platform.

2) They choose the recommender (cooking algorithm or cooking enthusiast).

3) They answer a set of questions (identical regardless of the recommender they chose) to provide input for what kind of dishes they enjoy & details of their request. They then submit their answers to the platform.

4) The recommender comes up with a tasty recipe for each user. Note that there is no further interaction between the user and the recommender. There is no add-on service

elements to the recommendation based on the recommender.

5) The user can now decide whether to follow the recommendation they receive.

As a reminder, Sam feels very knowledgeable[unknowledgeable] about cooking. To use the service and get a recipe recommendation, he can pick either a cooking algorithm or a cooking enthusiast.

Measures

- Comprehension check #1: We introduced you to Sam. According to the information you received about Sam, is Sam knowledgeable or unknowledgeable about cooking? (1 = Sam is knowledgeable, 2 = Sam is unknowledgeable, 3 = I do not know / I do not remember)

- Comprehension check #2: We introduced you a service: What's Cooking. Which recommender(s) does this service offer? (0 = both a cooking enthusiast and a cooking algorithm, 1 = only a cooking enthusiast, 2 = only a cooking algorithm, 3 = I do not remember)

- Recommender preference: To use this service, Sam has to pick the recommender that he wants to receive a recipe recommendation from. Which recommender do you think Sam would pick to get a recipe recommendation given that he feels very knowledgeable [unknowledgeable] about cooking? (1 = definitely the cooking algorithm to 9 = definitely the cooking enthusiast)

- Thought protocol: You indicated which recommender Sam would pick. Please elaborate on why Sam would pick this particular recommender over the recommender you did not pick. We are particularly interested in what Sam can get from this particular recommender that he could not get from the unchosen one. Said differently, what is the main reason why you think that Sam would go with the recommender you picked. Please be detailed. Please write at least 100 characters. (open-ended)

- General knowledge: Please indicate how knowledgeable you perceive yourself about cooking in general. Please make your judgment unrelated to the scenario you read about Sam but rely on your general perception when it comes to your knowledge about cooking (1 = not knowledgeable at all to 7 = very knowledgeable)

- Ease in imagining the scenario: It was easy for me to imagine the scenario I read about Sam (1 = strongly disagree to 7 = strongly agree)

- Age (open-ended)

- Gender (0 = male, 1 = female, 2 = prefer not to answer)

Additional Analyses

- In our main analysis, we did not exclude participants. Note that our results and the pattern we reported held when the main analysis was run without participants who failed comprehension checks (N = 191).

- Participants did not fail the comprehension checks significantly differently depending on their assigned condition (comprehension check #1: Pearson chi-square = .59, p = .44; comprehension check #2: Pearson chi-square = .96, p = .33).

- None of the exploratory measures we included in this study changed the results or the pattern we reported.

Appendix 3: Additional Materials for Chapter 4

Appendix 3A: Study Materials and Additional Analyses for Study 1

Scenario

This survey is about decision-making in courts [This survey is about decision-making by algorithms and artificial intelligence in the courts]. Suppose you have been married for some years. Lately, you and your partner feel that the love for each other has cooled down to almost zero. You agree to separate and file for divorce.

High technical complexity: You and your partner jointly own a house and some savings. You pay for 65% of the costs of daily living because your salary is much higher than that of your partner. On the other hand, 20% of the house was paid out of an inheritance that your partner had obtained after your partner's grandma passed away. The rest was paid out of a mortgage. It is very likely that for your partner, it will be hard to uphold the same standard of living after the divorce. For the divorce, you go to your local court.

High emotional complexity: You and your partner jointly own a house and some savings. The costs of your daily life are covered on an equal basis out of your salaries, where you both have full-time jobs. Your partner's mental health has suffered from the negative development in the marriage. Your partner has experienced many sleepless nights worrying about the future and suffered a nervous breakdown. As a result, your partner cannot go to work. You feel somewhat sad about the whole breakup and the impact it has on your partner, but at the same time look forward to a new life on your own. For the divorce, you go to your local court.

Low complexity: You and your partner jointly own a house and some savings. The costs of your daily life are covered on an equal basis out of your salaries, where you both have full-time jobs. For the divorce, you go to your local court.

Cases like yours are resolved by an experienced judge from the local court [At your local court, a new system has been in place for some time now, where cases are resolved by artificial intelligence and algorithms. Cases like yours are resolved by this new system, which is fully automated and uses the legislation and the relevant case law of your jurisdiction to resolve disputes].

Measures

- **Perceived trust (four-item):** Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = unfair / not trustworthy / unpredictable / biased to 9 = fair / trustworthy / predictable / unbiased)

- **Perceived speed:** Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = slow to 9 = fast)

- **Perceived cost:** Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = expensive to 9 = cheap)

- **Intentions to submit the case**: How likely would you be to submit your case that will be resolved by the judge [artificial intelligence] to the local court? (1 = not at all likely to 11 = very likely)

- **Manipulation check (two-item)**: When you think about the case that you read, how complicated do you think this divorce case is? and How complicated do you think this divorce case is for judge [artificial intelligence] to resolve? (1 = not at all complicated to 11 = very complicated)

- **Experience in courts:** How experienced are you in courts? (1 = completely unexperienced to 7 = completely experienced)

- ICT: To what extent are you an experienced user of ICT (information and communications technologies)? (1 = completely unexperienced to 7 = completely experienced)

- Age

- Gender (0 = male, 1 = female, 2 = other, 3 = prefer not to answer)

- Marital status (1 = married, 2 = widowed, 3 = divorced, 4 = separated, 5 = never married)

- Education: What is the highest degree that you have completed? (1 = less than high school to 7 = doctorate)

- Income: Approximately how much income do you personally make per year? (1 = less than $20,000 to 10 = over $250,000, 11 = prefer not to share)

- Open-ended question: Any comments?

Additional Analyses

In study 1, we found no systematic differences across conditions in terms of participants' age, gender, income, marital status, the extent that they were experienced in courts, and the extent that they use information consumer technologies (ICT). The only exception to this was that participants' experience in using ICT ($F(1, 602) = 8.32$, $p = .004$) differed depending on the judge condition that participants were assigned to. Importantly, controlling for this variable did not change the results for neither of our key variables (i.e., perceived trust, intentions to submit the case, perceived speed, perceived cost).

Additionally, Study 1 included an item to measure how negative participants perceive the relationship to be ("Based on the scenario that you read, how negative or compromised do you think that the relationship between you and your partner is?"; 1 = *extremely negative* to 7 = *extremely positive*). A 2 (judge type) x 3 (case complexity type) ANOVA revealed that the perceived negativity between parties was not perceived to be different depending on the judge (AI vs. human; $F(1, 602) = .02$, $p = .90$). Additionally, we found a significant main effect of type of case complexity ($F(2, 602) = 9.52$, $p < .001$): The relationship was perceived to be more negative when the case was high in emotional complexity ($M = 2.88$, $SD = 1.34$) compared to the cases that were uncomplicated ($M = 3.32$, $SD = 1.41$; $p = .002$) or high in technical complexity ($M = 3.45$, $SD = 1.42$; $p < .001$). The interaction effect between the judge and case complexity type was not statistically significant ($F(2, 602) = .67$, $p = .51$).

Appendix 3B: Study Materials and Additional Analyses for Study 2

Scenario

This survey is about decision-making in courts [This survey is about decision-making by algorithms and artificial intelligence in the courts]. Suppose you have been married for some years. Lately, you and your partner feel that the love for each other has cooled down to almost zero. You agree to separate and file for divorce.

High technical complexity: You and your partner jointly own a house and some savings. You pay for 65% of the costs of daily living because your salary is much higher than that of your partner. On the other hand, 20% of the house was paid out of an inheritance that your partner had obtained after your partner's grandma passed away. The rest was paid out of a mortgage. It is very likely that for your partner, it will be hard to uphold the same standard of living after the divorce. For the divorce, you go to your local court.

High emotional complexity: You and your partner jointly own a house and some savings. The costs of your daily life are covered on an equal basis out of your salaries, where you both have full-time jobs. Your partner's mental health has suffered from the negative development in the marriage. Your partner has experienced many sleepless nights worrying about the future and suffered a nervous breakdown. As a result, your partner cannot go to work. You feel somewhat sad about the whole breakup and the impact it has on your partner, but at the same time look forward to a new life on your own. For the divorce, you go to your local court.

Low complexity: You and your partner jointly own a house and some savings. The costs of your daily life are covered on an equal basis out of your salaries, where you both have full-time jobs. For the divorce, you go to your local court.

Cases like yours are resolved by an experienced judge from the local court [At your local court, a new system has been in place for some time now, where cases are resolved by artificial intelligence and algorithms. Cases like yours are resolved by this new system, which is fully automated and uses the legislation and the relevant case law of your jurisdiction to resolve disputes.]

Measures

- Perceived trust (four-item): Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = unfair / not trustworthy / unpredictable / biased to 9 = fair / trustworthy / predictable / unbiased)

- Perceived speed: Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = slow to 9 = fast)

- Perceived cost: Thinking about this divorce case and your future court experience, to what extent do you think that the judge [artificial intelligence] will be (1 = expensive to 9 = cheap)

- Intentions to submit the case (two-item): “How likely would you be to submit your case that will be resolved by the judge [artificial intelligence] to the local court?” (1 = not at all likely to 11 = very likely) and “In this situation, would you plan to submit your case that will be resolved by the judge [artificial intelligence] to the local court?" (1= no intention to submit to 11= very strong intention to submit)

- Manipulation check (two-item): "When you think about the case that you read, how complicated do you think this divorce case is?" and "How complicated do you think this divorce case is for judge [artificial intelligence] to resolve?" (1 = not at all complicated to 11 = very complicated)

- Experience in courts: How experienced are you in courts? (1 = completely unexperienced to 7 = completely experienced)

- ICT: To what extent are you an experienced user of ICT (information and communications technologies)? (1 = completely unexperienced to 7 = completely experienced)

- Age

- Gender (0 = male, 1 = female, 2 = other, 3 = prefer not to answer)

- Marital status (1 = married, 2 = widowed, 3 = divorced, 4 = separated, 5 = never married)

- Education: What is the highest degree that you have completed? (1 = less than high school to 7 = doctorate)

- **Income:** Approximately how much income do you personally make per year? (1 = less than $20,000 to 10 = over $250,000, 11 = prefer not to share)

- Open-ended question: Any comments?

Additional Analyses

In study 2, we again observed no systematic differences across conditions in terms of participants' age, gender, income, marital status, the extent that they were experienced in courts, and the extent that they use information consumer technologies (ICT). There were two exceptions. First, participants' experience in using ICT ($F(1, 1208) = 9.97$, $p = .002$) was again found to be different depending on the judge condition. Second, participants' level of education marginally differed depending on the case complexity condition that they were assigned to (F(1, 1208) = 2.80, p = .06). Importantly, controlling for these two items did not change the results of the key variables we reported (i.e., perceived trust, intentions to submit the case, perceived speed, perceived cost).

In study 2, we measured how negative participants perceive the relationship to be ("Based on the scenario that you read, how negative or compromised do you think that the relationship between you and your partner is?"; 1 = *extremely negative* to 7 = *extremely positive).* We found that the main effect of the judge type was non-significant (AI vs. human; F(1, 1208) = .85, p = .36). Moreover, we observed a significant main effect of type of case complexity (F(2, 1208) = 20.70, p < .001): participants perceived the relationship to be more negative when the legal case included emotional complexities (M = 2.92, SD = 1.34) than technical complexities (M = 3.29, SD = 1.38; p < .001) or no complexities (M = 3.54, SD = 1.45; p < .001). The contrast between high technical complexity and low complexity conditions was also shown to be significant (p = .007). Note that the interaction effect between the type of judge and complexity type was also statistically significant (F(2, 1208) = 4.286, p = .01).

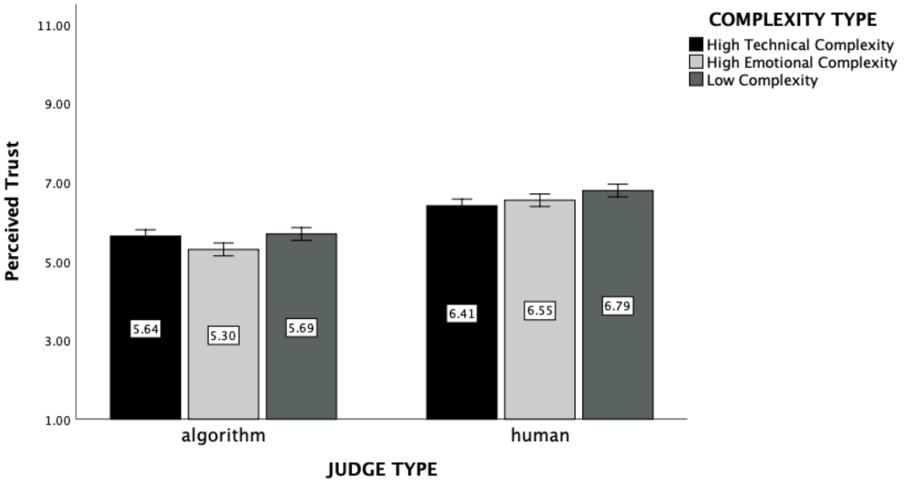
Appendix 3C: Additional Analyses for the Internal Meta-Analysis

In addition to the two studies reported in the paper, we conducted another study (N = 1,217 US residents, M_{age} = 37.4, 660 females) on Amazon Mturk for this research project. Participants were asked to imagine that they bought a second-hand car from Tempra Car Dealers. The car suddenly stopped working on the next day, but the car dealer was told to deny responsibility. Similar to other studies, participants were again randomly assigned to one condition of a 2 (judge type: algorithm vs. human) x 3 (case complexity type: low complexity vs. high emotional complexity vs. high technical complexity) and used the same items we measured in studies 1 and 2. The reason that this study was not included in the paper is that our manipulation for case complexity failed. Specifically, participants did not perceive the emotionally (M = 5.87, SD = 2.74) and technically (M = 5.54, SD = 2.62) complex cases equally complex as intended ($p < .05$).

Even though this study had problems as our manipulation check failed, to test the robustness of this effect and to show that we do not have a file drawer, we combined the data from all three studies in a single data file and submitted the data to an analysis similar to those reported above to test the robustness of the effects above regarding the trust perceptions of participants after reading about different types of judges (i.e., artificial intelligence, human) and different types of case complexity (i.e., low complexity, high technical complexity, high emotional complexity). Note that we have no file drawer, these are all the data collected for this paper.

In this internal meta-analysis, we tested participants' reactions to different types of judges (algorithmic versus human) in three different studies, with 3,039 participants in total (M_{age} = 37.8, 1,611 females). Aggregating these three studies, we again found for trust a significant main effect of judge type ($F(1, 3021) = 238.94$, $p < .001$, $\eta_p^2 = .07$, $d = .6$) and type of case complexity ($F(2, 3021) = 7.85$, $p < .001$, $\eta_p^2 = .005$). Importantly, we found a significant interaction effect between judge and case complexity type on perceived trust ($F(2, 3021) = 4.34$, $p = .01$, $\eta_p^2 = .003$). This interaction effect was in line with what we described in studies 1 and 2. For instance, zooming into the algorithm conditions, we again found that participants trusted the algorithm less when the case included emotional complexities compared to both simple cases ($p = .001$) and cases that are complex due to technicalities ($p = .004$). Interestingly, we did not observe a difference between simple and technically complex cases (p = .64), suggesting that technical complexity hurt algorithmic judges relatively less. Additionally, we found that participants trusted the human judge more when the case was uncomplicated compared to both technically (p = .001) and emotionally complex cases (p = .03). From these analyses we conclude that, although human judges are in general trusted much more than algorithmic judges, both technical and emotional complexities reduce trust in human judges, whereas only emotional complexities reduce trust in algorithmic judges.

Appendix 3C Figure 1. Perceived trust as a function of judge and case complexity type (Internal Meta-analysis)



Importantly, the three-way interaction with study as an additional factor is non-significant (F(4, 3021) = 1.71, p = .15), indicating that the magnitude of the interaction effect does not vary significantly across studies. This non-significance of the three-way interaction is especially noteworthy given the large samples used in all studies.

Appendix 3D: Summary of Key Results and Statistics

	Sample	Study Design	Perceived Trust	Intentions to Go to the Court	Perceived Cost	Perceived Speed
Study 1	608 American Mturkers (M_{age} = 38.17, 50.8 % F	3 (case complexity type: simple vs. technical high complexity vs. emotional high complexity) x 2 (judge type: human vs. algorithm) between ss design	**- Judge type:** M_{human} = 6.64 SD_{human} = 1.49 vs. $M_{algorithm}$ = 5.71 $SD_{algorithm}$ = 1.98; $F(1,602) = 42.00$, $p < .001$, $\eta_p^2 = .07$ **- Case Complexity:** $F(2, 602)= .84$, $p = .43$ **- Interaction effect:** $F(2,602) = 3.83$, $p = .02$, $\eta_p^2 = .01$	**- Judge type:** M_{human}= 8.39 SD_{human} = 2.11 vs. $M_{algorithm}$ = 5.61 $SD_{algorithm}$ = 3.32; $F(1, 602) = 152.30$, $p < .001$, $\eta_p^2 = .20$ **- Case Complexity:** M_{low} = 7.58 SD_{low} = 3.01 vs. $M_{highemo}$ = 6.67 $SD_{highemo}$ = 3.32 vs. $M_{hightech}$ = 6.77 $SD_{hightech}$ = 2.90; $F(2, 602) = 5.47$, $p = .004$, $\eta_p^2 = .02$ **- Interaction effect:** $F(2, 602) = 1.78$, $p = .17$	**- Judge type:** M_{human}= 5.68 SD_{human} = 1.84 vs. $M_{algorithm}$ = 4.17 $SD_{algorithm}$ = 2.32; $F(1, 602) = 80.17$, $p < .001$, $\eta_p^2 = .12$ **- Case Complexity:** M_{low} = 4.69 SD_{low} = 2.33 vs. $M_{highemo}$ = 5.12 $SD_{highemo}$ = 2.21 vs. $M_{hightech}$ = 4.96 $SD_{hightech}$ = 2.11; $F(2, 602) = 2.60$, $p = .08$, $\eta_p^2 = .01$ **- Interaction effect:** $F(2, 602) = .59$, $p = .56$	**- Judge type:** M_{human}= 5.70 SD_{human} = 1.82 vs. $M_{algorithm}$ = 7.24 $SD_{algorithm}$ = 1.80; $F(1, 602) = 110.29$, $p < .001$, $\eta_p^2 = .16$ **- Case Complexity:** $F(2, 602)= 1.70$, $p = .18$ **- Interaction effect:** $F(2,602)= .97$, $p = .38$
Study 2	1,214 American Mturkers (M_{age}= 38.1, 52.9% F)		**- Judge type:** M_{human} = 6.58 SD_{human} = 1.60 vs. $M_{algorithm}$ = 5.65 $SD_{algorithm}$ = 1.91; $F(1, 1208)= 89.51$, $p < .001$, $\eta_p^2 = .07$ **- Case Complexity:** M_{low}= 6.30 SD_{low} = 1.86 vs. $M_{highemo}$ = 5.93 $SD_{highemo}$ = 1.85; $M_{hightech}$ = 6.12 $SD_{hightech}$ = 1.74, $F(2,1208) = 6.72$; $p = .001$, $\eta_p^2 = .01$ **- Interaction effect:** $F(2, 1208) = 3.12$, $p = .04$, $\eta_p^2 = .01$	**- Judge type:** M_{human} = 8.3, SD_{human} = 2.34 vs. $M_{algorithm}$ = 5.36, $SD_{algorithm}$ = 3.25; $F(1, 1208) = 331.40$, $p < .001$, $\eta_p^2 = .22$ **- Case Complexity:** M_{low} = 7.01 SD_{low} = 3.20 vs. $M_{highemo}$ = 6.69 $SD_{highemo}$ = 3.32; $M_{hightech}$ = 6.8 $SD_{hightech}$ = 3.03; $F (2, 1208) = 3.61$, $p = .03$, $\eta_p^2 = .006$ **- Interaction effect:** $F(2, 1208) = .42$, $p = .66$	**- Judge type:** M_{human}= 5.54 SD_{human} = 2.03 vs. $M_{algorithm}$ = $SD_{algorithm}$ = 4.30 2.32; $F(1, 1208) = 96.33$, $p < .001$, $\eta_p^2 = .07$ **- Case Complexity:** M_{low} = 4.66 SD_{low} = 2.32 vs. $M_{highemo}$ = 5.17 $SD_{highemo}$ = 2.21 vs. $M_{hightech}$ = 4.95 $SD_{hightech}$ = 2.23; $F(2, 1208) = 3.74$, $p = .02$, $\eta_p^2 = .01$ **- Interaction effect:** $F(2, 1208) = 1.39$, $p = .25$	**- Judge type:** M_{human}= 5.84 SD_{human} = 1.93 vs. $M_{algorithm}$ = 7.12 $SD_{algorithm}$ = 1.95; $F(1, 1208) = 129.48$, $p < .001$, $\eta_p^2 = .10$ **- Case Complexity:** M_{low} = 6.69 SD_{low} = 1.95 vs. $M_{highemo}$ = 6.23 $SD_{highemo}$ = 2.05 vs. $M_{hightech}$ = 6.69 $SD_{hightech}$ = 1.95; $F(2, 1208) = 3.99$, $p = .02$, $\eta_p^2 = .01$ **- Interaction effect:** $F(2, 1208) = 3.77$, $p = .02$, $\eta_p^2 = .01$

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SUMMARY (IN ENGLISH)

Today consumers are increasingly interacting with algorithms and artificial intelligence (AI) technologies instead of or in addition to humans. Holding everything else constant, would merely framing a decision (e.g., an application outcome made about a consumer, a personalized recommendation) as made by an algorithm or a human still change the way consumers react? The goal of this dissertation is to examine whether and why consumers react to algorithms and humans differently. Offering a counterpoint on the pervasive algorithms-are-bad rhetoric in contemporary marketing literature, this dissertation adopts a nuanced perspective on consumers' reactions towards algorithms and humans and introduces three contextual factors that impact consumers' reactions. Specifically, it reveals how consumers' reactions towards algorithms and humans depends on what the outcome of the decision is (Chapter 2), who the consumer is (Chapter 3) and on what type of complexity the decision possesses (Chapter 4).

Chapter 2 examines how consumers react to favorable versus unfavorable decision outcomes made about themselves (e.g., acceptances vs. rejections) that are framed to be made by algorithms versus humans. Ten studies reveal that, in contrast to managers' predictions, consumers react less positively when a favorable decision is made by an algorithmic (vs. a human) decision-maker. This difference, however, is mitigated for an unfavorable decision.

Chapter 3 tests how consumers' subjective knowledge in a focal domain affects their reactions towards algorithmic versus human-based recommendations. Seven studies reveal that consumers with high subjective knowledge value recommendations from

algorithms (vs. human experts) more, whereas this greater valuation of algorithmic recommendations is mitigated for consumers with low subjective knowledge.

Chapter 4 studies the role of two types of decision complexity (i.e., emotional vs. technical) on individuals' perceptions towards algorithms versus humans making legal decisions. Two experiments and an internal meta-analysis demonstrate that individuals trust algorithmic (vs. human) judges less and have lower intentions to go to court when algorithms adjudicate. Trust for algorithmic judges is especially penalized when cases involve emotional complexities (vs. simple or technically complex cases). This chapter also reveals two relative advantages of algorithms that policymakers could consider emphasizing when communicating with citizens: algorithms' perceived speed and cost.

SAMENVATTING (IN DUTCH)

Consumenten interacteren tegenwoordig steeds vaker met algoritmes en kunstmatige intelligentie (AI-technologieën) in plaats van met mensen óf naast het contact met mensen. Zou het, wanneer verder alles gelijk blijft, voor de manier waarop consumenten reageren uitmaken of een beslissing (zoals de beoordeling van een aanvraag door een consument of een persoonlijke aanbeveling) wordt gebracht als afkomstig van een algoritme of van een mens? Het doel van dit proefschrift is om te onderzoeken of en waarom consumenten anders reageren op algoritmes dan op mensen. Dit proefschrift wil een tegenwicht bieden aan de wijdverbreide 'algoritmes zijn slecht'-retoriek in de hedendaagse marketingliteratuur door middel van een genuanceerd perspectief op de reactie van consumenten op algoritmes en mensen alsmede de introductie van drie contextuele factoren die de reacties van consumenten beïnvloeden. Het laat specifiek zien hoe de reacties van consumenten op algoritmes en mensen afhankelijk zijn van wat het resultaat van de beslissing is (hoofdstuk 2), wie de consument is (hoofdstuk 3) en welk type complexiteit aan de beslissing ten grondslag ligt (hoofdstuk 4).

In hoofdstuk 2 wordt onderzocht hoe consumenten reageren op gunstige of ongunstige beslissingen over henzelf (bijv. acceptatie vs. afwijzing) waarbij deze geframed worden als beslissingen genomen door algoritmes dan wel mensen. Uit tien onderzoeken blijkt dat, in tegenstelling tot wat managers voorspellen, wanneer een gunstige beslissing wordt genomen door een algoritmische beslisser (i.t.t. een menselijke) consumenten minder positief reageren. Dit verschil is echter kleiner bij een ongunstige beslissing.

In hoofdstuk 3 wordt getest hoe subjectieve kennis van consumenten op een bepaald focusgebied van invloed is op hun reacties op algoritmische of menselijke aanbevelingen.

Zeven onderzoeken tonen aan dat consumenten met veel subjectieve kennis aanbevelingen door algoritmes hoger waarderen (dan die door menselijke deskundigen), terwijl minder sprake is van hogere waardering van algoritmische aanbevelingen onder consumenten met weinig subjectieve kennis.

In hoofdstuk 4 wordt de rol onderzocht van twee typen beslissingscomplexiteit (te weten emotionele vs. technische) op de perceptie van het individu van juridische beslissingen genomen door algoritmes dan wel mensen. Met twee experimenten en een interne meta-analyse wordt aangetoond dat individuen algoritmische (i.t.t. menselijke) rechters minder vertrouwen en dat ze minder geneigd zijn naar de rechtbank te stappen wanneer algoritmes recht spreken. Het vertrouwen in algoritmische rechters wordt vooral geschaad wanneer het rechtszaken betreft met een hoge emotionele complexiteit (t.o.v. simpele of technisch complexe zaken). Dit hoofdstuk toont ook twee relatieve voordelen van algoritmes aan, die beleidsmakers zouden kunnen benadrukken in hun communicatie met burgers: de waargenomen snelheid en kosten van algoritmes.

ABOUT THE AUTHOR

Gizem Yalcin was born in Bursa on January 2, 1992. She completed her undergraduate studies (BSc) in Management at Bilkent University (summa cum laude) with a major in marketing & innovation and a minor in psychology. She graduated cum laude in 2017 from Erasmus University's research master (MPhil) program with a specialization in marketing. In 2017, she started her PhD studies in Marketing at Rotterdam School of Management (RSM) at Erasmus University. During her PhD, she was a visiting graduate researcher at University of British Columbia (2018) and Cornell University (2019).

Gizem's research mainly explores how consumers process and react to information (e.g., recommendations, decision outcomes) provided by algorithms or humans. In addition to this line of inquiry, she studies prosocial behavior, and work on how consumers decide where to donate to and how to motivate consumers to make more effective donations. She employs a mix of methods to address her research questions, including lab/online panel studies, field experiments, secondary data analysis, content analysis, and meta-analysis.

Gizem has received many grants during her graduate studies, including the ERIM Achievement Grant (2015) and grant from the European Institute of Advanced Studies in Management (2016). Additionally, she has received several awards during her studies including the Bruins Prize (2017), the Beattie Award (2019), Talent Placement Award (2020), and AMA Mathew Joseph Emerging Scholar Award (2021).

In August 2022, Gizem will start working as an Assistant Professor of Marketing at McCombs School of Business at the University of Texas at Austin.

PORTFOLIO

Publication and Manuscripts Under Review

Paolacci, Gabriele and **Gizem Yalcin** (2020), "Benevolent Partiality in Prosocial Preferences," *Judgment and Decision Making,* 15 (2), 173–81.

Yalcin, Gizem, Sarah Lim, Stefano Puntoni, and Stijn van Osselaer (2022), "Thumbs Up or Down: Consumer Reactions to Decisions by Algorithms versus Humans," *Journal of Marketing Research*, forthcoming.

Yalcin, Gizem, Anne-Kathrin Klesse, and Darren Dahl, "The Algorithm versus the Expert: High Subjective Knowledge in a Focal Domain Increases Consumers' Valuation of Algorithmic Recommendations," resubmitted for second round revision at *Journal of Marketing.*

Yalcin, Gizem, Stefano Puntoni, Erlis Themeli, Stefan Philipsen, and Evert Stamhuis, "Perceptions of Justice by Algorithms," invited for second round revision at *Artificial Intelligence & Law.*

Research in Progress

Yalcin, Gizem, Ravi Mehta, and Darren Dahl, "Cyber-Creativity: Unraveling the Role of Artificial Intelligence in Creative Processes," *work in progress (targeted at Journal of Consumer Research).*

Yalcin, Gizem, Chiara Longoni, Johannes Boegershausen, Rajkumar Venkatesan, Alix Barasch, Stefano Puntoni, and Luca Cian, "Looking into the Black Box: A Meta-Analytic Investigation of Consumer Responses to Artificial Intelligence," *coding in progress (targeted at Journal of Marketing Research).*

Schley, Dan, Evan Weingarten, and **Gizem Yalcin**, "A Meta-Analysis of Anchoring and Adjustment," *data analysis in progress (targeted at Management Science).*

Yalcin, Gizem and Gabriele Paolacci, "Placebic Rationales in Cause Marketing," *data collection in progress.*

Yalcin, Gizem and Joshua Lewis, "Consumer Reactions Towards Existential Risk from Artificial Intelligence," *data collection in progress.*

Selected Awards, Fellowships, Grants and Honors

- Mathew Joseph Emerging Scholar Award, Academy of Marketing Association (AMA) DocSIG, 2021
- Honorable Mention, Psychology of Technology Dissertation Award, 2021
- AMA Sheth Doctoral Consortium Fellow, 2020
- Talent Placement Award (about €30,000), Erasmus Research Institute of Management (ERIM), 2020
- Beattie Award ($750), Society for Judgment and Decision Making, 2019
- Research Visit Grant (€750), Erasmus TrustFonds Association, 2018
- Professor Bruins Prize for the best research student (€4,500), Erasmus TrustFonds Association, 2017
- High Honor student, Erasmus University Rotterdam, 2015-2017
- European Institute of Advanced Studies in Management Scholarship (€750), 2016

- Research Grant (€550), ERIM, 2016
- Erasmus University Scholarship (€30,500), 2015-2017
- Achievement Grant (€10,000), ERIM, 2015
- Bilkent Comprehensive Scholarship, Bilkent University, 2011-2015
- High Honor student, Bilkent University, 2011-2015

Chaired Symposia and Knowledge Forums

Yalcin, Gizem, and Gil Appel (October 2021), **"**Let's Get Digital: A Virtual Knowledge Forum on Marketing in the Age of Digitalization and Artificial Intelligence**,"** Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem, and Chiara Longoni (October 2021), "Artificial Intelligence in Marketing and Beyond: Interdisciplinary Perspectives on the Social Impact of AI," Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem, and Joshua Lewis (October 2021), "Marketing Effective Altruism: A Virtual Roundtable on How to Motivate Consumers to Maximize Their Prosocial Impact," Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem, and William Fritz (October 2020), "Back to the Future: A Virtual Roundtable of Senior Academics Sharing Insights from Consumer Research on Technology," Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem and Evan Weingarten (October 2020), "Objective and Subjective Value of Humans and Algorithms," Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem and Nofar Duani (October 2020), "Being a Human in the Age of Artificial Intelligence," Association for Consumer Research (ACR), virtual conference.

Yalcin, Gizem and Evan Weingarten (March 2020), "Objective and Subjective Value of Humans and Algorithms," Society for Consumer Psychology (SCP), Huntington Beach, CA.

Yalcin, Gizem and Nofar Duani (October 2019), "Perceptions of AI and Algorithmic Decision Making," Association for Consumer Research (ACR), Atlanta, GA.

Conference Presentations (* denotes presenter)

Thumbs Up vs. Thumbs Down
Society for Consumer Psychology (SCP), virtual conference (March 2021)*
Association for Consumer Research (ACR), virtual conference (October 2020)*
SCP Boutique Conference on Technology, Montreal (June 2019)

The Algorithm vs. the Expert
Society for Consumer Psychology (SCP), Huntington Beach, CA (March 2020)*
Association for Consumer Research (ACR), Atlanta, GA (October 2019)*
SCP Boutique Conference on Technology, Poster, Montreal (June 2019)*
Theory + Practice in Marketing (TPM), New York, NY (May 2019)*

Perceptions of Justice by Algorithms
Association for Consumer Research (ACR), virtual conference (October 2021)*
Society for Consumer Psychology (Huntington Beach, USA, 2020)*

Cyber-Creativity
Association for Consumer Research (ACR), virtual conference (October 2020)

Benevolent Partiality
Society for Judgment and Decision Making (SJDM), Montreal (November 2019)*
Subjective Probability, Utility, and Decision Making (SPUDM), Amsterdam (August 2019)*
La Londe Conference, La Londe Les Maures (June 2019)
Society for Consumer Psychology (SCP), Savannah, GA (February 2019)*
Association for Consumer Research (ACR), Dallas, TX (October 2018)
Tilburg Institute for Behavioral Economics Research (TIBER) Symposium, Tilburg (August 2019)*

<u>Invited Knowledge Forums and Talks</u>

- Chinese University of Hong Kong, virtual talk, 2021
- ESSEC Business School, virtual talk, 2021
- Harvard Business School, virtual talk, 2021
- IESE Business School, virtual talk, 2021
- McGill University, virtual talk, 2021
- Singapore Management University, virtual talk, 2021
- Stockholm School of Economics, virtual talk, 2021
- University of Alberta, virtual talk, 2021
- University of Cincinnati, virtual talk, 2021
- University of Illinois at Urbana-Champaign, virtual talk, 2021
- University of Iowa State, virtual talk, 2021
- University of Notre Dame, virtual talk, 2021
- University of Oregon, virtual talk, 2021
- University of Texas at Austin, virtual talk, 2021
- University of Toronto, virtual talk, 2021
- University of Western Ontario, virtual talk, 2021
- "Consumer Reactions to Decisions by Algorithms versus Humans", Bold Minds Mixer, George Washington University, virtual talk, 2020
- "The Dark Side of Automation in Marketing and Consumption," Association for Consumer Research (ACR), Atlanta, GA, 2019
- Montaigne Centre for Rule of Law and Administration of Justice, Utrecht, Netherlands, 2019

<u>Internal Department Seminars</u>

- Internal Marketing Talk, Leeds School of Business, University of Colorado Boulder, USA, April 2021
- Marketing Lab Meeting, Wharton School of the University of Pennsylvania, USA, June 2020
- Internal Marketing Seminar, Bocconi School of Management, Bocconi University, Italy, May 2020

- Marketing Lab Meeting, Stern School of Business, New York University, USA, May 2019
- PhD Seminar Series, SC Johnson College of Business, Cornell University, USA, May 2019
- PhD Seminar Series, Sauder School of Business, University of British Columbia, Canada, October 2018

Teaching Experience

English Proficiency: Cambridge Proficiency Examination (CPE) Certificate, C2 Proficiency

Instructor, Erasmus University, the Netherlands
Research Training and Bachelor Thesis, undergraduate-level course, Spring 2020, Spring 2021

- Instructor evaluation (2020): 9.6/10
- Instructor evaluation (2021): 9.7/10

Guest Lecturer, Erasmus University, the Netherlands
Customer Experience Management (with Christophe Lembregts), graduate-level course, Spring 2019

- Lecture on algorithms and their impact on customer experiences

Sensory Marketing (with Zachary Estes), graduate-level course, Spring 2018

- Lecture on the effect of technology on sensory experiences

Teaching Assistant, Erasmus University, the Netherlands
Marketing Management (Executive MBA course), Steven Sweldens, Spring 2015, Spring 2016
Teaching Assistant, Bilkent University, Turkey
Marketing Strategy and Innovation (Bachelor course), Olga Kravetz, Spring 2014, Spring 2015

Service to the School and Field

- Journal of Consumer Research, Ad-hoc Reviewer
- Judgment and Decision Making, Ad-hoc Reviewer
- Association for Consumer Research, Ad-hoc Reviewer
- Society for Consumer Psychology, Ad-hoc Reviewer
- European Association for Consumer Research, Ad-hoc Reviewer
- Journal of Consumer Research, Trainee Reviewer, 2020
- Research Fellow, Psychology of AI Lab, Erasmus Centre for Data Analytics
- Research Fellow, Erasmus Research Institute of Management
- Behavioral Lab Coordinator, Erasmus University, 2018-2019
- First-year PhD Representative, Erasmus University, 2017-2018
- PhD Council Member & Project Manager, Erasmus University, 2017-2018
- Research Master (MPhil) Council Member, Erasmus University, 2016-2017

Selected Graduate Level Courses and Workshops

Marketing and Behavioral Research

- Consumer Behavior (with Nicole Mead and Mirjam Tuk)
- Current Topics in Marketing Research (with Stefano Puntoni)
- Behavioral Decision Theory (with Peter Wakker)
- Doctoral Seminar on Consumer Research (with Luk Warlop and Simona Botti)
- Buyer Behavior (with Kate White, Joey Hoegg, and Darren Dahl)
- Research Clinic in Marketing (with Steven Sweldens and Bram van den Bergh)
- Creativity (with Darren Dahl)
- Advanced Marketing Decision Models (with Gui Liberali)

Research Methodology

- Advanced Mediation, Moderation, and Conditional Process Analysis Workshop (with Andrew Hayes)
- Methods Stumblers: Pragmatic Solutions to Everyday Challenges in Behavioral Research (with Uri Simonsohn)
- Applied Econometrics (with Marno Verbeek)
- Statistical Methods (with Patrick Groenen)
- Research Methodology and Measurement (with Robert Rooderkerk)
- Multivariate Analysis (with Jeremy Dawson)
- Experimental Method
- Advanced Data Analysis in R

Others: Scientific Integrity, Presentation Skills**,** GDPR Privacy Awareness

THE ERIM PHD SERIES

The ERIM PhD Series contains PhD dissertations in the field of Research in Management defended at Erasmus University Rotterdam and supervised by senior researchers affiliated to the Erasmus Research Institute of Management (ERIM). All dissertations in the ERIM PhD Series are available in full text through the ERIM Electronic Series Portal: http://repub.eur.nl/pub. ERIM is the joint research institute of the Rotterdam School of Management (RSM) and the Erasmus School of Economics (ESE) at the Erasmus University Rotterdam (EUR).

Dissertations in the Last Four Years

Ahmadi, S., *A motivational perspective to decision-making and behavior in organizations*, Promotors: Prof. J.J.P. Jansen & Dr T.J.M. Mom, EPS-2019-477-S&E, https://repub.eur.nl/pub/116727

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Gizem Yalcin was born in Bursa on January 2, 1992. She completed her undergraduate studies in Management at Bilkent University (summa cum laude) with a major in marketing and a minor in psychology. She graduated cum laude in 2017 from Erasmus University's research master program with a specialization in marketing. In 2017, she started her PhD studies in Marketing at Rotterdam School of Management at Erasmus University. During her PhD, she was a visiting graduate researcher at University of British Columbia (2018) and Cornell University (2019).

Gizem's research mainly explores how consumers process and react to information (e.g., recommendations, decision outcomes) provided by algorithms or humans. In addition to this line of inquiry, she investigates on how consumers decide where to donate to and how to motivate consumers to make more effective donations. She employs a mix of methods to address her research questions, including lab/online panel studies, field experiments, secondary data analysis, content analysis, and meta-analysis.

Gizem has received many grants during her graduate studies, including the ERIM Achievement Grant (2015) and a grant from the European Institute of Advanced Studies in Management (2016). Additionally, she has received several awards during her studies including the Professor Bruins Prize (2017), the Beattie Award (2019), ERIM's Talent Placement Award (2020), and AMA Mathew Joseph Emerging Scholar Award (2021).

In Summer 2022, Gizem will start working as an Assistant Professor of Marketing at McCombs School of Business at the University of Texas at Austin.

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