# ALGORITHM VERSUS HUMAN EXPERT RECOMMENDATIONS PREFERENCES IN DECISION SUPPORT: TWO ESSAYS

Aaron Lyvers

Dissertation submitted to the faculty of
the Virginia Polytechnic Institute and State University
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

In

Executive Business Research

Dipankar Chakravarti, Chair
Rajesh Bagchi
Paul Herr
Meng Zhu

September 16, 2024
Falls Church, VA

Keywords: AI, Algorithm Aversion, Algorithm Appreciation, Algorithms in Decision Making, Algorithm Use

# Algorithm Versus Human Expert Recommendations Preferences in Decision Support: Two Essays

Aaron Lyvers

**Abstract**

Algorithms refer to the software programs designed to support problem solving in a wide range of decision domains. Given the Artificial Intelligence (AI) revolution, algorithms have become an integral part of our personal, social, and professional lives. As technology rapidly advances, these algorithms are not only becoming more capable but are also finding a growing array of applications in managerial and consumer decision support. Despite their increasing presence, reactions to algorithms are mixed. While some research highlights a preference for algorithms over human judgment ("algorithm appreciation"), other studies reveal a contrary preference ("algorithm aversion"), where people favor human expertise.

This research provides a conceptual framework and empirical evidence regarding factors that may influence preference for algorithmic versus human expert recommendations in business decision contexts. We use experimental psychological methods to investigate how algorithm characteristics, decision-maker psychology, and situational factors shape these preferences. Essay 1 examines how decision makers align with algorithms (versus human experts) when the two sources provide conflicting recommendations. Essay 2 proposes and tests a process model showing that providing information about how algorithms work may sometimes facilitate, but at other times inhibit, the use of algorithmic support (over human experts). Our findings contribute to the literature on the adoption of algorithms for business decision making and also suggest how AI professionals may overcome managerial and consumer resistance to using algorithms for decision support.

# Algorithm Versus Human Expert Recommendations Preferences in Decision Support: Two Essays

Aaron Lyvers

**General Audience Abstract**

Amid the AI revolution, algorithms have become central to our personal, social, and professional lives, evolving rapidly in both capability and application. Reactions to these algorithms are mixed: some studies show a preference for algorithms over human judgment, known as "algorithm appreciation," while others reveal a preference for human judgment, or "algorithm aversion." Understanding these preferences is essential.

Our research helps to clarify this issue by examining the factors that influence whether people prefer algorithms or human experts in business decisions. Using experimental methods, we explore how algorithm features, decision-maker psychology, and situational factors impact these preferences. We focus on scenarios where algorithms and human experts are presented as competing options rather than complementary ones. Our findings, detailed in two empirical essays, aim to advance marketing literature on algorithms and decision-making, identify future research opportunities, and offer insights for industry professionals to overcome user and customer resistance to beneficial algorithms.

# Acknowledgements

This journey has been transformative and represents a significant milestone in my life. I am deeply grateful to all who have guided, encouraged, and supported me over the past few years.

I owe a profound debt of thanks to my advisor and committee chair, Dr. Dipankar Chakravarti. His innovative insights, sharp intellect, unparalleled ability to cut to the crux of any matter, and unwavering dedication have been instrumental in reaching this point. Working with such an esteemed academic has been an honor, and I hope to have the privilege of continuing our collaboration in the future.

My sincere gratitude also extends to my committee members: Dr. Rajesh Bagchi, Dr. Meng Zhu, and Dr. Paul Herr. Your counselling, challenging questions, and insightful feedback have been invaluable. I could not have asked for a more exceptional committee, and I am eternally appreciative of your contributions.

Finally, I wish to express my deepest thanks to my family. To my wife, Saori, you are my cornerstone. Your unwavering support, endless patience, and the time you have given me to dedicate to this doctoral journey have been gifts beyond measure. To my children, Izumi and Natsumi, thank you for your understanding during my educational sojourn and bringing joy and levity when I needed it most. To my parents, Ken and Maria, your sacrifices and guidance have been the foundation of my achievements; my gratitude for all you’ve done grows with each passing day. And to my brothers, Corwin and Darius, your encouragement, strength, and support (in all forms) have meant more than words can express. I am deeply appreciative of everything you have done for me.

# Table of Contents

# Chapter 1 – Dissertation Introduction and Overview

As part of the Artificial Intelligence (AI) revolution, algorithms have become ubiquitous in our personal, social and professional lives. They are widely deployed as service robots, and in the personal domain provide consumers with recommendations on product purchases as well as healthcare and entertainment options. Algorithms help us navigate social media and function effectively within our social networks. In the workplace, algorithms assist managers in hiring decisions, support doctors in medical diagnoses and patient interactions, and help bank officials evaluate loan applications. Rapid technological advances are enhancing the capabilities of algorithms, and the range of personal and professional applications continues to grow exponentially as we move into the digital age. Thus, we often find ourselves not only using algorithms in decision making, but also encounter situations in which we are the decision targets (i.e., are affected by an algorithm's recommendations).

Even as algorithms become an increasingly familiar presence, the popular press and academic researchers have reported that these algorithms often encounter mixed receptivity from both user decision makers as well as decision targets. Whereas some researchers have documented situations where decision makers and targets express "algorithm appreciation," (Logg et al. 2018), there is a significant parallel literature that reports widespread "algorithm aversion." In other words, these researchers find that that people prefer to rely on human experts rather than "machine algorithms" even in situations when these algorithms are known to be more accurate and outperform human experts. Algorithm aversion has been reported in various domains, including medicine, finance, military, aviation, and education. (Dawes et al, 1989; Dietvorst et al, 2014, 2018; Logg et al., 2018; Yeomans et al., 2018; Alexander et al., 2018).

Several recent review papers and meta-analyses (e.g., Jussupow et al, 2020; Mahmud et al 2022) have examined the factors that influence algorithm aversion. Their research points to several factors that relate to the characteristics of the decision environment, as well as the algorithm's complexity and lack of transparency. These factors interact with user personality characteristics, as well as psychological factors that may be both cognitive (e.g., objective and subjective knowledge, familiarity, etc.) and emotional (e.g., ego, trust, control and self-efficacy). More macro influences (social and cultural) have also been implicated in describing how and why people relate to artificial intelligence in general and decision algorithms in particular. The reasons for algorithm aversion and algorithm appreciation are complex and multifaceted. Although objective algorithm performance relative to a human expert is clearly an important influence, these performance differences may even be overridden by more subjective factors. Given the current prevalence and the increasing role of algorithms in decision making, it is important to understand the reasons behind people's preferences for algorithms or human experts.

The present research program sheds light on these issues by providing empirical evidence on factors that influence preference for algorithm versus human expert recommendations in business decision making scenarios. Our studies use experimental psychological methods to examine how algorithm characteristics, decision maker (decision target) psychology and situational factors influence preference for algorithmic and human expert recommendations in various decision contexts. We examine situations in which the algorithm and the human expert are presented as competing (as opposed to complementary) resources for the decision maker (decision target), but without explicit differentiation in their capabilities or features. We report our research in the two empirically based essays that comprise this dissertation. We also outline plans for future research based on the results of the work reported here.

The first stream of research is presented in Chapter 2. We present three studies that examine the extent to which a decision maker aligns in a final decision with recommendation from an algorithm versus a human expert when the two recommendations conflict. The scenario involves a loan manager deciding to approve/deny a loan application that presents a marginal credit profile. Study 1 analyzes the extent to which the decision maker is influenced by the algorithm versus the human expert when the task/algorithm varies in complexity and the recommendations conflict. Study 2 examines how the decision maker is influenced when provided with readily interpretable performance <u>accuracy</u> information (high versus low) for both recommenders. This study examines whether preference for the algorithm (versus the human expert) persists in the face of matched or differential performance data (either low or high). Study 3 shows how a decision maker's predisposition (approve/deny) is affected by the performance accuracy information for the two recommendation sources. Our studies highlight several novel features including (a) head-to-head competition stemming from conflicting recommendations from the algorithm versus human expert, (b) the effect of matching as well as differential accuracy levels for the two sources, and (c) decision maker predisposition. Prior work on algorithm aversion/appreciation has not examined these contingencies.

The second stream of research (Chapter 3) examines how providing information that provides more objective knowledge of the inner workings of an algorithm influences a decision maker's willingness to use an algorithm, versus a human expert. The setting, once again, is a consumer loan context with loan officer as the decision maker. Specifically, we examine situations in which the additional information reduces (versus expands) what is unknown about the problem domain. We develop a model of how providing such problem domain information influences both perceived complexity and objective knowledge and affects the decision maker's subjective knowledge (confidence) . These model relationships are presented as a set of formal hypotheses that we assess in an empirical study set in the consumer loan context. Our empirical results show that the information manipulation influences both perceived complexity and objective knowledge. However, only perceived complexity (but not objective knowledge) mediates the information effect on subjective knowledge. We find, as expected, that subjective knowledge, as determined via the preceding pathways, influences willingness to use the algorithm. The study also examines alternative propositions regarding the role of self-efficacy in influencing the model's constituent relationships. The model presents a novel dual process perspective that may capture underlying aspects of algorithm aversion and appreciation within the same framework.

We conclude the dissertation in Chapter 4 by outlining our future research agenda in this exciting research domain. We propose to extend Essay 1 by examining how algorithm appreciation and aversion is manifested as a function of the decision maker's cognitive and emotional profiles. We describe a set of studies that examine the impact of prior domain knowledge, privacy concerns, self-efficacy and control orientation. We also examine situations in which the focal actor is a decision maker versus a decision target. in an effort to identify where managers and their customers may have similar or different orientations or predispositions toward algorithms.

We also propose to conduct research that extends Essay 2. One obvious extension is to focus on a different application domain (specifically medical diagnostics) and once again examine contexts where the participant plays the role of decision maker (physician) or a decision target (patient) and is considering the use of a human expert or a diagnostic algorithm. In these studies, we plan to use more formal knowledge manipulations built on metacognitive principles.

We also plan to use more sophisticated manipulations of accuracy (i.e., sensitivity versus specificity) as well as the salience of the costs associated with a false positive or a false negative diagnosis.

The results of the studies completed to date contribute to our understanding of the factors that influence algorithm aversion and appreciation. Our findings inform the design of algorithms that are more user-friendly and transparent and build user trust and acceptance. The insights that result from the present and planned work should help develop strategies to break down resistance to algorithms in situations where they may be beneficial to decision makers and to consumers in decision maker or decision target roles. Importantly, our research points to situations where algorithms and human experts play complementary roles that build on each other's strengths and circumvent weakness. Our hope is that this research contributes to a better understanding of the role of algorithms in decision making and facilitate beneficial social impacts.

## Chapter 2 – Essay 1- The Loan Officer's Dilemma: Decision Making when Human Experts and AI Algorithms Provide Conflicting Recommendations.

### Introduction

Artificial intelligence (AI) algorithms are commonly used in a wide variety of business decisions such as demand forecasting, product recommendation systems, and customer screening for credit and healthcare decisions (Mahmud et al., 2022). There is significant evidence that AI algorithms outperform human experts in a variety of decision-making tasks (e.g., Dawes et al., 1989; Dietvorst et al., 2015; Yeomans et al. 2018). However, despite the rapid advances in AI algorithm capabilities, there is parallel evidence that both decision makers and decision targets display mixed receptivity to the use of AI algorithms (Jussupow et al. 2020; Mahmud et al. 2022). Such ambivalence is surprising given that AI tools are both widely used and are becoming increasingly familiar with time. It is particularly enigmatic since the evidence suggests that algorithms perform better than human experts in a wide variety of decision domains (Castelo et al., 2019).

"Algorithm aversion" is a common finding (Dietvorst et al., 2015, Longoni et al. 2019) and has been defined as a behavioral tendency "to discount algorithmic decisions with respect to own decisions or other's decision , either consciously or non-consciously" (Mahmud et al 2022). At the same time, other researchers (e.g., Logg et al. 2019) report "algorithm appreciation," i.e., that people exhibit a preference for using algorithms relative to making their own decisions or using input from other human decision makers. Thus, some decision makers tend to prefer algorithms relative to human experts. Algorithm appreciation is associated with higher numeracy skills and is more likely to be observed for objective (versus subjective) tasks, and when the algorithm is known to be more accurate than the human expert.

In this chapter, we first selectively examine the literature on algorithm aversion and appreciation in order to provide the conceptual background to our empirical work. We then report three experimental studies that examine decision maker preferences when human experts and AI algorithms provide conflicting recommendations. All three studies are set in a consumer financial services context: a loan officer making an approve/deny decision on a consumer loan application. We focus on the extent to which our study participants (role-playing the loan officer), provided with such conflicting recommendations, make decisions that are aligned with the recommendations of the human expert versus the AI algorithm.

Our results provide intriguing insights into the algorithm aversion/appreciation phenomenon. Study 1 examined this issue along with the potential moderating roles of task complexity (complex/simple) and the conflict configuration (algorithm approve/human expert deny the loan and vice-versa). Study 1 found no main or interactive effects involving task complexity, but conflict configuration had a significant effect. Although a significant majority of the participants approved (versus denied) the loan in all four conditions, approval levels were higher when the human expert (versus the algorithm) recommended approval. Thus, although participants did override the recommendation of both the algorithm and the human expert, the algorithm's' denial recommendations were overridden more often than those of the human experts.

Study 2 examined decision outcomes under conflict configuration and the moderating role of the accuracy levels of the human expert/algorithm. As in Study 1, the majority of participants chose to approve the loan, and approval levels were higher when the human expert recommended approval (the algorithm recommended denial) relative to when the algorithm recommended approval (the human recommended denial). Moreover, this conflict configuration effect was moderated by the accuracy level of the human expert/algorithm. When the human recommends approval (the algorithm recommends denial), lower algorithm accuracy raised participants' frequency of loan approval. When the algorithm recommends approval (the human recommends denial), lower algorithm accuracy also lowered participants' loan approval frequency. However, the impact was asymmetric. When its accuracy was lower, the algorithm was overruled to a greater extent than the human expert. In contrast, lower accuracy for the human expert did not have this asymmetric impact on participants' decisions. Indeed, when a low accuracy algorithm recommends approval (the human recommends denial), a large majority of the participants override the algorithm and deny the loan. In contrast, when a low accuracy human expert recommends approval (the algorithm recommends denial), the human expert is overridden, but to a lesser extent.

In Study 3, we examine whether the participants' final decision is influenced by the degree to which the algorithm (human expert) recommendation aligns with the decision maker's (participant) predisposition to approve/deny the loan. Not surprisingly, predisposition has a strong and significant main effect on the final decision. However, the effect is qualified by an interaction with accuracy level. When the predisposition is to deny, approval rates are uniformly lower. However, when the predisposition is to approve, the approval rates are highest when both the algorithm and the human expert are low on accuracy showing that participants generally kept their own counsel in this condition. In other words, their decisions tended to align with their predisposition.

## Algorithm Aversion and Appreciation

Decision researchers have extensively examined and cataloged evidence on both algorithm aversion (e.g., Dietvorst et al., 2015, Yeomans et al. 2019) and appreciation (e.g., Logg et al. 2019). Thus, Dietvorst et al (2015) found that when individuals saw an algorithm make performance errors, they were less confident and thus were less willing to use the algorithm, despite evidence that it would, on average, perform better than a human. However, when provided process information explaining how the algorithm worked, people preferred to use algorithms over human advice (Logg et al. , 2019). Without such explanations, individuals may view algorithms as "black boxes": they are aware of what algorithms do but not how they do it (Yeomans et al, 2019).

These mixed findings have prompted several meta-analytic efforts to reconcile the seemingly contradictory findings. A recent review (Jussupow et al., 2020) identified that algorithm aversion is influenced by "algorithm agency" (whether the algorithm plays an advisory or an autonomous decision-making role); algorithm performance (errors, reliability, etc.), task-related algorithm capabilities, and human involvement in the training and use of the algorithm. These authors also implicate human agent characteristics as potential drivers of algorithm aversion/appreciation. Thus, framing the human agent as an expert increases willingness to rely on the human over the algorithm. Among other factors, social closeness with the user also drives greater reliance on the human expert. We focus in our work on placing the algorithm and human expert in advisory (not autonomous) role and also examine how participants align with advice from the human expert versus the algorithm when the recommendations conflict and how performance (error levels) of advisors influence the final decision.

Another meta-analytic effort (Mahmud et al., 2022) identifies five broad classes of factors that influence algorithm aversion/appreciation. One set of high-level factors include organizational, societal, cultural and environmental drivers. A second set relates to individual differences in user characteristics, including demographics, personality, as well as other psychological drivers (cognitive and emotional). A third set of factors relates to the task characteristics (including complexity and subjectivity), whereas the algorithm's characteristics including design complexity, delivery mode (oral versus electronic) constitute a fourth set of drivers.

Like Jussupow, et al., (2020), Mahmud et al., (2022) also stress the importance of the algorithm's response speed, and interface anthropomorphism. The level of supporting detail and explanation provided makes a difference as does the perceived accuracy and reliability of the algorithm relative to the human expert. Finally, it matters whether the algorithm is designed to play an autonomous decision-making role or simply provides recommendations for the decision maker's consideration. The extent to which a decision maker is predisposed toward a particular decision option may also influence the extent to which their final decisions align with the recommendation made by the algorithm or the human expert.

## Focal Variables

Beyond the substantive factors that may drive algorithm aversion/appreciation, we examine the circumstances under which decision makers have intrinsic preferences between the recommendations of an algorithm and a human expert. We selected three focal factors: (a) the complexity of the algorithm or decision task; (b) the accuracy level of the recommendation source, and (c) the extent to which the recommendation aligned with the decision maker's predispositions (if any). We discuss each of these factors below.

## Algorithm (Task) Complexity

Complexity has been defined in many ways in natural and social sciences research (Ladyman et al, 2013). In general, a complex system or component is one that is difficult to understand and verify. Complexity stems from the number of system components and the ”intricacy” of the interfaces between them, the number and intricacy of conditionalities, the levels of nesting, and the variety of data structures (Weng et al, 1999). More specifically, complexity involves three core components. First, structural complexity increases when the probability space and classification systems are defined with greater granularity so as to reduce entropy/uncertainty and enhance predictive output capability (Shannon, 1948 and Piaget, 1971). Second, process complexity increases with larger numbers of components/subsystems and a larger number of component interactions (von Berthalanffy, 1969; Koopmans, 2017). Finally, transformative complexity increases when an input creates a transformative output or moves a system from one equilibrium to another (Goldstein, 1988; Nicolis and Prigogine, 1989; and Koopmans, 2017). In our recommendation algorithms context, task complexity increases with the number of variables considered, potential nonlinearities in their effects/implications, as well as the number of configural interactions between them. These features make a task more complex, and we draw on these ideas to manipulate task complexity in our experiments.

## Accuracy

Dietvorst et al. (2015) is a foundational paper on algorithm aversion. Respondents decided to either use human input (their own or past participants') or an algorithm to forecast student performance from a set of data, with rewards for accuracy. Although the algorithm performed better in the aggregate, the fragmented structure of their initial learning phase may have obscured understanding of which source (human or algorithm) provides better forecasts. In other research (Madhaven and Wiegmann, 2007b; Bigman and Gray, 2018), accuracy was manipulated between-subjects, and respondents did not see direct comparisons of the accuracy levels of the various decision aids. As such, their understanding of the comparative accuracy of human and algorithmic aids may have been incomplete.

Not surprisingly, these studies produced mixed and unexpected results. Madhaven and Wiegmann (2007b) expected greater preference for the algorithm decision. They used a high accuracy rate of 90%, but did not find significant results. Bigman and Gray (2018) showed significant levels of algorithm preference, but only with a high accuracy rate of 95%. Dietvorst et al. (2015) found lower preference for algorithms despite their overall higher accuracy rates. Given these mixed results, our manipulations allowed respondents to directly compare the accuracy levels of the human expert and the algorithm when making their decisions. We used base accuracy rates of 90% and 70% and presented the accuracy levels for both the human expert and the algorithm, allowing them to be readily compared.

## Predispositions

One psychological factor that (to our knowledge) remains unexamined in prior research on algorithm aversion/appreciation is the extent to which the human expert's or the algorithm's recommendation are aligned with the decision maker's predisposition. Decision makers often use recommendations for confirmation, i.e., to assess the extent to which an "external and objective" source aligns with their predisposition to select a decision option. There is a large literature on the tendency for selective exposure to (and influence of) information consistent with one's prior beliefs (Hart et al., 2009). On the one hand, such predispositions may lower reliance on inconsistent recommendations from external sources (whether human experts or algorithms). On the other hand, the source (human expert or algorithm) of the discrepant recommendation may make a difference, given that the latter may be seen as less likely to give personally motivated advice. However, if decision makers feel that the algorithm is less capable of standing in their shoes than a human expert, they may discount an algorithmic recommendation that contradicts their predisposition. Our research explores these possibilities.

## Overview of Empirical Work

The designs of the three studies reported here were guided by the literature cited above. The studies were set in the context of a loan officer's decision to approve or deny a consumer loan request. The loan applicant's profile was designed to be of marginal quality, such that the approval/denial decision could go either way. Moreover, given our desire to examine intrinsic preferences between advice received from an algorithm versus a human expert, we presented recommendation pairs where the two sources provide conflicting recommendations about loan approval. We manipulated conflict configuration (algorithm recommendation: approve and human expert recommendation: deny; and vice-versa). We provided no accompanying explanation for the recommendation, so that systematic differences in the final decision would be an intrinsic preference that could not be attributed to other substantive factors.

In Study 1, we manipulated the conflict configuration as well as the complexity of the task (i.e., the algorithm). Study 2 used the same basic scenario, except that the complexity manipulation was replaced with manipulations of the performance accuracy (high/low) of the algorithm and human expert. As before, we provided no substantive explanation for the accuracy differences. In Study 3 we used the same basic design as for Study 2 and added a manipulation wherein the participant was told that they had a predisposition to either approve or deny the loan (no substantive reason was provided for the predisposition). In each study, we asked participants whether they would approve/deny the loan and examined the extent to which the decision aligned with the recommendation made by the algorithm or the human expert. We also examined if the decision maker's propensity to overrule a recommendation inconsistent with their predisposition depends on the recommendation source. In the next section we provide the propositions that we explored in each study.

## Propositions- Study 1

The preceding literature review shows decidedly mixed evidence for algorithm aversion and algorithm appreciation. Trust in the algorithm versus the decision maker (Burton et al., 2018; Madhaven and Wiegmann, 2007a; Jussupow et al., 2020) is one substantive factor that influences recommendation adoption. Source credibility (perceived ability to perform the task) may also influence whether computer algorithms (Dzindolet et al., 2002; Goodyear et al., 2016; Prahl and Van Swol, 2017) or human experts (Lerch et al., 1997; Madhaven and Wiegmann, 2007b; Jussupow et al., 2020) are preferred.

Automated systems are seen as reliable unless the available evidence suggests otherwise (Madhaven and Wiegmann, 2007a). However, they may elicit greater distrust (Jian et al., 2000; Longoni et al., 2019; and Yalcin et al., 2022). Human error is considered random and repairable whilst algorithm error is not (Madhaven and Wiegmann, 2007a, Burton et al., 2019), but humans, relative to algorithms, may be seen as less objective. Moreover, the literature suggests that decision targets may be more accepting of negative decisions from human advisors versus "black box" algorithms (Burton et al., 2019; Madhaven and Wiegmann, 2007a; Lee, 2018). However, there is some evidence of teleological explanations which explain the algorithms goals without revealing the underlying mechanism may mitigate a decision target's experienced dissatisfaction when denied by an unexplainable algorithm (Tomaino et al., 2020).

In the face of mixed evidence, we examine whether decision makers have an intrinsic preference for recommendations from a human expert versus an algorithm. In particular, we proposes that when substantive evidence favoring either source is sparse, decision makers are more likely to align with the recommendations of a human expert than an algorithm. Thus:

**P1.1 Participants' decisions will be more aligned with a human expert's recommendation relative to that of a computer algorithm.**

The complexity of an algorithm may influence the likelihood of decision makers accepting its recommendations relative to that of a human expert. Increased algorithmic complexity may lower "subjective knowledge" or confidence (Brucks 1985). Given the "black box" nature of algorithms (users understanding "what they do but not the how") and a lack of transparency (Logg et al., 2018; and Yeomans et al., 2019), increased complexity may lower the decision maker's willingness to rely on the algorithm and drive higher relevance for a human expert's recommendation. In our loan officer context, a complex algorithm would incorporate more variables and configural interactions, along with more complex data that would make it harder to comprehend the basis of recommendation. Hence:

**P1.2 Increased algorithmic complexity will drive participants' decisions to be more aligned to the human expert's recommendation.**

## Propositions- Study 2

As noted earlier, much of the prior research on the impact of algorithm accuracy levels on the use of reliance has produced mixed findings. Some of these results may have stemmed from participants not fully grasping the accuracy manipulations given how relevant information was presented in a learning phase. Moreover, the accuracy level differences may not have been noticeably different and hence lacked impact. Also, the studies were implemented with between-subject designs where the algorithm and the human expert were not pitted in head-to-head competition. Hence within-subject designs may be more effective for investigating inherent differences in relative preferences to adopt recommendations from a human expert or an algorithm.

Keeping these issues in mind, the design of Study 2 presents the accuracy level information (a) via a direct manipulation at 90% (high) and 70% (low) respectively; and (b) such that participants can make head-to-head comparisons of the two sources. In other words, the Study 2 participants were randomly assigned to one of four accuracy level conditions in a 2 (Algorithm: High/Low) x 2 (Human Expert: High/Low) design. Our propositions relate to the decision maker's preferences for recommendations from the human expert versus that of the algorithm in each of the above four conditions. Hence:

**P2.1. Participants' decisions will be more aligned with the human expert's recommendation relative to that of the algorithm when both sources have equal accuracy levels (high-high or low-low).**

**P2.2 Participants' decisions will be less aligned with the recommendations from the source with a lower accuracy level when the two sources have unequal accuracy levels (high-low or low-high).**

**P2.3 The increase in alignment with the human expert's recommendations due to higher (versus lower) accuracy will be greater than the corresponding increase in alignment with the algorithm's recommendations due to higher (versus lower) accuracy.**

## Propositions- Study 3

In Study 3 we manipulated both accuracy level and decision maker predisposition (to approve/deny the loan). We then explore if the results corresponding to the three Study 2 propositions persist in the presence of a decision maker predisposition to deny/approve the loan. Thus, we propose the following moderating effects of predisposition:

**P3.1M Predisposition will moderate the tendency for participants' decisions to be more aligned to the human expert's recommendation relative to that of the algorithm when both sources have equal accuracy levels (high-high or low-low).**

**P3.2M Predisposition will moderate the tendency for participants' decisions to be more aligned with the recommendations from the source with a higher accuracy level when the two sources have unequal accuracy levels (high-low or low-high).**

**P3.3M Predisposition will moderate the asymmetry in participants' decisions to align more with the human expert (versus the algorithm) recommendation as a result of accuracy variations (high versus low).**

We offer two additional propositions regarding the effects of the predisposition manipulation. No formal proposition is offered for the interaction between source accuracy level and the predisposition factor but will explore this as part of our analysis.

**P3.4 Participants' decisions will be more aligned with the recommendations from the source that corresponds to the decision maker's predisposition.**

**P3.5. Participants' decisions will be more aligned with the recommendations from the human expert (versus the algorithm) when it corresponds to the decision maker's predisposition.**

## Research Methodology-

We conducted three experimental studies on MTurk via CloudResearch to examine the above propositions. We used CloudResearch's MTurk toolkit and offered monetary incentives between $0.60 and $0.80 for participation. Parameters were set to ensure that no participant was included in more than one of the three studies. The survey was developed on the Qualtrics platform. The core scenario was identical for the studies and allowed qualitative comparisons of the results from the three studies.

Core Scenario and Manipulations

Each participant played the role of a branch manager at a bank. The manager was tasked with making the final decision on whether to approve or deny a loan application where the applicant had a marginal credit score. All participants received identical detailed information on the various components of an overall credit (FICO) score calculation. They were then given the specific (marginal) credit score for the loan applicant. Next, they received some background detail on the human expert and the computer algorithm. This information indicated that both the human expert and the computer algorithm had access to the same credit information databases.

The scenario also stated that the manager had requested recommendations from both the human expert and the algorithm as to whether the loan should be approved/denied. As previously noted, the two recommendations were manipulated to be conflicting. The conflict configuration was manipulated at two levels: [Algorithm - Approve, Human Expert - Deny (A+E-); and Algorithm - Deny, Human Expert - Approve (A-E+)]. The cases where the recommendations agreed were not of interest. This specific manipulation of the conflict configuration was used in each of the three studies reported here.

Core and Secondary Dependent Measures

The core dependent measure in all three studies was the participants' response to the question, "What is your final decision regarding the loan application?" In Studies 2 and 3 we also asked the participants to rate their likelihood of approving the loan immediately prior to indicating their approve/deny decision. Other measures in each study included the appropriate manipulation checks, measures that provided insights regarding the underlying basis for the participants' decisions, as well as participant demographics. A complete list of the dependent and independent variables used in the three studies is provided in Table 1 below.

*Table 1-Independent and Dependent Variables*

| Variable | Type | Details |
|---|---|---|
| **Conflict Configuration (Recommendations)** | IV | Manipulation-Two Pairs-Algorithm + /Human Expert – and Algorithm -/Human Expert + |
| **Algorithm Complexity** | IV | Manipulation-Two levels-Simple and Complex |
| **Accuracy** | IV | Manipulation-4 Algo/Expert pairs with 90% (high) and 70% (low)-high/high, high/low, low/high, and low/low |
| **Predisposition** | IV | Manipulation-Two Levels-Predisposed Approve or Deny |
| **Loan Decision** | DV | Measure (Dichotomous)-Approve or Deny |
| **Likelihood of Loan Approval** | DV | Measure (Continuous)-7pt Likert Scale (1=Low Likelihood and 7=High Likelihood) |

## Study 1

In Study 1 we used the above conflict configuration manipulation, and also manipulated the complexity of the algorithm (simple/complex) using descriptions that varied in the number of components and their interactions that were incorporated into the FICO score. The study used a 2 (Conflict Configuration: A+E-/A-E+) x 2 (Complexity: Simple/Complex) between-subject design. A total of 207 participants recruited from M-Turk via CloudResearch (39% female; 81% Caucasian; Average Age of 38) completed the study for $0.60 compensation. They were randomly assigned to the four study conditions and examined the FICO score description, the applicant profile and the corresponding recommendations from the human expert and the algorithm. CH2-Appendix A provides FICO details in the complexity level conditions and the manipulation check test. They were then asked to indicate their final decision (approve/deny) regarding the loan application.

Results

The complexity manipulation was successful ($M_{Complex}$ =5.5; $M_{Simple}$ =4.6; $F(1, 204) = 17.63$, $p <.001$). The participants' decisions in each study condition are shown below (Table 2 - Study 1).

*Table 2-Study 1: Loan Approval Percentages by Condition*

| Complexity Level | Conflict Configuration | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | A -/E+ | | | A +/E- | | | |
| | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| Complex | 46 | 5 | 90.20% | 39 | 13 | 75.00% | 82.52% |
| Simple | 45 | 8 | 84.91% | 34 | 17 | 66.67% | 75.96% |
| % Average Approval Total | 87.50% | 12.50% | 87.50% | 70.87% | 29.13% | 70.87% | 79.23% |

Note 1-Conflict Configuration: A-/E+ =algorithm negative/expert postive recommendations and A+/E- =aglorithm positive /expert negative recommnedations

These categorical decision data were analyzed using a hierarchical loglinear model (see CH2-Appendix B for the detailed output). The analysis produced a final model that did not retain all effects. The likelihood ratio [$\chi^2(4)=1.587$, $p=.811$] indicated that the model fit the data well. We follow the guidance provided by Chen et al. (2010) for interpreting the odds ratios (95% confidence interval). Values of 1.52, 2.74 and 4.72 relate to Cohen's d values of 0.2, 0.5 and 0.8 (i.e., small, medium and large effect sizes, respectively). Odds ratios below 1.52 are deemed nonsignificant. Thus, contrary to Proposition P1.2, complexity level had no significant main effect on the decision maker's loan decision (Odds Ratio: 82.52/75.96 = 1.09) and [partial $\chi^2(1)=0.21$, $p=.65$]. The interaction between complexity and conflict configuration was also not significant [partial $\chi^2(1)= 1.53$, $p=.22$).

However, the final model also indicated that the conflict configuration (recommendation source) manipulation had a significant effect ( $\chi^2$ (1)=8.88, $p=.003$). Further analysis shows that the approval odds for the A-E+ condition were 87.5/12.5 = 7, whereas for the A+E- condition the odds were 70.87/29.13 = 2.43. This then implies that participants were 7/2.43 = 2.88 times more likely to approve the loan when the human expert (versus the algorithm) recommended approval. This significant and medium effect size indicates support for Proposition P1.1: participants' decisions were indeed more aligned with the human expert's recommendation relative to that of the computer algorithm.

<u>Discussion</u>

In summary, the data show a systematically higher alignment with the human expert's recommendation. Loan approval (versus denial) was 2.88 times more likely when the human (versus the algorithm) recommended approval of the loan for the marginal FICO profile. These results are consistent with previous findings regarding algorithm aversion. However, it is interesting that even when the human expert recommends denial, the decision maker approves the loan (aligning with the algorithm's recommendation) 70.9% of the time on average. This appears to reflect the possibility that the decision makers in this situation were predisposed to approve the loan (a factor whose effects we explicitly examine in Study 3).

## Study 2

Given that we did not observe a significant complexity effect in Study 1, we removed this manipulation in study 2 and simplified the background scenario. We retained the conflict configuration manipulation, as in Study 1, but added an accuracy manipulation that had four paired accuracy levels. These were: high accuracy algorithm/high accuracy expert (AH-EH); high accuracy algorithm/low accuracy expert (AH-EL), low accuracy algorithm/high accuracy expert (AL-EH) and low accuracy algorithm/low accuracy expert (AL-EL). The high and low accuracy rates were set at 90% and 70%, respectively. This design allows a direct, head-to-head comparison of the impact of recommender accuracy levels. In summary, the study used a 2 (conflict configuration: A+E-/A-E+) x 4 (Accuracy Levels: AH-EH, AH-EL, AL-EH and AL-EL) between- subjects design. A total of 406 participants (49% female; 83% Caucasian, Average Age of 41) were recruited from MTurk via CloudResearch and were randomly assigned to the eight study conditions. Each participant was paid $0.70 for participation.

<u>Results - Decision Data</u>

As in Study 1, participants indicated their final decision (approve/deny) regarding the loan. Moreover, in Study 2, immediately <u>prior</u> to indicating their approval/denial decision, participants also indicated their likelihood of approving the loan on a 7-point likelihood scale (1=Low, 7=High). Their decisions are shown by study condition in Table 3 – Study 2 below.

*Table 3-Study 2: Loan Approval Percentages by Condition*

| Accuracy Levels | Conflict Configuration | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | A -/E+ | | | A +/E- | | | |
| | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| **AH-EH** | 46 | 4 | 92.00% | 35 | 16 | 68.63% | 80.20% |
| **AH-EL** | 22 | 30 | 42.31% | 46 | 6 | 88.46% | 65.38% |
| **AL-EH** | 49 | 1 | 98.00% | 12 | 38 | 24.00% | 61.00% |
| **AL-EL** | 42 | 8 | 84.00% | 32 | 19 | 62.75% | 73.27% |
| **% Avg Approval Total** | 78.71% | 21.29% | 78.71% | 61.27% | 38.73% | 61.27% | 69.95% |

Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=aglorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low

As in Study 1, these categorical data were analyzed using a hierarchical loglinear model (see CH2-Appendix C for the detailed output). The final model retained all effects. The likelihood ratio [$\chi^2(0)= 0$, p=1.0] shows that the model fit the data almost perfectly. The highest-order interaction (Conflict Configuration x Accuracy) was significant, $\chi^2$ (3)=94.74, p<.001. As in Study 1, we follow the guidance provided by Chen et al. (2010) for interpreting odds ratios (95% confidence interval). Thus, values of 1.52, 2.74 and 4.72 correspond to small, medium and large effect sizes, respectively. Odds ratios below 1.52 are deemed nonsignificant.

We use counts instead of percentages to calculate the odds in each condition. Our analysis shows that when both the algorithm and the human were *high accuracy*, participants in the A-E+ condition were 46/4 = 11.5 times more likely to approve the loan. However, in the A+E- condition, participants were only 35/16 = 2.19 times as likely to approve. In other words, when both sources were high accuracy, participants were 11.5/2.19 = 5.26 times as likely to approve the loan when the human expert (A-E+) versus the algorithm (A+E-) recommended approval. This effect size is large.

A similar analysis for when both recommendation sources were *low accuracy* showed that A-E+ participants were 42/8 = 5.25 times more likely to approve. However, in the A+E-condition, participants were only 32/19 = 1.68 times as likely to approve. Thus, when both sources were low accuracy, participants were 5.25/1.68 = 3.12 times as likely to approve the loan when the human expert (A-E+) versus the algorithm (A+E-) recommended approval. This is a medium-sized effect. Overall, these results are consistent with Proposition P2.1 and show that participants' decisions were more aligned with the human expert's recommendations when the two sources were of comparable accuracy (whether high or low).

In order to examine Proposition P2.2 we first compared the odds of approval when the algorithm was high accuracy, but the human expert was low accuracy (AH-EL). These approval odds were 22/30 = 0.73 in the A-E+ condition and 46/6 = 7.67 in the A+E- condition. Thus, decision makers were more aligned with the approval recommendation of the higher accuracy algorithm relative to the lower accuracy human. A similar analysis showed that when the algorithm was low accuracy, but the human was high accuracy (AL-EH), the approval odds were 49/1 = 49 in the A-E+ condition and 12/38 = 0.32 in the A+E- conditions respectively. Thus, decision makers were more (7.67/0.32 = 23.97 times) aligned with the approval recommendation of the high accuracy human relative to the low accuracy algorithm. These data show strong support for Proposition P2.2. In other words, given the accuracy levels used in our study, decision makers strongly aligned with the recommendation of the source that they believed was more accurate.

Participants' decisions show greater alignment with the approval recommendation of the high accuracy algorithm (A+E-). Thus, they are (7.67/0.73 = 10.51 times) more likely to approve the loan when the high accuracy algorithm recommends approval (versus the low accuracy human expert). However, participants are 49/0.32 = 153 .1 times more likely to approve the loan in the A-E+ condition, where a high accuracy human expert recommends approval (versus the low accuracy algorithm). This asymmetric effect of accuracy for the algorithm and the human expert is consistent with Proposition P2.3.

Additional support for Proposition P2.3 emerges by comparing the odds of loan approval when the human expert (pooled over high and low accuracy) recommends approval (A-E+) when the algorithm's accuracy is high versus low. With a high accuracy algorithm, the pooled odds of loan approval are 68/34 = 2.0. With a low accuracy algorithm, the pooled odds are 91/9 = 10.1. Thus, the odds of loan approval increases 10.1/2.0 = 5.05 times when the algorithm's accuracy drops from high to low in the A-E+ condition. Next we compare when then algorithm (pooled over high and low accuracy) recommends approval (A+E-) when human expert's accuracy is high versus low. Here, with a high accuracy human, the pooled (high and low accuracy algorithm) odds of loan approval are 47/54 = 0.87. With a low accuracy human, the pooled odds are 78/25 = 3.12. Thus, the odds of loan approval show a medium-sized increase (3.12/0.87) of 3.59 times when the human's accuracy drops from high to low in the A+E-. This medium effect size (3.59) reflects a smaller gain in participant agreement with the algorithm recommendation when human accuracy goes from high to low vs. the large effect size (5.05) in participant agreement with the human recommendation when algorithm accuracy goes from high to low.

In summary, the decision data show consistent support for Propositions P2.1, P2.2, and P2.3. There is evidence of algorithm aversion, but this is contingent upon the accuracy level of the algorithm and the human expert. However, the effects are asymmetric – the impact is larger for the human expert than it is for the algorithm.

<u>Results - Decision Likelihood Data</u>

In Study 2, we asked participants immediately <u>prior</u> to indicating their approval/denial decision to indicate their <u>likelihood</u> of approving the loan on a 7-point likelihood scale (1=Low, 7=High). These data were subjected to an analysis of variance as a function of the conflict configuration and the accuracy level manipulations and their interaction. The analysis revealed a significant effect of conflict configuration ($F(1, 398) = 24.37$, $p < .001$) as well as a significant interaction of conflict configuration and accuracy (($F(3, 398) = 47.03$, $p < .001$). There was no significant main effect of accuracy ($F(3, 398) = 1.40$, $p = .242$). Table 4 – Study 2 below shows the mean likelihood ratings by conflict configuration and accuracy conditions.

*Table 4-Study 2: Likelihood of Approval - Means and Std. Deviations by Study Condition*

| **Accuracy Levels** | **Conflict Configuration** | | | |
|---|---|---|---|---|
| | **(A-E+): Algorithm - / Expert +** | | **(A+E-): Algorithm + / Expert -** | |
| | **Mean** | **Std. Deviation** | **Mean** | **Std. Deviation** |
| **AH-EH** | 5.26 | 1.34 | 4.35 | 1.89 |
| **AH-EL** | 3.56 | 1.89 | 5.52 | 1.35 |
| **AL-EH** | 6.06 | 0.65 | 2.90 | 1.71 |
| **AL-EL** | 5.30 | 1.43 | 4.37 | 1.72 |

Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=aglorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low.

These data closely mirror the decision data (see CH2-Appendix C-ANOVA Analysis.) Thus, when the human expert A-E+ (versus the algorithm, A+E-) recommended approval, participants reported a higher likelihood of loan approval when both sources had equal accuracy levels (AHEH: $M_{A\text{-}E+} = 5.26$ vs. $M_{A+E\text{-}} = 4.35$; $p = .003$; and ALEL: $M_{A\text{-}E+} = 5.30$ vs. $M_{A+E\text{-}} = 4.37$; $p = .003$). These results are consistent with Proposition P2.1. As proposed, participants' decisions were indeed more closely aligned to the human expert's recommendations when the accuracy level for the two sources were equal (high-high or low-low).

When the low accuracy human expert recommended approval in the A-E+ condition (versus the high accuracy algorithm in the A+E- condition), participants reported a significantly lower likelihood of loan approval. (AH-EL: $M_{A-E+}$ = 3.56 vs. $M_{A+E-}$ = 5.52; $p <.001$). When the high accuracy human expert recommended approval in the A-E+ condition (versus the low accuracy algorithm) participants reported a significantly higher likelihood of loan approval (AL-EH: $M_{A-E+}$= 6.06 vs. $M_{A+E-}$ = 2.90; p = $p<.001$). These results are consistent with Proposition P2.2. As proposed, participants' decisions were more closely aligned to the recommendation from the source with higher accuracy levels.

To examine Proposition P2.3, we first examine the change in approval likelihood in the A-E+ condition where the human expert recommended approval. The data are shown in Table 5-Study 2 and Table 6-Study 2 below. For high expert accuracy, the pooled approval likelihood over high and low algorithm accuracy is 5.66. For low expert accuracy, the corresponding pooled likelihood is 4.41. Thus, the increase in approval likelihood in the A-E+ condition (where the human expert recommends approval) for the high versus low accuracy human expert is (5.66 – 4.41) = 1.25; ($p< .001$). A similar computation for the A+E- condition when the algorithm recommends approval shows a corresponding decrease in approval likelihood (4.94 – 3.63) = 1.32; ($p< .001$).

*Table 5-Study 2-Approval Likelihood Means: Conflict Configuration and Pooled Accuracy Level*

| Conflict Configuration | Pooled Accuracy | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Algo-/Expert+ | ExpHigh | 5.66 | 1.121 | 100 |
| | ExpLow | 4.41 | 1.890 | 102 |
| Algo+/Expert- | ExpHigh | 3.63 | 1.932 | 101 |
| | ExpLow | 4.95 | 1.641 | 103 |
| Algo-/Expert+ | AlgoHigh | 4.39 | 1.846 | 102 |
| | AlgoLow | 5.68 | 1.171 | 100 |
| Algo+/Expert- | AlgoHigh | 4.94 | 1.731 | 103 |
| | AlgoLow | 3.64 | 1.858 | 101 |

Note 1 - AlgoHigh/Expert Low accuracy numbers were included in both AlgoHigh and ExpLow Pooled Accuracy means. AlgoLow/Expert High accuracy numbers were included in both AlgoLow and ExpHigh Pooled Accuracy means. Hence, two separate tests were run to ensure each data point was included only once.

*Table 6-Study 2-Approval Likelihood Means: Conflict Configuration and Pooled Accuracy Level*

| Conflict Configuration | Pooled Accuracy (I) | Pooled Accuracy (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Lower Bound | 95% Confidence Upper Bound |
|---|---|---|---|---|---|---|---|
| **Algo-/Expert+** | **ExpHigh** | **ExpLow** | 1.25 | 0.236 | p<.001 | 0.784 | 1.713 |
| **Algo+/Expert-** | **ExpLow** | **ExpHigh** | 1.32 | 0.235 | p<.001 | 0.856 | 1.780 |
| **Algo-/Expert+** | **AlgoLow** | **AlgoHigh** | 1.29 | 0.236 | p<.001 | 0.824 | 1.752 |
| **Algo+/Expert-** | **AlgoHigh** | **AlgoLow** | 1.30 | 0.235 | p<.001 | 0.836 | 1.760 |

In summary, the data above indicates that an increase in the accuracy level of the human expert produced a symmetric increase (decrease) in alignment likelihood with the recommendation of the human expert (algorithm).

Similar comparisons show that an increase in the algorithm's accuracy level produces a symmetric decrease (increase) in alignment with the human expert's recommendation (algorithm). The relevant decrease in alignment with the *human expert* in the A-E+ condition is (5.68 – 4.39) = 1.29, ($p < .001$). In the A+E- condition, the corresponding increase in alignment with the *algorithm* is: (4.94 – 3.64) = 1.30; ($p < .001$). Contrary to Proposition P2.3, the two magnitudes are similar (versus asymmetric)..

Discussion

In summary, the Study 2 decision data show consistent support for Propositions P2.1 to P2.3. There is evidence of algorithm aversion, but contingent upon the accuracy levels of the algorithm and the human expert. Participants tended to align with the higher accuracy source. However, the effects are asymmetric – the alignment is stronger for the human expert than for the algorithm. The decision likelihood data tend to mirror the decision data in supporting Proposition P2.1 and P2.2. There is evidence of algorithm aversion, but as in the decision data, it is contingent upon the accuracy level of the algorithm and the human expert. Notably, there is a dissociation between the actual decision and the decision likelihood judgments. The asymmetry observed in the decision data (consistent with Proposition P2.3) was absent in the decision likelihood data (inconsistent with Proposition P2.3).

## Study 3

Study 3 examines how the decision maker's level of alignment with the human expert's (versus the algorithm's) recommendations varied as a function of the accuracy level of each source, as well the decision maker's predisposition. The background scenario and study procedures were similar to those used in Study 2. Thus, conflict configuration and source accuracy levels were manipulated as in Study 2 to create a 2 (conflict configuration: A+E-/A-E+) x 4 (Accuracy Levels: AHEH, AHEL, ALEH and ALEL) between subjects design. As in Study 2, the high and low accuracy rates were set at 90% and 70%, respectively. However, in Study 3, this base design was fully crossed with a manipulation of decision-maker predisposition to approve/deny the loan. This creates a total of sixteen study conditions.

A total of 800 participants (48% female; 82% Caucasian, Average Age of 43) were recruited from MTurk via CloudResearch and were randomly assigned to the sixteen study conditions. Each participant was paid $ .80 for participation. As in Study 2, participants first reviewed the relevant information for their study condition and then indicated their final (approve/deny) decision on the loan. Also, as in Study 2, immediately prior to their approval/denial decision, participants also indicated their likelihood of approving the loan on a 7-point likelihood scale (1= Low, 7= High).

### Results - Decision Data

The categorical (Approve/Deny) decision data were analyzed using a hierarchical loglinear model (see CH2-Appendix D for the detailed output) as in Study 2. The analysis produced a final model that did not retain all effects. The model likelihood ratio [$\chi^2(4)$= 9.14, p= 0.058] suggests a marginal fit to the data. There were three significant 3-way interactions: (Predisposition x Accuracy x Decision: $\chi^2(3)$=12.85, p= .005; Conflict Configuration x Accuracy x Decision: $\chi^2(3)$=107.05, p<.001; and Predisposition x Conflict Configuration x Accuracy: $\chi^2(3)$=24.75, p<.001). We focus next on selected interactions of interest. As before, following Chen et al. (2010), we interpret odds ratio (95% confidence interval) values of 1.52, 2.74 and 4.72 as corresponding to small, medium and large effect sizes, respectively and below 1.52 as nonsignificant. We use counts instead of percentages to calculate the odds in each condition.

We first examine the results related to Propositions 3.1M, 3.2M and 3.3M, which explore how decision maker predisposition moderates Propositions 2.1, 2.2 and 2.3 for Study 2. These tests are conducted by pooling the decision data over the two predisposition conditions in Study 3 and examining the correspondence of the results obtained in Study 2. We present these analyses in sequence below.

*Conflict Configuration and Accuracy*. The table below (Table 7 – Study 3) shows the results for the conflict configuration by accuracy interaction (pooled over the predisposition manipulation). These results are used to examine P3.1M, P3.2M and P3.3M which correspond to P2.1, P2.2 and P2.3 respectively in Study 2.

*Table 7-Study 3: Loan Approval Percentages – Conflict Configuration and Accuracy*

| | Conflict Configuration | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | A -/E+ | | | A +/E- | | | |
| Accuracy Levels | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| AH-EH | 61 | 35 | 63.54% | 62 | 38 | 62.00% | 62.76% |
| AH-EL | 42 | 60 | 41.18% | 84 | 17 | 83.17% | 62.07% |
| AL-EH | 91 | 10 | 90.10% | 40 | 60 | 40.00% | 65.17% |
| AL-EL | 73 | 26 | 73.74% | 61 | 40 | 60.40% | 67.00% |
| % Avg Approval Total | 67.09% | 32.91% | 67.09% | 61.44% | 38.56% | 61.44% | 64.25% |

Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=aglorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low.

Our analysis shows that when both the algorithm and the human featured *high accuracy* levels, participants in the A-E+ condition were 61/35 = 1.74 times more likely to approve the loan. Similarly, in the A+E- condition, participants were 62/38 = 1.63 times as likely to approve. This implies that when both sources were high accuracy, participants were about equally likely to approve the loan whether it was the human expert (A-E+) or the algorithm (A+E-) that recommended approval. Thus, introducing decision maker predisposition (whether to deny or approve) generated equivalent alignment for both the *high accuracy* sources.

A similar analysis for when both recommendation sources were *low accuracy* showed that A-E+ participants were 73/26 = 2.81 times more likely to approve the loan. In the A+E- condition, participants were 61/40 = 1.52 times as likely to approve. Thus, when both sources were low accuracy, participants were 2.81/1.52 = 1.84 times more likely to approve the loan when it was the human expert (A-E+) versus the algorithm (A+E-) that recommended approval. This small effect size shows that introducing decision maker predisposition left a small residual preference for the human expert over the algorithm when both sources were of *low accuracy*. Overall, these data imply that when a decision maker has a predisposition (denial/approval), there is a moderating effect (Proposition 3.1M) such that recommendation sources tend to lose differential impact. When both sources have *high accuracy*, the decision maker's alignment levels with the recommendation of the human expert and the algorithm are equivalent. When both sources are of *low accuracy* only a mild residual preference remains for the human expert. These results are consistent with Proposition 3.1M and show that the Proposition 2.1 effect is moderated in the presence of decision maker predisposition.

We examined Proposition 3.2M by first comparing the odds of approval when the algorithm was high accuracy, but the human expert was low accuracy. These approval odds were

42/60 = 0.70 in the A-E+ condition and 84/17 = 4.94 in the A+E- condition. Thus, as in Study 2, decision makers aligned with the approval recommendation of the higher accuracy algorithm versus the lower accuracy human expert . A similar analysis showed that when the algorithm was low accuracy, but the human was high accuracy, the approval odds were 91/10 = 9.1 in the A-E+ condition and 40/60 = 0.67 in the A+E- conditions, respectively. Decision makers were more aligned (9.1/0.67 = 13.58 times) with the approval recommendation of the high accuracy human relative to the low accuracy algorithm. These results show that even when they had a predisposition, decision makers aligned with the recommendation of the *more accurate* source. However, a comparison with the degree of alignment in Study 2 (23.97 times higher approval likelihood) the alignment level in Study 3 was lower (13.58 times higher approval likelihood). These results are consistent with Proposition 3.2M and show that the effect observed in Proposition 2.2 is moderated by the presence of decision maker predisposition.

Participants' decisions show greater alignment with the approval recommendation of the high accuracy algorithm (A+E-). Thus, they are (4.94/0.70 = 7.05 times) more likely to approve the loan when the high accuracy algorithm recommends approval (versus the low accuracy human expert). However, participants are 9.1/.67 = 13.6 times more likely to approve the loan (A-E+ condition) when a high accuracy human expert recommends approval (versus the low accuracy algorithm). Thus, even when they have a predisposition, decision makers exhibit there an asymmetric preference for the human expert versus the algorithm. However, the degree of asymmetry (153.1/10.51 = 14.57) observed in Study 2 (Proposition 2.3) is smaller in Study 3 (13.6/7.05 = 1.93) in the presence of a decision maker predisposition. Thus, consistent with Proposition 3.3M, the preference asymmetry for the human expert versus the algorithm is moderated when the decision maker has a predisposition.

In summary, when the decision maker has a predisposition to approve or deny the loan, the results differ from those in Study 2. As proposed (Proposition 3.1M, 3.2M and 3.3M) predisposition moderates the effects seen in Study 2. First, when both sources have *high accuracy*, the decision maker's alignment with the recommendation of the human expert and the algorithm is equivalent. When both sources have *low accuracy* only a small residual preference remains for the human expert. This is consistent with Proposition 3.1M. Second, even with a predisposition, decision makers aligned with the recommendation of the *more accurate* source. However, the alignment level in Study 3 was lower than in Study 2. The results (consistent with Proposition 3.2M) show the moderating effect of decision maker predisposition. Third, even with a predisposition, the decision makers in Study 3 show an asymmetric preference for the human expert versus the algorithm (given varying accuracy). However, predisposition moderates (attenuates) this asymmetry, consistent with Proposition 3.3M.

*Predisposition and Accuracy*. The pertinent data are shown in Table 8 – Study 3 below. The data show a medium sized main effect of predisposition. Participants were (78.84/21.16 = 3.72 times) more likely to approve the loan when predisposed to approve. However, they were equally likely to approve (49.88%) or deny (50.12%) the loan when their predisposition was to deny. The fact that they were more likely to make an approve (versus deny) decision shows that the recommendations had some influence. Recommender accuracy played a small role when they were predisposed to approve but had negligible impact when predisposed to deny.

*Table 8-Study 3: Loan Approval %s by Predisposition and Accuracy Conditions*

| Accuracy Levels | Predisposition | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | Approve | | | Deny | | | |
| | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| AH-EH | 72 | 14 | 83.72% | 51 | 59 | 46.36% | 62.76% |
| AH-EL | 78 | 38 | 67.24% | 48 | 39 | 55.17% | 62.07% |
| AL-EH | 77 | 24 | 76.24% | 54 | 46 | 54.00% | 65.17% |
| AL-EL | 86 | 8 | 91.49% | 48 | 58 | 45.28% | 67.00% |
| % Avg Approval Total | 78.84% | 21.16% | 78.84% | 49.88% | 50.12% | 49.88% | 64.25% |

Note 1-Predisposition: Approve=participant predisposed to approve the loan and Deny=participant predisposed to deny the loan
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low

*Approval Predisposition, Conflict Configuration and Accuracy.* The three-way interaction data allows us to address Propositions 3.4 and 3.5. The three tables (Table 9 – Study 3, Table 10 – Study 3, and Table 11 – Study 3) show the pertinent data.

*Table 9-Study 3: Loan Approval % by Approve Predisposition, Conflict Configuration and Accuracy*

| Accuracy Levels | Predisposition-Approve | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | Conflict Configuration | | | | | | |
| | A -/E+ | | | A +/E- | | | |
| | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| AH-EH | 28 | 2 | 93.33% | 44 | 12 | 78.57% | 83.72% |
| AH-EL | 33 | 32 | 50.77% | 45 | 6 | 88.24% | 67.24% |
| AL-EH | 52 | 4 | 92.86% | 25 | 20 | 55.56% | 76.24% |
| AL-EL | 46 | 0 | 100.00% | 40 | 8 | 83.33% | 91.49% |
| % Avg Approval Total | 80.71% | 19.29% | 80.71% | 77.00% | 23.00% | 77.00% | 78.84% |

*Table 10-Study 3: Loan Approval %s by Deny Predisposition, Conflict Configuration and Accuracy*

| Accuracy Levels | Predisposition-Deny | | | | | | % Average Approval Total |
|---|---|---|---|---|---|---|---|
| | Conflict Configuration | | | | | | |
| | A -/E+ | | | A +/E- | | | |
| | Approval Count | Deny Count | % Approval | Approval Count | Deny Count | % Approval | |
| AH-EH | 33 | 33 | 50.00% | 18 | 26 | 40.91% | 46.36% |
| AH-EL | 9 | 28 | 24.32% | 39 | 11 | 78.00% | 55.17% |
| AL-EH | 39 | 6 | 86.67% | 15 | 40 | 27.27% | 54.00% |
| AL-EL | 27 | 26 | 50.94% | 21 | 32 | 39.62% | 45.28% |
| % Avg Approval Total | 53.73% | 46.27% | 53.73% | 46.04% | 53.96% | 46.04% | 49.88% |

Notes apply to both Tables 9 and 10 above-
Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=algorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low.

We test Proposition 3.4 by pooling over the uncertainty conditions to extract the number of instances where decisions were consistent or inconsistent with the recommendations of the human expert and the algorithm respectively. Thus, when the decision maker's predisposition was Approve, the A-E+ data show that the decision was consistent (inconsistent) with the human expert's recommendation in 159 (38) instances. When the decision maker predisposition was Deny, the A-E+ data show that the decision was consistent (inconsistent) with the human expert recommendation in 93 (108) instances. Similar computations were also performed for the A+E- conditions for both predispositions. The data are tabulated below (Table 11-Study 3) and show a small overall effect (odds = 1.81) supporting Proposition 3.4.

*Table 11-Study 3-Predisposition by Source Match/Mismatch Counts and Odds*

| Predisposition | Source/Condition | Match | Mismatch | Total | Odds |
|---|---|---|---|---|---|
| Approve | Human (A-E+) | 159 | 38 | 197 | 4.18 |
| | Algorithm (A+E-) | 154 | 46 | 200 | 3.35 |
| Deny | Human (A+E-) | 109 | 93 | 202 | 1.17 |
| | Algorithm (A-E+) | 93 | 108 | 201 | 0.86 |
| Pooled | Human (A-E+) | 268 | 131 | 399 | 2.05 |
| | Algorithm (A+E-) | 247 | 154 | 401 | 1.60 |
| Overall | Both Sources | 515 | 285 | 800 | 1.81 |

Proposition 3.5 examines the degree to which the recommendation of each source aligns with the decision maker's predisposition. The above data show that when the predisposition is to approve, the odds of agreement with human expert's recommendation is 159/38 = 4.18 (A-E+ condition). The corresponding odds in (A+E- condition) of agreement with the algorithm's recommendation is 154/46 = 3.35. When the predisposition is to deny, the matching recommendation for the human expert is in the A+/E- condition and odds of the match is 109/93 = 1.17. For the algorithm, the matching recommendation is in the A-E+ condition and odds of

the match is 93/108 = 0.86. Thus, when the predisposition is to approve, the overall odds ratio for agreement with the human/algorithm is 4.18/3.35 = 1.25. When the predisposition is to deny, the overall odds ratio for agreement with the human/algorithm is 1.17/0.86 = 1.36. Thus, we see no significant difference for either predisposition. In other words, we do not find support for Proposition 3.5 and the expected larger overall alignment with the human source did not materialize.

Further examination of the data shows that when the predisposition was to approve (deny) , there was greater (lesser) alignment with a consistent recommendation from either source. This suggests a potential asymmetry in that decision makers were more likely to be influenced by consistent recommendations when their predisposition was favorable versus unfavorable. Also, an examination of these data by the source accuracy configurations shows the following match/mismatch proportions: AH-EH: 131/65; AL-EL: 144/56. Thus, when the two sources were of equivalent accuracy (high or low), decision makers showed a greater inclination to go with their own predispositions. Also, when the recommendation sources differed in accuracy level: AH-EL: 117/86; AL-EH: 123/78, match/mismatch with predisposition mattered less. We did not offer propositions regarding these differences. However, these empirically derived insights warrant further investigation.

Results - Decision Likelihood Data

Participants had also stated their likelihood of approving the loan on a 7-point likelihood scale (1=Low, 7=High) immediately prior to their final approval/denial decision. The data were analyzed using an ANOVA as a function of predisposition, conflict configuration and accuracy level, and their two-way and three-way interactions (see CH2-Appendix D-ANOVA Analysis) for the detailed output). We find significant effects of predisposition ($F(1,784) = 125.58$, p<.001), and conflict configuration ($F(1, 784) = 4.92$, $p = .027$), as well as two two-way interactions: conflict configuration and accuracy ($F(3, 784) = 56.1$, $p < .001$); and predisposition and accuracy ($F(3, 784) = 3.48$, $p = .016$). Although no other effects were significant, we briefly discuss the results of the predisposition, conflict configuration, and accuracy interaction as it may warrant further research/analysis.

*Conflict Configuration and Accuracy.* Table 12- Study 3 below shows the details of the interaction. These data show that when the human expert, A-E+ (versus the algorithm, A+E-) recommends approval, participants report a higher likelihood of loan approval when both sources have equal accuracy levels (AHEH: $M_{A-E+} = 4.87$ vs. $M_{A+E-} = 4.39$; $p = .043$; and ALEL: $M_{A-E+} = 4.76$ vs. $M_{A+E-} = 4.38$; $p = .095$). Although the ALEL difference is only marginally significant, these results show that when both sources are equally accurate (high or low) participants' decisions are more closely aligned to the human expert's recommendations.

*Table 12- Study 3: Likelihood of Approval Means and Std. Errors by Conflict Configuration and Accuracy*

| | Conflict Configuration | | | |
|---|---|---|---|---|
| | A -/E+ | | A +/E- | |
| **Accuracy Levels** | **Mean** | **Std. Error** | **Mean** | **Std. Error** |
| **AH-EH** | 4.87 | 0.18 | 4.39 | 0.16 |
| **AH-EL** | 3.33 | 0.16 | 5.32 | 0.16 |
| **AL-EH** | 5.58 | 0.16 | 3.43 | 0.16 |
| **AL-EL** | 4.76 | 0.16 | 4.38 | 0.16 |

Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=aglorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low.

When the low accuracy human expert recommended approval in the A-E+ condition (versus the high accuracy algorithm in the A+E- condition), the likelihood of loan approval was significantly lower (AHEL: $M_{A-E+} = 3.33$ vs. $M_{A+E-} = 5.32$; $p < .001$). When the high accuracy human expert recommended approval in the A-E+ condition (versus the low accuracy algorithm in the A+E- condition), likelihood of loan approval was significantly higher (ALEH $M_{A-E+}$= 5.58 vs. $M_{A+E-}$ = 3.43; p<.001). Thus, decisions were more closely aligned to the recommendation from the source with higher accuracy levels.

Table 13 – Study 3 shows the data for the change in approval likelihood in the A-E+ condition (the human expert recommends approval). For high (low) human expert accuracy, the mean approval likelihoods pooled over high and low algorithm accuracy are 5.11 (4.07). Thus, approval likelihood increases in the A+E- condition (algorithm recommends approval) for the high versus low accuracy human expert by (5.11 – 4.07) = 1.04, p< .001. Similarly, in the A+E- condition (the algorithm recommends approval, there is a significant (p< .001) decrease in approval likelihood (4.83 – 3.92) = 0.91. Thus, an increase in the human expert's accuracy drives a symmetric increase (decrease) in alignment with the human expert (algorithm).

*Table 13-Study 3-Likelihood of Approval Means by Conflict Configuration and Pooled Accuracy Levels*

| Conflict Configuration | Pooled Accuracy | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Algo-/Expert+ | ExpHig | 5.11 | 1.636 | 197 |
| | ExpLow | 4.07 | 1.902 | 201 |
| Algo+/Expert- | ExpHig | 3.92 | 1.927 | 200 |
| | ExpLow | 4.83 | 1.717 | 202 |
| Algo-/Expert+ | AlgoHigh | 4.01 | 1.896 | 198 |
| | AlgoLow | 5.16 | 1.611 | 200 |
| Algo+/Expert- | AlgoHigh | 4.90 | 1.709 | 201 |
| | AlgoLow | 3.86 | 1.898 | 201 |

Note 1-AlgoHigh/Expert Low accuracy numbers were included in both AlgoHigh and ExpLow Pooled Accuracy and AlgoLow/Expert High accuracy numbers were included in AlgoLow and ExpHigh Pooled Accuracy Mean averages. As such two separate tests were run to ensure each data point was included only once.

A similar set of comparisons shows that an increase in the algorithm's accuracy produces a symmetric decrease (increase) in alignment with the recommendation of the human expert (algorithm). The relevant decrease in alignment with the human expert in the A-E+ condition is:

(5.16 – 4.01) = 1.15 (p <.001) . In the A+E- condition, the relevant increase in alignment with the algorithm is (4.90 -3.86) = 1.04; p<.001). Table 14 – Study 3 tabulates the above differences and the significance tests. Overall, the results show that increased accuracy for one source symmetrically lowers alignment with the recommendation of the other source. This pattern of results is consistent with the results of Study 2, but inspection suggests that the differences are somewhat smaller.

*Table 14-Study 3 Pairwise Comparisons of Approval Likelihood Means by Conflict Configuration and Pooled Accuracy Levels*

| Conflict Configuration | Pooled Accuracy (I) | Pooled Accuracy (J) | Mean Difference (I-J) | Std. Error | Sig. | 95% Confidence Interval for Difference | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| Algo-/Expert+ | ExpHig | ExpLow | 1.04 | 0.180 | p<.001 | 0.678 | 1.386 |
| Algo+/Expert- | ExpLow | ExpHig | 0.91 | 0.180 | p<.001 | 0.559 | 1.264 |
| Algo-/Expert+ | AlgoLow | AlgoHigh | 1.15 | 0.179 | p<.001 | 0.794 | 1.496 |
| Algo+/Expert- | AlgoHigh | AlgoLow | 1.04 | 0.178 | p<.001 | 0.696 | 1.394 |

*Table 15-Study 3: Likelihood of Approval Means and Std. Errors Predisposition and Accuracy*

| Accuracy Levels | Predisposition | | | |
|---|---|---|---|---|
| | Approve | | Deny | |
| | Mean | Std. Error | Mean | Std. Error |
| AH-EH | 5.37 | 0.18 | 3.89 | 0.16 |
| AH-EL | 4.81 | 0.15 | 3.84 | 0.17 |
| AL-EH | 4.96 | 0.16 | 4.05 | 0.16 |
| AL-EL | 5.46 | 0.17 | 3.67 | 0.16 |

Note 1-Predisposition: Approve=participant predisposed to approve the loan and Deny=participant predisposed to deny the loan
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low

*Predisposition and Accuracy.* The significant predisposition x accuracy configuration conditions bears comment (see above Table 15-Study 3). First, when both the algorithm and the human expert are high on accuracy (AHEH) , the predisposition difference (approve-deny) lowers approval likelihood by (5.37- 3.89) = 1.480. The corresponding drop is (5.46-3.67) = 1.793 when both sources are low on accuracy (ALEL). Both drops are significant ($p<.001$). There is a significant ($ps< .001$) reduction in the gap in both the AH-EL (4.81 – 3.84 = 0.97) and the AL-EH (4.96 – 4.05 = 0.91) conditions. All differences are significant ($p<.001$). As expected, predisposition has the largest impact when both sources have low accuracy. Surprisingly, with asymmetric accuracy levels (one source has lower accuracy), predisposition has a smaller impact.

*Predisposition, Conflict Configuration and Accuracy.* The following two tables (Table 16 - Study 3 - Approve and Table 17 - Study 3 - Deny) provide the data necessary to analyze the three-way interaction between the Predisposition, Conflict Configuration and Accuracy Level factors. The data suggest that the source accuracy signal was informative. Given the conflicting signals, one of the sources was consistent and the other inconsistent with the decision maker's predisposition and influenced decisions when it had high accuracy.

*Table 16-Study 3-Likelihood of Approval Means and Std. Deviation by Approve Predisposition, Conflict Configuration and Accuracy Conditions*

| Accuracy Levels | Predisposition-Approve | | | |
|---|---|---|---|---|
| | Conflict Configuration | | | |
| | A -/E + | | A +/E - | |
| | Mean | Std. Deviation | Mean | Std. Deviation |
| **AH-EH** | 5.67 | 1.06 | 5.07 | 1.48 |
| **AH-EL** | 3.88 | 1.82 | 5.75 | 1.23 |
| **AL-EH** | 5.89 | 1.30 | 4.02 | 1.84 |
| **AL-EL** | 5.72 | 0.96 | 5.21 | 1.44 |

*Table 17-Study 3: Likelihood of Approval Means and Std. Deviation by Deny Predisposition, Conflict Configuration and Accuracy Conditions*

| Accuracy Levels | Predisposition-Deny | | | |
|---|---|---|---|---|
| | Conflict Configuration | | | |
| | A -/E+ | | A +/E- | |
| | Mean | Std. Deviation | Mean | Std. Deviation |
| **AH-EH** | 4.08 | 1.76 | 3.70 | 1.95 |
| **AH-EL** | 2.78 | 1.86 | 4.90 | 1.59 |
| **AL-EH** | 5.27 | 1.37 | 2.84 | 1.75 |
| **AL-EL** | 3.79 | 1.73 | 3.55 | 1.74 |

Note 1-Conflict Configuration: A-/E+=algorithm negative/expert postive recommendations and A+/E-=aglorithm positive /expert negative recommnedations
Note 2-Accuracy Levels: AH-EH=algorithm high-expert high, AH-EL=algorithm high-expert low, AL-EH-algorithm low-expert high, AL-EL=algorithm low-expert low

In other words, an initial inspection of the three-way tables above suggests that when a high accuracy source makes a recommendation inconsistent with the decision maker's predisposition, it may act to counter the predisposition. Note also, that the mean approval level tends to be lower in the cells when the source supporting the predisposition has lower accuracy. These data imply that decision makers are not impervious to recommendations that come from reliable sources, whether human or algorithmic. Moreover, they are not entirely fixed in either their predispositions or in their preference for human experts (over algorithms). Insights into the factors that influence such flexibility would help identify the circumstances where algorithms may be helpful for decision makers and overcome barriers to their receptivity.

Discussion

In summary, the results of Study 3 were generally consistent with the propositions that we offered regarding how decision maker predisposition may influence the interactive effects of conflict configuration and source accuracy identified in Study 2. In general, the presence of a predisposition moderated (and weakened) the effects observed in Study 2. First, consistent with Proposition 3.1M, predisposition moderated (weakened) the tendency for participants' decisions to be more aligned to the human expert's recommendation relative to that of the algorithm when both sources had similar accuracy levels (high-high or low-low). Second, we found that a predisposition moderates (attenuates) the degree to which participants' decisions tend to align with the recommendations from the source with a lower accuracy level when the two sources have unequal accuracy levels (high-low or low-high). Third, the presence of a predisposition also attenuated the asymmetry in the degree to which participants' decisions aligned more with recommendations from the human expert (versus the algorithm) as a function of accuracy variations (high versus low).

The results also strongly supported Proposition 3.4. Participants' decisions tend to align with the recommendations from the source that corresponds to their predispositions. This was supported through a strong main effect of predisposition that persists across the manipulation of the accuracy levels for the two sources (but with variations influenced by the specific configuration of source accuracy). However, we did not find support for Proposition 3.5. Participants' decisions did not align more with the human expert (versus the algorithm) when it corresponded to the decision maker's predisposition. The predisposition effect was similar whether the recommendation came from a human expert or an algorithm.

## General Discussion

### Summary of Results

The results of Studies 1-3 provide consistent support for algorithm aversion. Study 1, set in a consumer loan decision context, showed that recommendations had greater impact when they came from a "human expert," (versus an algorithm) and more so when they recommended loan approval (versus denial). However, in our situation of head-to-head conflict between human expert versus algorithmic recommendations (Studies 2) we consistently find evidence that decision makers align themselves to recommender sources that they perceive as having greater accuracy. Also, we find evidence that decision makers align asymmetrically with the recommendations of a high accuracy human expert (relative to a high accuracy algorithm). The results were comparable for categorical approve/deny decisions and, for the most part, a likelihood of approval dependent measure.

Study 3 was similar in design to Study 2. However, we also introduced an additional predisposition manipulation which allowed us to examine if recommendations from a human expert or an algorithm successfully countered or reinforced such predispositions. The Study 3 results (detailed in the preceding section) showed effects consistent with those in Study 2. However, they also showed how decision maker predisposition may moderate the interactive effects of conflict configuration and source accuracy and attenuated the effects seen in Study 2.

First, predisposition weakened the tendency for participants' decisions to be more aligned to the human expert's recommendation (versus that of the algorithm) when the two sources had similar accuracy levels (high-high or low-low) in support of P3.1M. Second, predisposition also attenuated the degree to which participants aligned with the recommendations of a lower accuracy source when source accuracy levels were unequal (high-low or low-high) in support of P3.2M. Third, a predisposition also attenuated the asymmetry in the degree to which decisions aligned with the human expert's (versus the algorithm's) recommendation across accuracy variations in support of P3.3M. Fourth, participants' decisions aligned more with the recommendations that were consistent with the decision maker's predispositions, regardless of source identity in support of P3.4. This tendency persisted across all configurations of the source accuracy level, but with some variation for specific accuracy level configurations. However, contrary to expectations (P3.5), decisions across accuracy variations did <u>not</u> show greater alignment with the human expert (versus the algorithm) for recommendations consistent with the decision maker's predisposition. The predisposition effect was similar whether the recommendation came from a human expert or an algorithm.

## Study Limitations

Although participants showed strong predisposition effects, their decisions were also influenced by the accuracy signals provided for the recommendation sources. Our head-to head manipulation of source accuracy enables us to examine the associated dynamics of source level influences. However, we acknowledge that the limited domain in which we conducted this study has its strengths and weaknesses. Our domain is consumer finance, and we used very sparse instructions in setting up the study scenario. This was motivated by a desire to explore if algorithm aversion/appreciation is driven by substantive aspects of task instructions and environmental influences that cue participants at conscious or non-conscious levels. Thus, the research can be extended to examine context-specific boundary conditions that define the effects of source accuracy on the choice between algorithms and human experts.

Additionally, examining these issues in other domains would allow us to explore factors that remain unexplored in our work to date. For example, examining similar uses in medical decision making would allow examination in other contexts where the stakes are higher for both decision makers and decision targets. In this regard, one might also examine more sophisticated accuracy concepts such as specificity and sensitivity. These and other possible extensions of this work are discussed in Chapter 4.

## Contributions

In a Sloan Management Review interview (Michelman, 2017), Dietvorst argues that if you can convince individuals to compare algorithm performance to their own rather than some "lofty performance goal," and they buy in that algorithms outperform personal performance, then this would counter algorithm aversion. The three studies reported here provide some initial results relevant to this expectation.

Our studies deliberately used simple instruction sets to examine whether participants recognized the environmental structure clearly so that the underlying drivers of algorithm orientation could be sharply assessed. Thus, we dispensed with elaborate learning trails in order to ensure that focal variables were not distorted by attention limitations, leaning deficiencies and environmental distractions. For example, Dietvorst et al. (2015) used fairly cumbersome learning procedures that may have inhibited participants' understanding that the overall performance of the algorithm was better. With simpler procedures, we do find evidence of algorithm aversion, but also locate boundary conditions where the algorithm is preferred based on performance accuracy.

Our research (Study 3) also pits decision makers' predispositions front and center in the recommendation utilization process. We show that predispositions do bias choice, accuracy information can lead to greater openness to advice, and recommendations can have a debiasing influence when information sources are more reliable on performance. However, as we conjecture in the next chapter, it is possible that simple-minded efforts to provide greater transparency and understanding of complex algorithmic models may backfire because perceived complexity may override objective knowledge gains and reduce subjective knowledge or confidence in one's ability to interpret the algorithm's recommendations.

Our results confirm "algorithm aversion" at a visceral level, i.e., that decision makers remain uncomfortable in turning over decision autonomy to algorithms that they may be unable to control. This "concern" remains, despite widespread awareness of algorithm performance and market penetration. While performance accuracy information may be a cue to resolving this problem, it may be ineffective without other assurances that the algorithm is fair, acts with transparency and accountability and will complement decisions makers in their tasks, rather than wrest control and (God forbid!) replace them. Contemporary concerns surrounding generative AI innovations such as Large Language models and ChatGPT can exacerbate such concerns.

## CH2-Appendix A- Complexity Details and Manipulation Check

<u>Complex and Simple Scenario Details-</u>

**<u>Complex Analytical Algorithm-</u>**

The calculation of the applicant's FICO Score involves using a complex analytical algorithm which weights five components of an applicant's credit profile. The applicant's calculated component and overall score is compared to a database of individuals who successfully paid off their loans. The final recommendation is based on the overall score. The weights are given below along with table of the maximum points that can be obtained for each component.

| FICO Components | % Weight | Possible Points |
|---|---|---|
| Payment history | 35% | 300 |
| Amounts owed | 30% | 250 |
| Length of credit history | 15% | 130 |
| New credit | 10% | 85 |
| Types of credit | 10% | 85 |
| **Totals** | **100%** | **850** |

**<u>Simple Statistical Algorithm-</u>**

The calculation of the applicant's FICO Score involves using a simple statistical algorithm that analyzes the components of an applicant's credit profile. The applicant's calculated component and overall score is compared to a database of individuals who successfully paid off their loans. The final recommendation is based on the overall score.

<u>Complexity Manipulation Check-</u>

**Group Statistics**

| | CorS | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| Complexity | Complex | 103 | 5.50 | 1.399 | .138 |
| | Simple | 104 | 4.60 | 1.698 | .167 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Significance | | Mean Difference | Std. Error Difference | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | One-Sided p | Two-Sided p | | | Lower | Upper |
| Complexity | Equal variances assumed | 4.348 | .038 | 4.199 | 205 | <.001 | <.001 | .909 | .216 | .482 | 1.335 |
| | Equal variances not assumed | | | 4.203 | 198.454 | <.001 | <.001 | .909 | .216 | .482 | 1.335 |

**Independent Samples Effect Sizes**

| | | Standardizer[a] | Point Estimate | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower | Upper |
| Complexity | Cohen's d | 1.557 | .584 | .305 | .861 |
| | Hedges' correction | 1.562 | .582 | .304 | .858 |
| | Glass's delta | 1.698 | .535 | .252 | .816 |

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

**CH2-Appendix B-Study 1 Tests**

Study 1-Hierarchical Loglinear Analysis-NorP*CorSn*DecN

## Hierarchical Loglinear Analysis

### Warnings

| |
|---|
| For Design 1, .500 has been added to all observed cells for this saturated model, This value may be changed by using the CRITERIA = DELTA subcommand. |

### Data Information

| | | N |
|---|---|---|
| Cases | Valid | 207 |
| | Out of Range[a] | 0 |
| | Missing | 0 |
| | Weighted Valid | 207 |
| Categories | NorP | 2 |
| | CorSn | 2 |
| | DecN | 2 |

a. Cases rejected because of out of range factor values

**Backward Elimination Statistics Step Summary**

| Step[a] | | | Effects | Chi-Square[c] | df | Sig. | Number of Iterations |
|---|---|---|---|---|---|---|---|
| 0 | Generating Class[b] | | NorP*CorSn*DecN | .000 | 0 | . | |
| | Deleted Effect | 1 | NorP*CorSn*DecN | .013 | 1 | .908 | 3 |
| 1 | Generating Class[b] | | NorP*CorSn, NorP*DecN, CorSn*DecN | .013 | 1 | .908 | |
| | Deleted Effect | 1 | NorP*CorSn | .210 | 1 | .647 | 2 |
| | | 2 | NorP*DecN | 9.049 | 1 | .003 | 2 |
| | | 3 | CorSn*DecN | 1.526 | 1 | .217 | 2 |
| 2 | Generating Class[b] | | NorP*DecN, CorSn*DecN | .223 | 2 | .894 | |
| | Deleted Effect | 1 | NorP*DecN | 8.883 | 1 | .003 | 2 |
| | | 2 | CorSn*DecN | 1.359 | 1 | .244 | 2 |
| 3 | Generating Class[b] | | NorP*DecN, CorSn | 1.582 | 3 | .663 | |
| | Deleted Effect | 1 | NorP*DecN | 8.883 | 1 | .003 | 2 |
| | | 2 | CorSn | .005 | 1 | .945 | 2 |
| 4 | Generating Class[b] | | NorP*DecN | 1.587 | 4 | .811 | |
| | Deleted Effect | 1 | NorP*DecN | 8.883 | 1 | .003 | 2 |
| 5 | Generating Class[b] | | NorP*DecN | 1.587 | 4 | .811 | |

a. At each step, the effect with the largest significance level for the Likelihood Ratio Change is deleted, provided the significance level is larger than .050.
b. Statistics are displayed for the best model at each step after step 0.
c. For 'Deleted Effect', this is the change in the Chi-Square after the effect is deleted from the model.

**Partial Associations**

| Effect | df | Partial Chi-Square | Sig. | Number of Iterations |
|---|---|---|---|---|
| NorP*CorSn | 1 | .210 | .647 | 2 |
| NorP*DecN | 1 | 9.049 | .003 | 2 |
| CorSn*DecN | 1 | 1.526 | .217 | 2 |
| NorP | 1 | .005 | .945 | 2 |
| CorSn | 1 | .005 | .945 | 2 |
| DecN | 1 | 75.437 | <.001 | 2 |

**Parameter Estimates**

| Effect | Parameter | Estimate | Std. Error | Z | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| NorP*CorSn*DecN | 1 | 0.008 | 0.091 | 0.086 | 0.932 | -0.17 | 0.186 |
| NorP*CorSn | 1 | -0.036 | 0.091 | -0.398 | 0.691 | -0.214 | 0.142 |
| NorP*DecN | 1 | 0.257 | 0.091 | 2.834 | 0.005 | 0.079 | 0.436 |
| CorSn*DecN | 1 | 0.106 | 0.091 | 1.172 | 0.241 | -0.072 | 0.285 |
| NorP | 1 | -0.148 | 0.091 | -1.623 | 0.104 | -0.326 | 0.031 |
| CorSn | 1 | -0.067 | 0.091 | -0.74 | 0.459 | -0.245 | 0.111 |
| DecN | 1 | 0.696 | 0.091 | 7.655 | <.001 | 0.517 | 0.874 |

**CH2-Appendix C-Study 2 Tests**

Study 2-Hierarchical Loglinear Analysis-DecN*NorP*AccN

## Hierarchical Loglinear Analysis

### Warnings

| |
|---|
| For Design 1, .500 has been added to all observed cells for this saturated model, This value may be changed by using the CRITERIA = DELTA subcommand. |

### Data Information

| | | N |
|---|---|---|
| Cases | Valid | 406 |
| | Out of Range[a] | 0 |
| | Missing | 0 |
| | Weighted Valid | 406 |
| Categories | DecN | 2 |
| | NorP | 2 |
| | AccN | 4 |

a. Cases rejected because of out of range factor values.

## Backward Elimination Statistics

### Step Summary

| Step[a] | | | Effects | Chi-Square[c] | df | Sig. | Number of Iterations |
|---|---|---|---|---|---|---|---|
| 0 | Generating Class[b] | | DecN*NorP*AccN | .000 | 0 | . | |
| | Deleted Effect | 1 | DecN*NorP*AccN | 94.744 | 3 | <.001 | 3 |
| 1 | Generating Class[b] | | DecN*NorP*AccN | .000 | 0 | . | |

a. At each step, the effect with the largest significance level for the Likelihood Ratio Change is deleted, provided the significance level is larger than .050.

b. Statistics are displayed for the best model at each step after step 0.

c. For 'Deleted Effect', this is the change in the Chi-Square after the effect is deleted from the model.

## Partial Associations

| Effect | df | Partial Chi-Square | Sig. | Number of Iterations |
|---|---|---|---|---|
| DecN*NorP | 1 | 15.375 | <.001 | 2 |
| DecN*AccN | 3 | 11.163 | .011 | 2 |
| NorP*AccN | 3 | .531 | .912 | 2 |
| DecN | 1 | 66.475 | <.001 | 2 |
| NorP | 1 | .010 | .921 | 2 |
| AccN | 3 | .088 | .993 | 2 |

## Parameter Estimates

| Effect | Parameter | Estimate | Std. Error | Z | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| DecN*NorP*AccN | 1 | 0.079 | 0.129 | 0.61 | 0.542 | -0.174 | 0.332 |
| | 2 | -0.882 | 0.119 | -7.411 | <.001 | -1.115 | -0.648 |
| | 3 | 0.842 | 0.176 | 4.779 | <.001 | 0.497 | 1.187 |
| DecN*NorP | 1 | 0.314 | 0.079 | 3.965 | <.001 | 0.159 | 0.469 |
| DecN*AccN | 1 | 0.197 | 0.129 | 1.526 | 0.127 | -0.056 | 0.45 |
| | 2 | -0.163 | 0.119 | -1.368 | 0.171 | -0.396 | 0.07 |
| | 3 | 0.014 | 0.176 | 0.081 | 0.935 | -0.331 | 0.36 |
| NorP*AccN | 1 | -0.092 | 0.129 | -0.716 | 0.474 | -0.345 | 0.161 |
| | 2 | 0.37 | 0.119 | 3.111 | 0.002 | 0.137 | 0.603 |
| | 3 | -0.302 | 0.176 | -1.716 | 0.086 | -0.647 | 0.043 |
| DecN | 1 | 0.579 | 0.079 | 7.316 | <.001 | 0.424 | 0.734 |
| NorP | 1 | -0.165 | 0.079 | -2.087 | 0.037 | -0.32 | -0.01 |
| AccN | 1 | 0.005 | 0.129 | 0.04 | 0.968 | -0.248 | 0.258 |
| | 2 | 0.137 | 0.119 | 1.149 | 0.251 | -0.097 | 0.37 |
| | 3 | -0.303 | 0.176 | -1.72 | 0.085 | -0.648 | 0.042 |

Study 2-Two-way ANOVA Test-NorPC*Accuracy

## Univariate Analysis of Variance

### Between-Subjects Factors

| | | N |
|---|---|---|
| NorPc | Negative | 202 |
| | Positive | 204 |
| Accuracy | AHEH | 101 |
| | AHEL | 104 |
| | ALEH | 100 |
| | ALEL | 101 |

### Descriptive Statistics

Dependent Variable: LikeA

| NorPc | Accuracy | Mean | Std. Deviation | N |
|---|---|---|---|---|
| Negative | AHEH | 5.26 | 1.337 | 50 |
| | AHEL | 3.56 | 1.893 | 52 |
| | ALEH | 6.06 | .652 | 50 |
| | ALEL | 5.30 | 1.432 | 50 |
| | Total | 5.03 | 1.675 | 202 |
| Positive | AHEH | 4.35 | 1.885 | 51 |
| | AHEL | 5.52 | 1.350 | 52 |
| | ALEH | 2.90 | 1.705 | 50 |
| | ALEL | 4.37 | 1.720 | 51 |
| | Total | 4.30 | 1.905 | 204 |
| Total | AHEH | 4.80 | 1.691 | 101 |
| | AHEL | 4.54 | 1.910 | 104 |
| | ALEH | 4.48 | 2.042 | 100 |
| | ALEL | 4.83 | 1.644 | 101 |
| | Total | 4.66 | 1.829 | 406 |

### Tests of Between-Subjects Effects

Dependent Variable: LikeA

| Source | Type III Sum of Squares | Df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 401.955[a] | 7 | 57.422 | 23.986 | <.001 | .297 |
| Intercept | 8834.266 | 1 | 8834.266 | 3690.153 | <.001 | .903 |
| NorPc | 58.340 | 1 | 58.340 | 24.369 | <.001 | .058 |
| Accuracy | 10.071 | 3 | 3.357 | 1.402 | .242 | .010 |
| NorPc * Accuracy | 337.752 | 3 | 112.584 | 47.027 | <.001 | .262 |
| Error | 952.816 | 398 | 2.394 | | | |
| Total | 10181.000 | 406 | | | | |
| Corrected Total | 1354.771 | 405 | | | | |

a. R Squared = .297 (Adjusted R Squared = .284)

### Custom Hypothesis Tests #1

#### Contrast Results (K Matrix)[a]

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | .907 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | .907 |
| | Std. Error | | .308 |
| | Sig. | | .003 |
| | 95% Confidence Interval for Difference | Lower Bound | .302 |
| | | Upper Bound | 1.512 |

a. Based on the user-specified contrast coefficients (L') matrix: ANAHEH VS APAHEH-human pos rec both high accuracies vs algo pos rec both high accuracies

## Test Results

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 20.773 | 1 | 20.773 | 8.677 | .003 |
| Error | 952.816 | 398 | 2.394 | | |

## Custom Hypothesis Tests #2

## Contrast Results (K Matrix)[a]

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | .927 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | .927 |
| | Std. Error | | .308 |
| | Sig. | | .003 |
| | 95% Confidence Interval for Difference | Lower Bound | .322 |
| | | Upper Bound | 1.533 |

a. Based on the user-specified contrast coefficients (L') matrix: ANALEL VS APALEL-human pos rec both low accuracies vs algo pos rec both low accuracies

**Test Results**

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 21.717 | 1 | 21.717 | 9.071 | .003 |
| Error | 952.816 | 398 | 2.394 | | |

## Custom Hypothesis Tests #3

**Contrast Results (K Matrix)[a]**

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | 2.502 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | 2.502 |
| | Std. Error | | .306 |
| | Sig. | | <.001 |
| | 95% Confidence Interval for Difference | Lower Bound | 1.900 |
| | | Upper Bound | 3.105 |

a. Based on the user-specified contrast coefficients (L') matrix: ANALEH VS ANAHEL-Human pos rec and human high vs human low accuracy

## Test Results

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 159.608 | 1 | 159.608 | 66.670 | <.001 |
| Error | 952.816 | 398 | 2.394 | | |

## Custom Hypothesis Tests #4

### Contrast Results (K Matrix)[a]

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | 2.619 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | 2.619 |
| | Std. Error | | .306 |
| | Sig. | | <.001 |
| | 95% Confidence Interval for Difference | Lower Bound | 2.017 |
| | | Upper Bound | 3.222 |

a. Based on the user-specified contrast coefficients (L') matrix: APAHEL VS APALEH-Algo pos rec and algo high vs algo low accuracy

## Test Results

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 174.872 | 1 | 174.872 | 73.046 | <.001 |
| Error | 952.816 | 398 | 2.394 | | |

## Custom Hypothesis Tests #5

### Contrast Results (K Matrix)[a]

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | .658 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | .658 |
| | Std. Error | | .306 |
| | Sig. | | .032 |
| | 95% Confidence Interval for Difference | Lower Bound | .055 |
| | | Upper Bound | 1.260 |

a. Based on the user-specified contrast coefficients (L') matrix: ANAHEL VS APALEH-human pos rec human low accuracy vs. algo pos rec algo low accuracy

## Test Results

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 11.026 | 1 | 11.026 | 4.606 | .032 |
| Error | 952.816 | 398 | 2.394 | | |

## Custom Hypothesis Tests #6

### Contrast Results (K Matrix)[a]

| Contrast | | | Dependent Variable LikeA |
|---|---|---|---|
| L1 | Contrast Estimate | | .541 |
| | Hypothesized Value | | 0 |
| | Difference (Estimate - Hypothesized) | | .541 |
| | Std. Error | | .306 |
| | Sig. | | .078 |
| | 95% Confidence Interval for Difference | Lower Bound | -.062 |
| | | Upper Bound | 1.143 |

a. Based on the user-specified contrast coefficients (L') matrix: ANALEH VS APAHEL-human pos rec human high accuracy vs. algo pos rec algo high

## Test Results

Dependent Variable: LikeA

| Source | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|
| Contrast | 7.454 | 1 | 7.454 | 3.114 | .078 |
| Error | 952.816 | 398 | 2.394 | | |

## Estimated Marginal Means

## 1. NorPc * Accuracy

## Estimates

Dependent Variable: LikeA

| NorPc | Accuracy | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| Negative | AHEH | 5.260 | .219 | 4.830 | 5.690 |
| | AHEL | 3.558 | .215 | 3.136 | 3.980 |
| | ALEH | 6.060 | .219 | 5.630 | 6.490 |
| | ALEL | 5.300 | .219 | 4.870 | 5.730 |
| Positive | AHEH | 4.353 | .217 | 3.927 | 4.779 |
| | AHEL | 5.519 | .215 | 5.097 | 5.941 |
| | ALEH | 2.900 | .219 | 2.470 | 3.330 |
| | ALEL | 4.373 | .217 | 3.947 | 4.798 |

## Pairwise Comparisons

Dependent Variable: LikeA

| Accuracy | (I) NorPc | (J) NorPc | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| AHEH | Negative | Positive | .907* | .308 | .003 | .302 | 1.512 |
| | Positive | Negative | -.907* | .308 | .003 | -1.512 | -.302 |
| AHEL | Negative | Positive | -1.962* | .303 | <.001 | -2.558 | -1.365 |
| | Positive | Negative | 1.962* | .303 | <.001 | 1.365 | 2.558 |
| ALEH | Negative | Positive | 3.160* | .309 | <.001 | 2.552 | 3.768 |
| | Positive | Negative | -3.160* | .309 | <.001 | -3.768 | -2.552 |
| ALEL | Negative | Positive | .927* | .308 | .003 | .322 | 1.533 |
| | Positive | Negative | -.927* | .308 | .003 | -1.533 | -.322 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| Accuracy | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| AHEH | Contrast | 20.773 | 1 | 20.773 | 8.677 | .003 |
| | Error | 952.816 | 398 | 2.394 | | |
| AHEL | Contrast | 100.038 | 1 | 100.038 | 41.787 | <.001 |
| | Error | 952.816 | 398 | 2.394 | | |
| ALEH | Contrast | 249.640 | 1 | 249.640 | 104.277 | <.001 |
| | Error | 952.816 | 398 | 2.394 | | |
| ALEL | Contrast | 21.717 | 1 | 21.717 | 9.071 | .003 |
| | Error | 952.816 | 398 | 2.394 | | |

Each F tests the simple effects of NorPc within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

### 2. NorPc * Accuracy

## Estimates

Dependent Variable: LikeA

| NorPc | Accuracy | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|
| Negative | AHEH | 5.260 | .219 | 4.830 | 5.690 |
| | AHEL | 3.558 | .215 | 3.136 | 3.980 |
| | ALEH | 6.060 | .219 | 5.630 | 6.490 |
| | ALEL | 5.300 | .219 | 4.870 | 5.730 |
| Positive | AHEH | 4.353 | .217 | 3.927 | 4.779 |
| | AHEL | 5.519 | .215 | 5.097 | 5.941 |
| | ALEH | 2.900 | .219 | 2.470 | 3.330 |
| | ALEL | 4.373 | .217 | 3.947 | 4.798 |

## Pairwise Comparisons

Dependent Variable: LikeA

| NorPc | (I) Accuracy | (J) Accuracy | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|---|
| Negative | AHEH | AHEL | 1.702* | .306 | <.001 | 1.100 | 2.305 |
| | | ALEH | -.800* | .309 | .010 | -1.408 | -.192 |
| | | ALEL | -.040 | .309 | .897 | -.648 | .568 |
| | AHEL | AHEH | -1.702* | .306 | <.001 | -2.305 | -1.100 |
| | | ALEH | -2.502* | .306 | <.001 | -3.105 | -1.900 |
| | | ALEL | -1.742* | .306 | <.001 | -2.345 | -1.140 |
| | ALEH | AHEH | .800* | .309 | .010 | .192 | 1.408 |
| | | AHEL | 2.502* | .306 | <.001 | 1.900 | 3.105 |
| | | ALEL | .760* | .309 | .014 | .152 | 1.368 |
| | ALEL | AHEH | .040 | .309 | .897 | -.568 | .648 |
| | | AHEL | 1.742* | .306 | <.001 | 1.140 | 2.345 |
| | | ALEH | -.760* | .309 | .014 | -1.368 | -.152 |
| Positive | AHEH | AHEL | -1.166* | .305 | <.001 | -1.766 | -.567 |
| | | ALEH | 1.453* | .308 | <.001 | .848 | 2.058 |
| | | ALEL | -.020 | .306 | .949 | -.622 | .583 |
| | AHEL | AHEH | 1.166* | .305 | <.001 | .567 | 1.766 |
| | | ALEH | 2.619* | .306 | <.001 | 2.017 | 3.222 |
| | | ALEL | 1.147* | .305 | <.001 | .547 | 1.746 |
| | ALEH | AHEH | -1.453* | .308 | <.001 | -2.058 | -.848 |
| | | AHEL | -2.619* | .306 | <.001 | -3.222 | -2.017 |
| | | ALEL | -1.473* | .308 | <.001 | -2.078 | -.867 |
| | ALEL | AHEH | .020 | .306 | .949 | -.583 | .622 |
| | | AHEL | -1.147* | .305 | <.001 | -1.746 | -.547 |
| | | ALEH | 1.473* | .308 | <.001 | .867 | 2.078 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| NorPc | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Negative | Contrast | 172.055 | 3 | 57.352 | 23.956 | <.001 |
| | Error | 952.816 | 398 | 2.394 | | |
| Positive | Contrast | 175.710 | 3 | 58.570 | 24.465 | <.001 |
| | Error | 952.816 | 398 | 2.394 | | |

Each F tests the simple effects of Accuracy within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

## CH2-Appendix D-Study 3 Tests

Study 3-Hierarchical Loglinear Test-DecN*PriorN*NorP*AccN

# Hierarchical Loglinear Analysis

### Warnings

| |
|---|
| For Design 1, .500 has been added to all observed cells for this saturated model, This value may be changed by using the CRITERIA = DELTA subcommand. |

### Data Information

| | | N |
|---|---|---|
| Cases | Valid | 800 |
| | Out of Range[a] | 0 |
| | Missing | 0 |
| | Weighted Valid | 800 |
| Categories | DecN | 2 |
| | PriorN | 2 |
| | NorP | 2 |
| | AccN | 4 |

a. Cases rejected because of out of range factor values.

### Partial Associations

| Effect | df | Partial Chi-Square | Sig. | Number of Iterations |
|---|---|---|---|---|
| DecN*PriorN*NorP | 1 | 2.495 | .114 | 5 |
| DecN*PriorN*AccN | 3 | 13.797 | .003 | 8 |
| DecN*NorP*AccN | 3 | 109.540 | <.001 | 4 |
| PriorN*NorP*AccN | 3 | 26.060 | <.001 | 6 |
| DecN*PriorN | 1 | 76.917 | <.001 | 2 |
| DecN*NorP | 1 | 3.180 | .075 | 4 |
| PriorN*NorP | 1 | .408 | .523 | 4 |
| DecN*AccN | 3 | 3.185 | .364 | 3 |
| PriorN*AccN | 3 | 9.618 | .022 | 3 |
| NorP*AccN | 3 | .142 | .986 | 4 |
| DecN | 1 | 65.890 | <.001 | 2 |
| PriorN | 1 | .045 | .832 | 2 |
| NorP | 1 | .020 | .888 | 2 |
| AccN | 3 | .130 | .988 | 2 |

## Parameter Estimates

| Effect | Parameter | Estimate | Std. Error | Z | Sig. | 95% Confidence Interval | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower Bound | Upper Bound |
| DecN*PriorN*NorP*AccN | 1 | 5.68E-05 | 0.097 | 0.001 | 1 | -0.19 | 0.19 |
| | 2 | -0.048 | 0.088 | -0.547 | 0.584 | -0.222 | 0.125 |
| | 3 | -0.166 | 0.093 | -1.787 | 0.074 | -0.349 | 0.016 |
| DecN*PriorN*NorP | 1 | 0.101 | 0.063 | 1.59 | 0.112 | -0.023 | 0.224 |
| DecN*PriorN*AccN | 1 | 0.064 | 0.097 | 0.66 | 0.509 | -0.126 | 0.254 |
| | 2 | -0.214 | 0.088 | -2.418 | 0.016 | -0.387 | -0.041 |
| | 3 | -0.215 | 0.093 | -2.31 | 0.021 | -0.397 | -0.033 |
| DecN*NorP*AccN | 1 | 0.012 | 0.097 | 0.127 | 0.899 | -0.178 | 0.202 |
| | 2 | -0.709 | 0.088 | -8.021 | <.001 | -0.882 | -0.536 |
| | 3 | 0.447 | 0.093 | 4.806 | <.001 | 0.265 | 0.63 |
| PriorN*NorP*AccN | 1 | -0.245 | 0.097 | -2.528 | 0.011 | -0.435 | -0.055 |
| | 2 | 0.343 | 0.088 | 3.882 | <.001 | 0.17 | 0.516 |
| | 3 | 0.128 | 0.093 | 1.376 | 0.169 | -0.054 | 0.311 |
| DecN*PriorN | 1 | 0.444 | 0.063 | 7.023 | <.001 | 0.32 | 0.568 |
| DecN*NorP | 1 | 0.178 | 0.063 | 2.818 | 0.005 | 0.054 | 0.302 |
| PriorN*NorP | 1 | -0.116 | 0.063 | -1.829 | 0.067 | -0.24 | 0.008 |
| DecN*AccN | 1 | -0.041 | 0.097 | -0.425 | 0.671 | -0.231 | 0.149 |
| | 2 | -0.195 | 0.088 | -2.208 | 0.027 | -0.368 | -0.022 |
| | 3 | -0.019 | 0.093 | -0.207 | 0.836 | -0.202 | 0.163 |
| PriorN*AccN | 1 | -0.139 | 0.097 | -1.431 | 0.152 | -0.328 | 0.051 |
| | 2 | 0.311 | 0.088 | 3.513 | <.001 | 0.137 | 0.484 |
| | 3 | 0.157 | 0.093 | 1.686 | 0.092 | -0.025 | 0.339 |
| NorP*AccN | 1 | -0.004 | 0.097 | -0.04 | 0.968 | -0.194 | 0.186 |
| | 2 | 0.248 | 0.088 | 2.801 | 0.005 | 0.074 | 0.421 |
| | 3 | -0.062 | 0.093 | -0.662 | 0.508 | -0.244 | 0.121 |
| DecN | 1 | 0.459 | 0.063 | 7.264 | <.001 | 0.335 | 0.583 |
| PriorN | 1 | -0.19 | 0.063 | -3.01 | 0.003 | -0.314 | -0.066 |
| NorP | 1 | -0.149 | 0.063 | -2.364 | 0.018 | -0.273 | -0.026 |
| AccN | 1 | 0.037 | 0.097 | 0.378 | 0.705 | -0.153 | 0.226 |
| | 2 | 0.111 | 0.088 | 1.258 | 0.208 | -0.062 | 0.284 |
| | 3 | 0.025 | 0.093 | 0.271 | 0.786 | -0.157 | 0.208 |

<u>Study 3-Three-way ANOVA Test-Prior*NorP*AccN</u>

# Univariate Analysis of Variance

## Between-Subjects Factors

| | | Value Label | N |
|---|---|---|---|
| PriorN | 1 | I-APPROVE | 397 |
| | 2 | I-DENY | 403 |
| NorP | 1 | Algo- /Human+ | 398 |
| | 2 | Algo+ /Human- | 402 |
| AccN | 1 | AHEH | 196 |
| | 2 | AHEL | 203 |
| | 3 | ALEH | 201 |
| | 4 | ALEL | 200 |

**Descriptive Statistics**

Dependent Variable: LikeA

| PriorN | NorP | AccN | Mean | Std. Deviation | N |
|---|---|---|---|---|---|
| I-APPROVE | Algo- /Human+ | AHEH | 5.67 | 1.061 | 30 |
| | | AHEL | 3.88 | 1.816 | 65 |
| | | ALEH | 5.89 | 1.303 | 56 |
| | | ALEL | 5.72 | .958 | 46 |
| | | Total | 5.15 | 1.656 | 197 |
| | Algo+ /Human- | AHEH | 5.07 | 1.475 | 56 |
| | | AHEL | 5.75 | 1.230 | 51 |
| | | ALEH | 4.02 | 1.840 | 45 |
| | | ALEL | 5.21 | 1.443 | 48 |
| | | Total | 5.04 | 1.610 | 200 |
| | Total | AHEH | 5.28 | 1.369 | 86 |
| | | AHEL | 4.70 | 1.833 | 116 |
| | | ALEH | 5.06 | 1.816 | 101 |
| | | ALEL | 5.46 | 1.250 | 94 |
| | | Total | 5.10 | 1.632 | 397 |
| I-DENY | Algo- /Human+ | AHEH | 4.08 | 1.757 | 66 |
| | | AHEL | 2.78 | 1.858 | 37 |
| | | ALEH | 5.27 | 1.372 | 45 |
| | | ALEL | 3.79 | 1.725 | 53 |
| | | Total | 4.03 | 1.860 | 201 |
| | Algo+ /Human- | AHEH | 3.70 | 1.948 | 44 |
| | | AHEL | 4.90 | 1.594 | 50 |
| | | ALEH | 2.84 | 1.751 | 55 |
| | | ALEL | 3.55 | 1.738 | 53 |
| | | Total | 3.72 | 1.899 | 202 |
| | Total | AHEH | 3.93 | 1.836 | 110 |
| | | AHEL | 4.00 | 2.000 | 87 |
| | | ALEH | 3.93 | 1.996 | 100 |
| | | ALEL | 3.67 | 1.728 | 106 |
| | | Total | 3.88 | 1.883 | 403 |
| Total | Algo- /Human+ | AHEH | 4.57 | 1.734 | 96 |
| | | AHEL | 3.48 | 1.897 | 102 |
| | | ALEH | 5.61 | 1.364 | 101 |
| | | ALEL | 4.69 | 1.712 | 99 |
| | | Total | 4.59 | 1.847 | 398 |
| | Algo+ /Human- | AHEH | 4.47 | 1.823 | 100 |
| | | AHEL | 5.33 | 1.477 | 101 |
| | | ALEH | 3.37 | 1.878 | 100 |
| | | ALEL | 4.34 | 1.802 | 101 |
| | | Total | 4.38 | 1.878 | 402 |
| | Total | AHEH | 4.52 | 1.776 | 196 |
| | | AHEL | 4.40 | 1.933 | 203 |
| | | ALEH | 4.50 | 1.985 | 201 |
| | | ALEL | 4.51 | 1.762 | 200 |

## Tests of Between-Subjects Effects

Dependent Variable: LikeA

| Source | Type III Sum of Squares | Df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|
| Corrected Model | 784.332[a] | 15 | 52.289 | 20.565 | <.001 | 0.282 |
| Intercept | 15666.829 | 1 | 15666.829 | 6161.77 | 0 | 0.887 |
| PriorN | 319.302 | 1 | 319.302 | 125.582 | <.001 | 0.138 |
| NorP | 12.507 | 1 | 12.507 | 4.919 | 0.027 | 0.006 |
| AccN | 9.757 | 3 | 3.252 | 1.279 | 0.28 | 0.005 |
| PriorN * NorP | 0.094 | 1 | 0.094 | 0.037 | 0.848 | 0 |
| PriorN * AccN | 26.549 | 3 | 8.85 | 3.481 | 0.016 | 0.013 |
| NorP * AccN | 427.917 | 3 | 142.639 | 56.1 | <.001 | 0.177 |
| PriorN * NorP * AccN | 5.999 | 3 | 2 | 0.787 | 0.502 | 0.003 |
| Error | 1993.387 | 784 | 2.543 | | | |
| Total | 18843 | 800 | | | | |
| Corrected Total | 2777.719 | 799 | | | | |

## Estimated Marginal Means

### 1. NorP * AccN

**Estimates**

Dependent Variable: LikeA

| NorP | AccN | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|
| Algo- /Human+ | AHEH | 4.871 | .176 | 4.527 | 5.216 |
| | AHEL | 3.330 | .164 | 3.008 | 3.653 |
| | ALEH | 5.580 | .160 | 5.266 | 5.893 |
| | ALEL | 4.755 | .161 | 4.440 | 5.070 |
| Algo+ /Human- | AHEH | 4.388 | .161 | 4.073 | 4.703 |
| | AHEL | 5.323 | .159 | 5.011 | 5.634 |
| | ALEH | 3.429 | .160 | 3.115 | 3.744 |
| | ALEL | 4.378 | .159 | 4.066 | 4.690 |

**Pairwise Comparisons**

Dependent Variable: LikeA

| AccN | (I) NorP | (J) NorP | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound |
|---|---|---|---|---|---|---|
| AHEH | Algo- /Human+ | Algo+ /Human- | .483* | .238 | .043 | .016 |
| | Algo+ /Human- | Algo- /Human+ | -.483* | .238 | .043 | -.950 |
| AHEL | Algo- /Human+ | Algo+ /Human- | -1.992* | .228 | <.001 | -2.440 |
| | Algo+ /Human- | Algo- /Human+ | 1.992* | .228 | <.001 | 1.544 |
| ALEH | Algo- /Human+ | Algo+ /Human- | 2.150* | .226 | <.001 | 1.706 |
| | Algo+ /Human- | Algo- /Human+ | -2.150* | .226 | <.001 | -2.594 |
| ALEL | Algo- /Human+ | Algo+ /Human- | .377 | .226 | .095 | -.066 |
| | Algo+ /Human- | Algo- /Human+ | -.377 | .226 | .095 | -.821 |

## Pairwise Comparisons

Dependent Variable: LikeA

| AccN | (I) NorP | (J) NorP | 95% Confidence Interval for Difference Upper Bound |
|---|---|---|---|
| AHEH | Algo- /Human+ | Algo+ /Human- | .950 |
| | Algo+ /Human- | Algo- /Human+ | -.016 |
| AHEL | Algo- /Human+ | Algo+ /Human- | -1.544 |
| | Algo+ /Human- | Algo- /Human+ | 2.440 |
| ALEH | Algo- /Human+ | Algo+ /Human- | 2.594 |
| | Algo+ /Human- | Algo- /Human+ | -1.706 |
| ALEL | Algo- /Human+ | Algo+ /Human- | .821 |
| | Algo+ /Human- | Algo- /Human+ | .066 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| AccN | | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|---|
| AHEH | Contrast | 10.487 | 1 | 10.487 | 4.124 | .043 | .005 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| AHEL | Contrast | 193.556 | 1 | 193.556 | 76.126 | <.001 | .089 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| ALEH | Contrast | 229.837 | 1 | 229.837 | 90.395 | <.001 | .103 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| ALEL | Contrast | 7.086 | 1 | 7.086 | 2.787 | .095 | .004 |
| | Error | 1993.387 | 784 | 2.543 | | | |

## Univariate Tests

Dependent Variable: LikeA

| AccN | | Noncent. Parameter | Observed Power[a] |
|---|---|---|---|
| AHEH | Contrast | 4.124 | .527 |
| | Error | | |
| AHEL | Contrast | 76.126 | 1.000 |
| | Error | | |
| ALEH | Contrast | 90.395 | 1.000 |
| | Error | | |
| ALEL | Contrast | 2.787 | .385 |
| | Error | | |

Each F tests the simple effects of NorP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.
a. Computed using alpha = .05

## 2. NorP * AccN

### Estimates

Dependent Variable: LikeA

| NorP | AccN | Mean | Std. Error | 95% Confidence Interval | |
|---|---|---|---|---|---|
| | | | | Lower Bound | Upper Bound |
| Algo- /Human+ | AHEH | 4.871 | .176 | 4.527 | 5.216 |
| | AHEL | 3.330 | .164 | 3.008 | 3.653 |
| | ALEH | 5.580 | .160 | 5.266 | 5.893 |
| | ALEL | 4.755 | .161 | 4.440 | 5.070 |
| Algo+ /Human- | AHEH | 4.388 | .161 | 4.073 | 4.703 |
| | AHEL | 5.323 | .159 | 5.011 | 5.634 |
| | ALEH | 3.429 | .160 | 3.115 | 3.744 |
| | ALEL | 4.378 | .159 | 4.066 | 4.690 |

## Pairwise Comparisons

Dependent Variable: LikeA

| NorP | (I) AccN | (J) AccN | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound |
|---|---|---|---|---|---|---|
| Algo- /Human+ | AHEH | AHEL | 1.541* | .240 | <.001 | 1.069 |
| | | ALEH | -.709* | .237 | .003 | -1.174 |
| | | ALEL | .116 | .238 | .625 | -.351 |
| | AHEL | AHEH | -1.541* | .240 | <.001 | -2.013 |
| | | ALEH | -2.249* | .229 | <.001 | -2.699 |
| | | ALEL | -1.425* | .230 | <.001 | -1.876 |
| | ALEH | AHEH | .709* | .237 | .003 | .243 |
| | | AHEL | 2.249* | .229 | <.001 | 1.800 |
| | | ALEL | .825* | .226 | <.001 | .380 |
| | ALEL | AHEH | -.116 | .238 | .625 | -.583 |
| | | AHEL | 1.425* | .230 | <.001 | .974 |
| | | ALEH | -.825* | .226 | <.001 | -1.269 |
| Algo+ /Human- | AHEH | AHEL | -.935* | .226 | <.001 | -1.378 |
| | | ALEH | .959* | .227 | <.001 | .513 |
| | | ALEL | .010 | .226 | .964 | -.433 |
| | AHEL | AHEH | .935* | .226 | <.001 | .491 |
| | | ALEH | 1.893* | .226 | <.001 | 1.451 |
| | | ALEL | .945* | .225 | <.001 | .504 |
| | ALEH | AHEH | -.959* | .227 | <.001 | -1.404 |
| | | AHEL | -1.893* | .226 | <.001 | -2.336 |
| | | ALEL | -.948* | .226 | <.001 | -1.391 |
| | ALEL | AHEH | -.010 | .226 | .964 | -.454 |
| | | AHEL | -.945* | .225 | <.001 | -1.386 |
| | | ALEH | .948* | .226 | <.001 | .506 |

## Pairwise Comparisons

Dependent Variable: LikeA

| NorP | (I) AccN | (J) AccN | 95% Confidence Interval for Difference Upper Bound |
|---|---|---|---|
| Algo- /Human+ | AHEH | AHEL | 2.013 |
| | | ALEH | -.243 |
| | | ALEL | .583 |
| | AHEL | AHEH | -1.069 |
| | | ALEH | -1.800 |
| | | ALEL | -.974 |
| | ALEH | AHEH | 1.174 |
| | | AHEL | 2.699 |
| | | ALEL | 1.269 |
| | ALEL | AHEH | .351 |
| | | AHEL | 1.876 |
| | | ALEH | -.380 |
| Algo+ /Human- | AHEH | AHEL | -.491 |
| | | ALEH | 1.404 |
| | | ALEL | .454 |
| | AHEL | AHEH | 1.378 |
| | | ALEH | 2.336 |
| | | ALEL | 1.386 |
| | ALEH | AHEH | -.513 |
| | | AHEL | -1.451 |
| | | ALEL | -.506 |
| | ALEL | AHEH | .433 |
| | | AHEL | -.504 |
| | | ALEH | 1.391 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| NorP | | Sum of Squares | Df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| Algo- /Human+ | Contrast | 255.615 | 3 | 85.205 | 33.511 | <.001 |
| | Error | 1993.387 | 784 | 2.543 | | |
| Algo+ /Human- | Contrast | 179.200 | 3 | 59.733 | 23.493 | <.001 |
| | Error | 1993.387 | 784 | 2.543 | | |

## Univariate Tests

Dependent Variable: LikeA

| NorP | | Partial Eta Squared | Noncent. Parameter | Observed Power[a] |
|---|---|---|---|---|
| Algo- /Human+ | Contrast | .114 | 100.533 | 1.000 |
| | Error | | | |
| Algo+ /Human- | Contrast | .082 | 70.480 | 1.000 |
| | Error | | | |

Each F tests the simple effects of AccN within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = .05

## 3. PriorN * AccN

## Estimates

Dependent Variable: LikeA

| PriorN | AccN | Mean | Std. Error | 95% Confidence Interval Lower Bound | 95% Confidence Interval Upper Bound |
|---|---|---|---|---|---|
| I-APPROVE | AHEH | 5.369 | .180 | 5.015 | 5.723 |
| | AHEL | 4.811 | .149 | 4.518 | 5.104 |
| | ALEH | 4.958 | .160 | 4.644 | 5.271 |
| | ALEL | 5.463 | .165 | 5.140 | 5.786 |
| I-DENY | AHEH | 3.890 | .155 | 3.586 | 4.195 |
| | AHEL | 3.842 | .173 | 3.503 | 4.181 |
| | ALEH | 4.052 | .160 | 3.737 | 4.366 |
| | ALEL | 3.670 | .155 | 3.366 | 3.974 |

## Pairwise Comparisons

Dependent Variable: LikeA

| AccN | (I) PriorN | (J) PriorN | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound |
|---|---|---|---|---|---|---|
| AHEH | I-APPROVE | I-DENY | 1.479* | .238 | <.001 | 1.012 |
| | I-DENY | I-APPROVE | -1.479* | .238 | <.001 | -1.946 |
| AHEL | I-APPROVE | I-DENY | .969* | .228 | <.001 | .521 |
| | I-DENY | I-APPROVE | -.969* | .228 | <.001 | -1.417 |
| ALEH | I-APPROVE | I-DENY | .906* | .226 | <.001 | .462 |
| | I-DENY | I-APPROVE | -.906* | .226 | <.001 | -1.350 |
| ALEL | I-APPROVE | I-DENY | 1.793* | .226 | <.001 | 1.350 |
| | I-DENY | I-APPROVE | -1.793* | .226 | <.001 | -2.237 |

## Pairwise Comparisons

Dependent Variable: LikeA

| AccN | (I) PriorN | (J) PriorN | 95% Confidence Interval for Difference Upper Bound |
|---|---|---|---|
| AHEH | I-APPROVE | I-DENY | 1.946 |
| | I-DENY | I-APPROVE | -1.012 |
| AHEL | I-APPROVE | I-DENY | 1.417 |
| | I-DENY | I-APPROVE | -.521 |
| ALEH | I-APPROVE | I-DENY | 1.350 |
| | I-DENY | I-APPROVE | -.462 |
| ALEL | I-APPROVE | I-DENY | 2.237 |
| | I-DENY | I-APPROVE | -1.350 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| AccN | | Sum of Squares | df | Mean Square | F | Sig. | Partial Eta Squared |
|---|---|---|---|---|---|---|---|
| AHEH | Contrast | 98.222 | 1 | 98.222 | 38.631 | <.001 | .047 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| AHEL | Contrast | 45.803 | 1 | 45.803 | 18.014 | <.001 | .022 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| ALEH | Contrast | 40.798 | 1 | 40.798 | 16.046 | <.001 | .020 |
| | Error | 1993.387 | 784 | 2.543 | | | |
| ALEL | Contrast | 160.134 | 1 | 160.134 | 62.981 | <.001 | .074 |
| | Error | 1993.387 | 784 | 2.543 | | | |

## Univariate Tests

Dependent Variable: LikeA

| AccN | | Noncent. Parameter | Observed Power[a] |
|---|---|---|---|
| AHEH | Contrast | 38.631 | 1.000 |
| | Error | | |
| AHEL | Contrast | 18.014 | .989 |
| | Error | | |
| ALEH | Contrast | 16.046 | .979 |
| | Error | | |
| ALEL | Contrast | 62.981 | 1.000 |
| | Error | | |

Each F tests the simple effects of PriorN within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = .05

## 4. PriorN * AccN

**Estimates**

Dependent Variable: LikeA

| PriorN | AccN | Mean | Std. Error | 95% Confidence Interval Lower Bound | Upper Bound |
|---|---|---|---|---|---|
| I-APPROVE | AHEH | 5.369 | .180 | 5.015 | 5.723 |
| | AHEL | 4.811 | .149 | 4.518 | 5.104 |
| | ALEH | 4.958 | .160 | 4.644 | 5.271 |
| | ALEL | 5.463 | .165 | 5.140 | 5.786 |
| I-DENY | AHEH | 3.890 | .155 | 3.586 | 4.195 |
| | AHEL | 3.842 | .173 | 3.503 | 4.181 |
| | ALEH | 4.052 | .160 | 3.737 | 4.366 |
| | ALEL | 3.670 | .155 | 3.366 | 3.974 |

**Pairwise Comparisons**

Dependent Variable: LikeA

| PriorN | (I) AccN | (J) AccN | Mean Difference (I-J) | Std. Error | Sig.[b] | 95% Confidence Interval for Difference[b] Lower Bound |
|---|---|---|---|---|---|---|
| I-APPROVE | AHEH | AHEL | .558* | .234 | .017 | .099 |
| | | ALEH | .412 | .241 | .088 | -.061 |
| | | ALEL | -.094 | .244 | .701 | -.573 |
| | AHEL | AHEH | -.558* | .234 | .017 | -1.017 |
| | | ALEH | -.147 | .218 | .503 | -.575 |
| | | ALEL | -.652* | .222 | .003 | -1.088 |
| | ALEH | AHEH | -.412 | .241 | .088 | -.884 |
| | | AHEL | .147 | .218 | .503 | -.282 |
| | | ALEL | -.505* | .229 | .028 | -.955 |
| | ALEL | AHEH | .094 | .244 | .701 | -.385 |
| | | AHEL | .652* | .222 | .003 | .216 |
| | | ALEH | .505* | .229 | .028 | .055 |
| I-DENY | AHEH | AHEL | .048 | .232 | .835 | -.408 |
| | | ALEH | -.161 | .223 | .470 | -.599 |
| | | ALEL | .220 | .219 | .315 | -.210 |
| | AHEL | AHEH | -.048 | .232 | .835 | -.504 |
| | | ALEH | -.210 | .236 | .374 | -.672 |
| | | ALEL | .172 | .232 | .459 | -.284 |
| | ALEH | AHEH | .161 | .223 | .470 | -.277 |
| | | AHEL | .210 | .236 | .374 | -.253 |
| | | ALEL | .382 | .223 | .087 | -.056 |
| | ALEL | AHEH | -.220 | .219 | .315 | -.651 |
| | | AHEL | -.172 | .232 | .459 | -.628 |
| | | ALEH | -.382 | .223 | .087 | -.819 |

**Pairwise Comparisons**

Dependent Variable: LikeA

| PriorN | (I) AccN | (J) AccN | 95% Confidence Interval for Difference<br>Upper Bound |
|---|---|---|---|
| I-APPROVE | AHEH | AHEL | 1.017 |
| | | ALEH | .884 |
| | | ALEL | .385 |
| | AHEL | AHEH | -.099 |
| | | ALEH | .282 |
| | | ALEL | -.216 |
| | ALEH | AHEH | .061 |
| | | AHEL | .575 |
| | | ALEL | -.055 |
| | ALEL | AHEH | .573 |
| | | AHEL | 1.088 |
| | | ALEH | .955 |
| I-DENY | AHEH | AHEL | .504 |
| | | ALEH | .277 |
| | | ALEL | .651 |
| | AHEL | AHEH | .408 |
| | | ALEH | .253 |
| | | ALEL | .628 |
| | ALEH | AHEH | .599 |
| | | AHEL | .672 |
| | | ALEL | .819 |
| | ALEL | AHEH | .210 |
| | | AHEL | .284 |
| | | ALEH | .056 |

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

## Univariate Tests

Dependent Variable: LikeA

| PriorN | | Sum of Squares | df | Mean Square | F | Sig. |
|---|---|---|---|---|---|---|
| I-APPROVE | Contrast | 29.439 | 3 | 9.813 | 3.860 | .009 |
| | Error | 1993.387 | 784 | 2.543 | | |
| I-DENY | Contrast | 7.589 | 3 | 2.530 | .995 | .395 |
| | Error | 1993.387 | 784 | 2.543 | | |

## Univariate Tests

Dependent Variable: LikeA

| PriorN | | Partial Eta Squared | Noncent. Parameter | Observed Power[a] |
|---|---|---|---|---|
| I-APPROVE | Contrast | .015 | 11.579 | .824 |
| | Error | | | |
| I-DENY | Contrast | .004 | 2.985 | .272 |
| | Error | | | |

Each F tests the simple effects of AccN within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

a. Computed using alpha = .05

## CH2-References-Essay 1


Bigman, Y. E. and K. Gray. (2018). "People are averse to machines making moral decisions." *Cognition*, 181, 21–34.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research, 12.* 1-16.

Burton, J. W., M. Stein and T. B. Jensen. (2019). "A systematic review of algorithm aversion in augmented decision making." *Journal of Behavioral Decision Making*, 1–20.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5), 809-825.

Chen, Henian & Cohen, Patricia & Chen, Sophie. (2010). How Big is a Big Odds Ratio? Interpreting the Magnitudes of Odds Ratios in Epidemiological Studies. *Communications in Statistics - Simulation and Computation*.

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science, 243*(4899), 1668–1674.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114-126.

Dzindolet, M. T., L. G. Pierce, H. P. Beck and L. A. Dawe. (2002). "The Perceived Utility of Human and Automated Aids in a Visual Detection Task." *Human Factors*, 44(1), 79–94.

Festinger, L. (1957) A Theory of Cognitive Dissonance. *Stanford University Press*, Stanford, 58-63.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics* (5th ed.). SAGE Publications.

Fuchs, C., & Diamantopoulos, A. (2009). Using Single-Item Measures for Construct Measurement in Management Research: Conceptual Issues and Application Guidelines. *Die Betriebswirtschaft*. 69. 195-210.

Goldstein, J. (1988). A far-from-equilibrium systems approach to resistance to change. *Organizational Dynamics*, *17*, 16-26.

Goodman, J. K., & Paolacci, G. (2017). Crowdsourcing Consumer Research. *Journal of Consumer Research, 44*, 196-210.

Goodyear, K., R. Parasuraman, S. Chernyak, P. Madhavan, G. Deshpande and F. Krueger. (2016). "Advice Taking from Humans and Machines: An fMRI and Effective Connectivity Study." *Frontiers in Human Neuroscience*, 10(542).

Hauser, D. J., & Schwarz, N. (2016). Attentive Turkers: MTurk participants perform better on online attention checks than do subject pool participants. *Behavior Research Methods, 48*, 400-407.

Jian, Jiun-Yin & Bisantz, Ann & Drury, Colin. (2000). Foundations for an Empirically Determined Scale of Trust in Automated Systems. *International Journal of Cognitive Ergonomics*. 4. 53-71.

Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion.

Kees, J., Berry, C., Burton, S., & Sheehan, K. (2017). An Analysis of Data Quality: Professional Panels, Student Subject Pools, and Amazon's Mechanical Turk. *Journal of Advertising, 46*, 141-155.

Koopmans, M. (2017), Perspectives on Complexity, Its Definition and Applications in the Field. *Complicity: An International Journal of Complexity and Education*, Volume 14, Number 1, pp. 16-35.

Kruglanski, A. W., Shah, J. Y., Fishbach, A., Friedman, R., Chun, W. Y., & Sleeth-Keppler, D. (2002). A theory of goal systems. In M. P. Zanna & M. P. Zanna (Eds.), *Advances in experimental social psychology* (Vol. 34, pp. 331–378). San Diego, CA: Academic Press.

Hart, W., Albarracín, D., Eagly, A. H., Brechan, I., Lindberg, M. J., & Merrill, L. (2009). Feeling validated versus being correct: a meta-analysis of selective exposure to information. Psychological bulletin, 135(4), 555.

Horton, J. J., Rand, D. G., & Zeckhauser, R. J. (2011). The online laboratory: Conducting experiments in a real labor market. *Experimental economics*, *14*, 399-425.

Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a complex system?. *European Journal for Philosophy of Science*, *3*, 33-67.

Lee, Min Kyung (2018), "Understanding Perception of Algorithmic Decisions: Fairness, Trust, and Emotion in Response to Algorithmic Management," *Big Data & Society*, 5 (1), 1–16.

Lerch, F.J., Prietula, M.J. and Kulik, C.T., 1997, The Turing effect: the nature of trust in expert system advice. *In Expertise in Context: Human and Machine*, P.J. Feltovich and K.M. Ford (Eds), pp. 417–448 (Cambridge, MA: The MIT Press).

Litman, L., Robinson, J. & Abberbock, T. TurkPrime.com: A versatile crowdsourcing data acquisition platform for the behavioral sciences. *Behavior Research Methods* 49, 433–442 (2017).

Logg, J., Minson, J., & Moore, D. A. (2018). Algorithm Appreciation: People Prefer Algorithmic To Human Judgment. *Organizational Behavior and Human Decision Processes*, 151, 90-103.

Longoni, Chiara, Andrea Bonezzi, and Carey Morewedge (2019), "Resistance to Medical Artificial Intelligence," *Journal of Consumer Research*, 46 (4), 629–50.

Madhavan, P., & Wiegmann, D. A. (2007a). Similarities and differences between human-human and human-automation trust: An integrative review. *Theoretical Issues in Ergonomics Science*, 8, 277–301.

Madhavan, P., & Wiegmann, D. A. (2007b). Effects of information source, pedigree, and reliability on operator interaction with decision support systems. *Human factors*, 49(5), 773–785.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. Technological Forecasting and Social Change, 175, 121390.

Mayer, R. C., Davis, J. H., & Schoorman, F. D. (1995). An integrative model of organizational trust. *Academy of Management Review*, 20(3), 709–734.

Michelman, P. (2017). When People Don't Trust Algorithms. *MIT Sloan Management Review*, *59*(1), 11.

Miles J. & Shevlin M. (2001). Applying regression & correlation : a guide for students and researchers. *Sage Publications*.

Morwitz, V.G. and Munz, K.P. (2021). Intentions. *Consumer Psychology Review*, 4: 26-41.

Nicolis, G., & Prigogine, I. (1989). *Exploring complexity: An introduction*. New York: Freeman.

Park, C. W., & Lessig, V. P. (1981). Familiarity and its impacts on consumer decision biases and heuristics. *Journal of Consumer Research*, 8, 223-230.

Piaget, J. (1971). *Biology and knowledge: An essay on the relations between organic regulations and cognitive processes.* Chicago: University of Chicago Press.

Prahl, A., & Van Swol, L. (2017). Understanding algorithm aversion: When is advice from automation discounted? *Journal of Forecasting*, 36, 691–702.

Raju, P. S., Lonial, S. C., & Mangold, W. G. (1995). Differential Effects of Subjective Knowledge, Objective Knowledge, and Usage Experience on Decision Making: An Exploratory Investigation. *Journal of Consumer Psychology (Taylor & Francis Ltd)*, 4(2), 153.

Selnes, F., & Grønhaug, K. (1986). Subjective and Objective Measures of Product Knowledge Contrasted. *Advances in Consumer Research*, 13(1), 67–71.

Shannon, C. E. (1948). A mathematical theory of communication. *The Bell system technical journal*, *27*(3), 379-423.

Tomaino, G., Teow, J., Carmon, Z., Lee, L., Ben-Akiva, M., Chen, C., ... & Zhao, J. (2020). Mobility as a service (MaaS): The importance of transportation psychology. *Marketing Letters*, *31*, 419-428.

von Berthalanffy, L. S. (1969). *General system theory*. New York: George Braziller.

Weng, G., Bhalla, U., & Iyengar, R. (1999). Complexity in Biological Signaling Systems. *Science, 284*(5411), 92-96.

Yalcin, Gizem & Lim, Sarah & Puntoni, Stefano & van Osselaer, Stijn. (2022). Thumbs Up or Down: Consumer Reactions to Decisions by Algorithms versus Humans. *Journal of Marketing Research*. 59.

Yeomans, M, Shah, A, Mullainathan, S, Kleinberg, J. (2019). Making sense of recommendations. *Journal Behavior Decision Making*, 1– 12.

## Chapter 3 - Essay 2 – Knowledge, Perceived Complexity, and Algorithm Use.

### Introduction

AI algorithms form the core machinery of contemporary and emerging managerial decision support tools. These algorithms have proliferated across the business landscape and are increasingly used to support decision making in business domains such as finance and marketing, as well as in application domains such as aviation, military, healthcare and education. The evidence suggests that algorithms outperform human judgment (Dawes et al, 1989; Dietvorst et al, 2014, 2018; Logg et al, 2019; Yeomans et al, 2018; Alexander et al, 2018) and businesses invest in and use algorithms to sift through and analyze data to garner valuable customer and competitor insights. Predictive use of such models (e.g., Google, Facebook, and Netflix) supports decision making and enables firms to remain competitive and create customer value.

Even as advances in technology and computing power are instilling greater algorithmic functionality and accuracy, as well as covering more application domains, the core algorithms are increasing in complexity. Such complexity may reflect the nature of the decision itself or stem from task environment factors. Yet, ironically, as the models become increasingly complex, the human users of such decision support algorithms may become less and less knowledgeable about their inner "machinery." How is such evolution likely to affect algorithm aversion and appreciation phenomena? Will this emerging complexity discourage users from using and relying upon such decision support algorithms (Dietvorst et al, 2014; Yeomans et al, 2019) or will evidence of performance improvements and increasing familiarity drive greater appreciation and use of algorithms in decision making (Logg et al, 2019)?

Given today's business and technological climate, one approach to stimulating greater adoption and use of computer software and algorithms in decision making is to provide more information and knowledge about the inner workings of the algorithm. This may mitigate the view that an algorithm is an opaque "black box" and enhance willingness to use it. Yet, somewhat counterintuitively, such education may even exacerbate algorithm aversion as users see the algorithm's limitations and the errors that human decision makers could easily avoid. It is also likely that users become overwhelmed by a greater appreciation of the complexity of the decision task and environment. Thus, additional information may, on the one hand, decrease the level of unknowns in the domain. On the other hand, the information may actually increase the decision maker's appreciation of what remains unknown about the decision domain.

In this empirically based essay, we examine how providing knowledge of the algorithm's inner workings may influence a decision maker's objective knowledge as well as the perceived complexity of the decision task. We also examine how these in turn, influence their subjective knowledge (i.e., confidence) of the problem domain (algorithm and task) and thereby affect their willingness to use the algorithm (relative to a human expert). We also examine how self-efficacy (a critical individual difference) may play a role in the sequence of processes that eventually influence the decision maker's willingness to use an algorithm.

## Literature Review

### Models and Managers

We turn to the management science and decision-making literature for prior research findings on how complexity and information provision impact the use of decision support algorithms. Over fifty years ago, Little authored several seminal papers (e.g., Little, 1970;

Little, 1979) regarding the managerial use of management science models for real-world decision making. Lamenting the lack of managerial use of such models, Little (1970) listed a set of desirable model properties that he felt would stimulate greater managerial use. These properties of a "decision calculus" stressed that such models should be 1) simple - easy to understand; 2) robust - avoid providing patently bad answers; 3) easy to control – transparent links between inputs and outputs; 4) adaptive - updatable with new information; 5) complete on important issues - able to handle phenomena without being bogged down in detail; and 6) easy to communicate with – i.e., readily change inputs and obtain quick outputs.

Influential as they were, these criteria have not been easy to meet. Decision calculus models based on these principles have shown mixed performance (Chakravarti et al., 1979, 1981). Managers find implications of phenomena such as lagged and carryover effects of advertising difficult to model and have limited ability to extrapolate prior domain experience to unfamiliar regions. These limitations have created challenges that have limited the efficacy of such models (Wierenga et al 1999). Fast forwarding to present day AI algorithms, the decision task and the decision environment have not only become more complex, but the inner workings of the core model and algorithms have also become less transparent. This comprehension gap contributes to inhibition of managerial willingness to use the decision support tool – the so-called algorithm aversion phenomenon.

Complexity

There are a multitude of forms and definitions for complexity given its historical and current use across the natural and social sciences (Ladyman et al, 2013). As Weng (1999) points out, the adjective "complex" implies a system or component whose design and/or function are difficult to grasp. Factors that contribute to complexity include the number of components, the intricacy of their interfaces, including conditional branches, the degree of nesting, and the types of data structures.

*Structural Complexity*. Complexity has been used to describe system structure. An early example in information theory (Shannon 1948) uses complexity to describe the organization of probability space in terms of previous outcome distributions. Reducing entropy (randomness in an environment) involves increased complexity but enhances predictability. Along similar lines, complexity has been used to describe biological systems. In the 18$^{th}$ century Carl Linnaeus created the Linnaean system which allowed classification and naming of organisms. The system increased complexity but reduced uncertainty in identifying animal types and predicting their behavior (Piaget, 1971). Thus, an increase in the number of variables that describe a given structure increases the objective complexity of the system.

*Process Complexity.* System complexity involves describing properties of systems. General Systems Theory (GST - von Berthalanffy 1969) identifies the shared features of all systems, across all fields, their components, and the interactions of components with each other. Interactions imply exchange of matter, energy, or information (von Berthalanffy, 1969). Components are considered subsystems within the larger system. GST posits that systems must be analyzed as an irreducible whole (i.e., including constituent parts) to be understood. This theory may be applied flexibly to understand hierarchical subsystems and their interaction in diverse contexts such as organizations, groups, individuals, and even software. This mutual interdependency of a system and its components and its irreducible nature characterizes complexity as a process and is distinct from the notion of complexity as merely a multifaceted phenomenon or behavioral manifestation" (Koopmans, 2017). Thus, understanding a system involves not only understanding <u>what</u> it does, but also <u>how</u> it does what it does.

*Complexity as Transformative Behavior.* Complexity can also be used to interpret transformative behaviors whose scope and nature are hard to deduce from conditions within a system (Nicolis & Prigogine, 1989; Koopmans, 2017). Systems generally have equilibrium states where it is relatively predictable and shows little variation. However, sometimes, small "perturbations" produce large effects that are unpredictable and volatile and move it to a new equilibrium state (Goldstein, 1988). In such cases complexity is evaluated by the nonlinearity of the relation between initial conditions and outcomes(Nicolis & Prigogine, 1989). Inputs to an algorithmic model that create unpredictable and variable output increase complexity.

In summary, structural complexity increases when probability spaces and classification systems are introduced to reduce entropy/uncertainty and enhance predictive capability. Process complexity is driven by consideration of the number of components within a system and the interactions between them. Transformative complexity is revealed when an input creates an unpredictable and variable output or moves a system from one equilibrium to another. These characteristics of algorithmic models will enhance complexity and potentially alter user understanding.

Information and Knowledge

Lay intuition suggests that providing information should generally enhance objective knowledge and reduce the perceived complexity of a decision domain or decision system. The belief stems from an assumption that as individuals acquire relevant additional information, their knowledge of a given domain expands, thus lowering the portion of the domain that is unknown. One would therefore normally expect that as an individual's grasp of a domain expands (i.e., their objective knowledge expands), their perceptions of domain complexity should decrease with a concomitant increase in confidence with respect to the properties of the domain and relevant decision outcomes. Thus, in the context of decision support algorithms, a decision maker who acquires a stronger understanding of the inner workings of a decision algorithm and how it addresses the pertinent decision task (via information acquired through formal knowledge acquisition or through usage experience) may display greater willingness to use the algorithm for decision making.

*Objective and Subjective Knowledge.* Brucks (1985) drew a distinction between objective knowledge (what an individual actually knows) and what she called "subjective knowledge," which she described as what the individual thinks or believes they know. She asserted that subjective knowledge is akin to confidence and followed Park and Lessig (1981) in asserting that such knowledge influences perceptions and decision outcomes. Whereas providing domain information may improve a user's understanding and raise objective knowledge, the impact on subjective knowledge is less predictable. On the one hand, objective knowledge can enhance subjective knowledge or confidence based on the pool of domain information (Gill et al., 1998). On the other hand, more information (particularly about the algorithm's limitations or failings) may lower subjective knowledge (confidence) by making what remains unknown more salient. Lowering subjective knowledge (confidence) about an individual's algorithmic understanding may, in turn, lower the individual's willingness to use the algorithm in decision making.

Researchers have also reported other unexpected downstream effects of additional objective knowledge or expertise about a domain. For example, Arkes, et al. (1986) found that individuals who have expertise (or think they do) often forgo using a decision tool and hence end up performing poorly. Kruger and Dunning (1999) found that individuals who lack the necessary knowledge and skills for specific tasks are often unaware of these deficiencies and overestimate their own prowess. Although there is controversy surrounding the genesis of the effect as a metacognitive failure or a mere statistical artifact, the effect itself and its practical ramifications are well documented. Indeed, Akturk and Sahin (2022) argue that a hallmark of people with advanced metacognitive skills is that they are "aware of what they have learned" and also "what they do not know." In more recent treatment metacognition involves not only thinking about one's thought processes, but also involves awareness of one's knowledge, cognitive processes and emotional states along with conscious regulation of these processes (see e.g., Costa and Kalick 2009; Mahdavi, 2014).

Subjective knowledge can also have counterintuitive effects. Thus, Hall, Ariss and Todorov (2007) show that increased knowledge can lower prediction accuracy (even as it enhances confidence in a prediction). Arguing that knowledge is sometimes illusory, these authors show that reliance on a larger repository of objective (but irrelevant) knowledge can reduce reliance on more relevant and reliable inventory of information and lead to lower predictive accuracy. Transferring the import of some of these results to the context of managerial use of algorithms in decision making, one recognizes the possibility that as managers learn more about a decision tool and the associated domain, their subjective knowledge could increase as a direct effect. However, along an indirect path, more information could enhance the perceived complexity of the algorithm or domain which may then lower subjective knowledge or confidence in using the algorithm to make decisions.

Support for the above reasoning comes from a variety of sources. Thus, the well-known saying, "The more you know, the more you realize you don't know" is variously attributed to Aristotle, Socrates or Confucius (and variants are attributed to many others). Modern proponents of similar ideas include Donald Rumsfeld (2002), "There are known knowns. These are things that we know that we know. There are known unknowns. That is to say, there are things that we know we don't know." But there are also unknown unknowns. These are things we don't know that we don't know." These enigmatic statements may capture latent wisdom regarding the impact of new knowledge. Even as learning new information expands objective knowledge, it may disproportionately raise the decision maker's appreciation of domain unknowns relative to domain knowns. Objective knowledge of an algorithm that creates a disproportionate change in the domain unknowns relative to knowns may then reduce subjective knowledge (confidence) in the algorithm and lower willingness to use it for decision making. Generally speaking, when domain unknowns (knowns) increase disproportionate to domain knowns (unknowns) one can interpret this as an increase in domain unknowns (decrease in domain unknowns).

*The Role of Self Efficacy.* Self-Efficacy is an important individual difference factor that is likely to play a key role in how information and knowledge influences perceptions of complexity and subjective knowledge. The concept is defined (Bandura 1994) as an individual's belief in their own capacity to execute tasks and achieve specific performance levels, as well as their perceived ability to influence and manage the events that shape their lives. The concept extends beyond confidence in a specific situation and is a more general conceptualization of a person's assessment of their own skills and ability to handle challenges effectively. Those with high self-efficacy exhibit a robust belief in their ability to succeed, approach challenges with determination, and persist in the face of adversity. They set high goals for themselves, invest more effort and exhibit greater resilience following setbacks. Conversely, individuals low in self-efficacy harbor doubts about their capabilities that can profoundly affect behaviors and outcomes. They tend to avoid challenging tasks, experience greater anxiety and lower perseverance in the face of challenge and difficulties. Such diminished self-belief can lead to an unwillingness to embrace potentially rewarding challenges.

In our algorithmic decision-making context, a manager's self-efficacy level may play a role in determining how new information and domain knowledge influences willingness to use an algorithm in decision making. For a given level of subjective knowledge (confidence), self-efficacy may moderate the willingness to use an algorithm. On the other hand, self-efficacy may be a factor that plays a role in determining how new information influences perceptions of domain complexity, as well as how such complexity perceptions translate to subjective knowledge and thereby willingness to use an algorithm for decision making. In this broader conceptualization, self-efficacy would contribute to all component relationships in our model. We examine both conceptualizations in our empirical work.

## Conceptual Model

We build on the preceding concepts to develop a model that helps us conceptualize the genesis of algorithm aversion and a better understanding of factors that may influence a decision maker's (un)willingness to use an AI algorithm in their decision making. The model provides potential insights into why providing information to enhance knowledge of a decision algorithm may backfire and lower willingness to adopt such algorithms.

To set context, we clarify the terminology we use in our conceptual model. By "algorithm" we mean a set of carefully defined instructions that take a set of inputs (data or judgments), manipulate them using defined rules, and produce output relevant to a decision. Our discussion focuses on computer-based models and software that embed algorithms that are intended to support decision making in various business domains. We use the label "process information" to describe information that is pertinent to understanding "how" a computing (decision support) algorithm works. Our preceding discussion argues that providing such information may have differential effects. In some cases, the provided process information may enhance what is objectively known about the decision domain, relative to what is unknown. In other instances, the process information adds to what is objectively known about the domain, but at the same time creates an appreciation that what remains unknown about the domain space may actually be significantly larger than originally anticipated.

In this scenario, one might argue that, although providing process information enhances objective knowledge, subjective knowledge (confidence) that stems from this objective knowledge may actually decline in some instances. This is because the provided process information actually increases perceived complexity of the decision domain, which then reduces subjective knowledge (confidence). In such instances, providing process information could actually lower a decision maker's willingness or propensity to use the algorithmic model for decision making. Thus, depending on whether objective knowledge has a stronger direct and positive impact on subjective knowledge, the indirect effect (through perceived complexity) may be negative. The net outcome would be determined by the relative strength of the two effects and is an empirical question. Finally, as noted earlier, self-efficacy may moderate the very last process step, i.e., the link between subjective knowledge and willingness to use the decision algorithm. Alternatively, it may influence all antecedent relationships preceding this last link (and its effects controlled by specifying it as a covariate in each such relationship).

Formal Hypotheses and Path Diagram

Our hypotheses focus on a scenario where a decision maker faces a decision task and has the option of using an algorithm-based model to accomplish the task. We consider three alternative process information scenarios. In a baseline (control) situation, the decision maker is provided with a baseline information set but is not given any additional process information regarding how the algorithm functions. We consider two other process information conditions where the decision maker receives additional information beyond the baseline information. However, we manipulate the implication of the information regarding the complexity of the domain space. In one case, the participant (decision maker) is told that the information is useful and "will help them understand how algorithms work, and that this understanding can result in higher quality decisions." This manipulation is intended to lower the set of unknowns about the decision algorithm and task domain and <u>decreases</u> domain unknowns for the decision maker. In the contrasting case, the participant is told that the information is useful, but that "there are quite a few complex nuances that must be understood" and that "an incomplete understanding can result in a lower quality decision." This manipulation is intended to imply that the set of (decision algorithm and task domain) unknowns is larger than originally believed. (i.e., the process information <u>increases</u> the domain unknowns).

Our first hypothesis speaks to the relative effects of these three process information conditions on the perceived complexity of the decision domain. Thus:

**H1: The process information manipulation (SD - domain unknowns decrease; SI - domain unknowns increase SI; SN control no information) will influence the perceived complexity (PC) of the decision (algorithm and task) domain. Specifically:**

- **H1a: Relative to decision makers in the SD condition, perceived complexity (PC) will be higher for those in the SI condition.**
- **H1b: Relative to decision makers in the SN condition, perceived complexity (PC) will be higher for decision makers in both the SD and SI conditions.**

Our second hypothesis speaks to the impact of the process information manipulation (SI, SD and SN) on objective knowledge (OK). Relative to the SN condition where no information is provided, decision makers in each of the SI and SD conditions will indicate higher levels of objective knowledge. This follows from the fact that the <u>substantive</u> process information is identical in both the SI and SD conditions and adds objective knowledge relative to the SN (control, no information) condition .  Thus:

**H2:  The process information manipulation  (both SD - domain unknowns decrease; and SI - domain unknowns increase) will raise the decision maker's objective knowledge (OK) level relative to the SN (control no information) condition.**

Our third hypothesis makes the straightforward prediction that an increase in the level of objective knowledge (OK) will ordinarily reduce the level of perceived complexity (PC). Thus:

**H3:  Increases in the level of objective knowledge (OK) will lower the decision maker's level of perceived complexity (PC) of the decision (algorithm and task) domain.**

We note that our reasoning introduces two influence pathways of the process information manipulation on perceived complexity. H1 posited the direct path which proposes an increase in perceived complexity. H2 and H3 together posit an indirect effect that operates through objective knowledge (OK) that implies a decrease in perceived complexity. We offer no formal hypothesis regarding the relative strengths of the two paths but recognize that the observed impact of process information would be determined along multiple paths. Our empirical results will shed light on the relative strengths of these effects.

Our fourth hypothesis concerns the relationship between perceived complexity (PC) and subjective knowledge (SK). On a direct path, this relationship is expected to be negative as increased domain complexity is likely to reduce the decision maker's confidence regarding their ability to solve the decision problem. This path is posited below:

**H4:  Higher levels of perceived complexity (PC) will lower subjective knowledge (SK).**

Our conceptual model also posits multiple pathways along which objective knowledge can influence subjective knowledge. First, prior empirical evidence (e.g., Brucks 1985) suggests that objective knowledge generally has a direct positive impact on subjective knowledge. Our next hypothesis affirmatively follows this evidence. In other words:

**H5: Higher levels of objective knowledge (OK) will increase subjective knowledge (SK).**

Here too, we note that objective knowledge (OK) lowers perceived complexity (PC) as posited in H3. This effect is also expected to propagate to subjective knowledge (SK). As H4 implies, lower perceived complexity should increase subjective knowledge. We make no formal hypothesis regarding the relative strengths of these two effects, other than to note that the indirect path through perceived complexity may fully mediate the direct relationship between objective knowledge and subjective knowledge. The empirical outcome may provide a more granular understanding of the OK-SK relationship noted in the prior literature.

The ultimate goal of our research is to examine the mechanism by which the process information about the decision domain (algorithm and task) influences the willingness to use the algorithm. To the extent that the mechanisms proposed earlier influence subjective knowledge (SK), they should impact the decision maker's willingness to use the algorithm (WTU). Higher (lower) levels of subjective knowledge (SK) is expected to raise (lower) the willingness to use the decision algorithm. This prediction is captured below:

**H6: Higher (lower) levels of subjective knowledge (SK) will raise (lower) a decision maker's willingness to use the algorithm (WTU).**

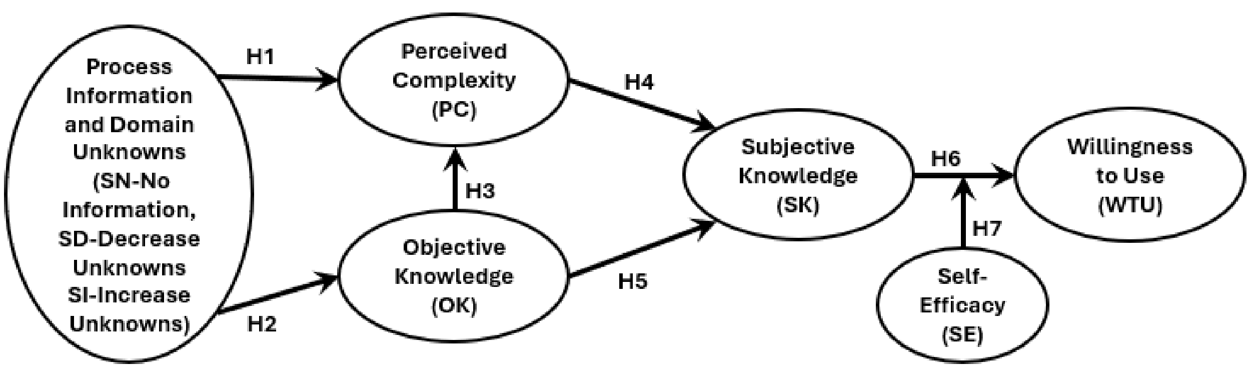
We note that because providing process information can impact what people feel they know (or do not know) about the decision domain, there may be differential impact on perceived complexity of the decision domain and raise or lower subjective knowledge (confidence) in using the decision algorithm. Thus, the process model provides a way to interpret both a positive effect on the willingness to use an algorithm (algorithm appreciation) as well as a negative effect (algorithm aversion) that drives reluctance.

As a final step in our conceptual framework, we argue that this effect of subjective knowledge (SK) on willingness to use the decision algorithm (WTU) may be moderated by the decision makers' innate sense of self-efficacy (SE). Thus:

**H7: Self-Efficacy (SE) will moderate the relationship between subjective knowledge (SK) and willingness to use the decision algorithm (WTU). The effect of subjective knowledge (SK) will be smaller for higher levels of self-efficacy.**

The path diagram below in Figure 1 captures the above hypotheses as a process model. Postulated relationships indicate the flows through which the manipulated process information translates into willingness to use the target algorithm in decision making.

*Figure 1-Initial Model-Path Diagram*




## Empirical Testing

A total of 291 participants were recruited from the Prolific web panel.(47% female, 76% Caucasian, Average Age of 37 ) were to participate in an empirical study portrayed as examining how a bank loan officer makes loan approval/denial decisions. Participants were paid $1.50, and the survey was developed on the QuestionPro platform. This decision maker has the option of using either a human appraiser's recommendation or to use a (fictitious) computer-based decision algorithm (ALGO) that computes FICO scores based on the applicants' personal credit information. The participants were randomly assigned to three process information conditions that manipulated what participants were told about the decision algorithm's inner workings. In the control condition, participants simply received the basic scenario and were not provided with any additional information to help them navigate the algorithm. In the two remaining process information conditions, participants were provided a baseline information set describing the programing process, processing instructions, as well as input, output and interaction variables that contributed to the computations of an accurate and valid FICO score. This basic process information is shown in CH3-Appendix A. This appendix also shows the instructions that were used to create the Domain Unknowns Increase and Domain Unknowns Decrease conditions respectively. Participants were randomly assigned to the three process information conditions and, following a review of the instructions, asked to respond to a set of measures described below.

Measurement

The data on the various model constructs were collected in a carefully specified order to avoid introducing artifactual relationships due to adjacency of measurement. The order of measurement was "WTU: willingness to use the algorithm relative to the human appraiser" (3 scale items); "OK: objective knowledge of algorithms" (a 7-item multiple-choice test adapted to knowledge of algorithms; "PC: perceived complexity of the algorithm/task domain" (3 scale items); "SK: subjective knowledge of how the algorithm calculates the FICO score" (3 scale items); and "SE - self-efficacy" (six scale items). Details of the specific scale items used for each construct, along with the Cronbach α scores are provided in CH3-Appendix B. Additionally, discriminant validity between measures was assessed and specifics can be found in CH3-Appendix C.

As a quick overview, the willingness to use (WTU) and perceived complexity (PC), measures were constructed by the researcher to fit the decision scenario and used 7-point Likert scales (1= Disagree, 7= Agree). The objective knowledge (OK) measure followed Brucks (1985) to create a 7-item multiple choice test designed to capture knowledge of terminology, pertinent product attributes, attribute evaluation criteria, and attribute co-variation. Subjective knowledge (SK) was measured using three Likert scale items (1=Disagree to 7=Agree) that modified a 5-item scale created by Flynn and Goldsmith (1999). Finally, Self-Efficacy was measured using a modified version of the New General Self Efficacy Scale (NGSE-Chen et al, 2001) that used six Likert scale items (1=Disagree, 7=Agree) comprised of three general and three analytical items.

**Research Methodology**

Core Scenario and Manipulations

As noted earlier, each participant played the role of a branch manager at a bank and was asked to indicate their preference for using an algorithm (versus a human appraiser) to obtain a FICO score to decide whether to approve or deny loan applications. All participants were provided identical baseline information of an overall credit (FICO) score calculation. In the control condition (SN), participants received no decision relevant information and no domain unknowns information. They read information regarding COVID-19 that was of similar structure and length to information provided in the two process information conditions. Participants in the two process information conditions received identical additional information about how the algorithm used an applicant's credit history to calculate the FICO. In the SI condition, participants were told that the information provided, though useful, *increased* the domain unknowns (i.e., what  remains unknown about the algorithm and the decision task). In contrast, those in the SD condition, participants were told that the provided information was useful and *decreased* the domain unknowns.

The core dependent measure (WTU)  was the participants' willingness to use the computer algorithm (relative to the human appraise). Other measures related to the relevant intervening constructs such as objective knowledge (OK), perceived complexity (PC), subjective knowledge (SK) and self-efficacy (SE) and were collected as indicated earlier. In addition, the study included relevant manipulation checks, as well as participant demographics. After completing the study questionnaire subjects were thanked and compensated ($1.50).

**Initial Analyses**

Initial Model Test

We first tested the process model described in Figure 1 which captures the relations described in the seven hypotheses. The data were analyzed using variant of Hayes 2018 Parallel Serial Moderated Mediation in PROCESS SPSS, baseline model 80 with customized syntax that added paths corresponding to H3 and H7. We used bootstrapping with 5000 replicated samples and a  confidence interval (CI) of 95%. The details of the results and associated output are presented in CH3-Appendix D. These initial model results are summarized  in the path diagram below (Figure 2) and are also tabulated in Table 3.

Before proceeding to the results, we note the process information conditions were recoded to create three variables X1, X2 and X3 to capture the contrasts essential in testing H1 and H2.

These variables were defined as follows:

X1: SI – SD [Domain Unknowns Increase vs. Domain Unknowns Decrease condition]
X2: SD – SN [Domain Unknowns Decrease vs. Control (No information) condition]
X3: SI - SN [Domain Unknowns Increase vs. Control (No information) condition]

Initial Model-Results

*Figure 2-Initial Model-Pathway Results*

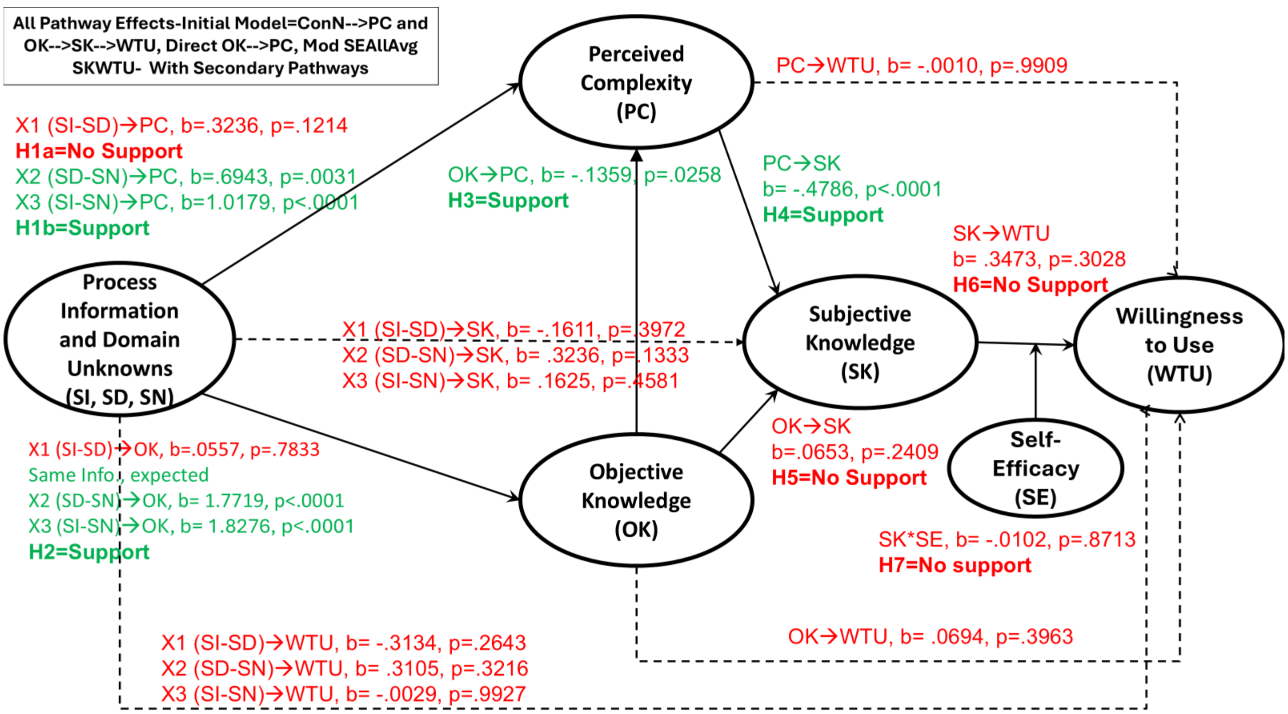



*Table 1-Initial Model-All Pathway*

| Outcome | Source | | | | | | |
|---|---|---|---|---|---|---|---|
| | X1 (SI-SD) | X2 (SD-SN) | X3 (SI-SN) | OK | PC | SK | Mod SE |
| OK | b= .0557, p=.7833 | b= 1.7719, p<.0001 | b= 1.8276, p<.0001 | | | | |
| PC | b= .3236, p=.1214 | b= .6943, p=.0031 | b= 1.0179, p<.0001 | b= -.1359, p=.0258 | | | |
| SK | b= -.1611, p=.3972 | b= .3236, p=.1333 | b= .1625, p=.4581 | b= .0653, p=.2409 | b= -.4786, p<.0001 | | |
| WTU | b= -.3134, p=.2643 | b= .3105, p=.3216 | b= -.0029, p=.9927 | b= .0694, p=.3963 | b= -.0010, p=.9909 | b= .3473, p=.3028 | b=-.0102, p=.8713 |

Even at first glance, Figure 2 and Table 1 shows that the basic process model outlined in Figure 1 received mixed support. The contrast between SI (unknowns increase) and SD (unknowns decrease) did have a higher average perceived complexity scores but was not statistically significant. Therefore, Hypothesis 1a was not supported. Both SI (unknowns increase) and SD (unknowns decrease) contrasts relative to SN (Control-No Information) were significant (contrasts X2 and X3). Perceived complexity scores associated with both "domain unknowns" conditions (SI and SD) were significantly higher than the control-no information condition (SN) and therefore H1b was supported. Overall, H1 received only partial support..

H2 was supported. Objective knowledge scores for both domain unknowns conditions (SI and SD) were significantly higher than in the control-no information condition (SN). Additionally, the SI (unknowns increase) vs SD (unknowns decrease) contrast showed no significant difference. This was as expected given that the process information provided was identical in these two conditions.

H3 postulates a negative relationship between objective knowledge (OK) and perceived complexity (PC) and was supported. So is H4, which predicts a negative relationship between perceived complexity (PC) and subjective knowledge (SK). OK shows no relationship with SK (thus, H5 was not supported). Surprisingly, there was no support for H6 which postulates a focal link between subjective knowledge SK and willingness to use the algorithm (WTU) in our initial conceptual development. Moreover, H7, which predicted that self-efficacy (SE) would moderate the relationship between SK and WTU was also not supported. Other direct relationships (shown as dotted lines in Figure 2 show that there were no other unexpected, but statistically significant, links between the model constructs.

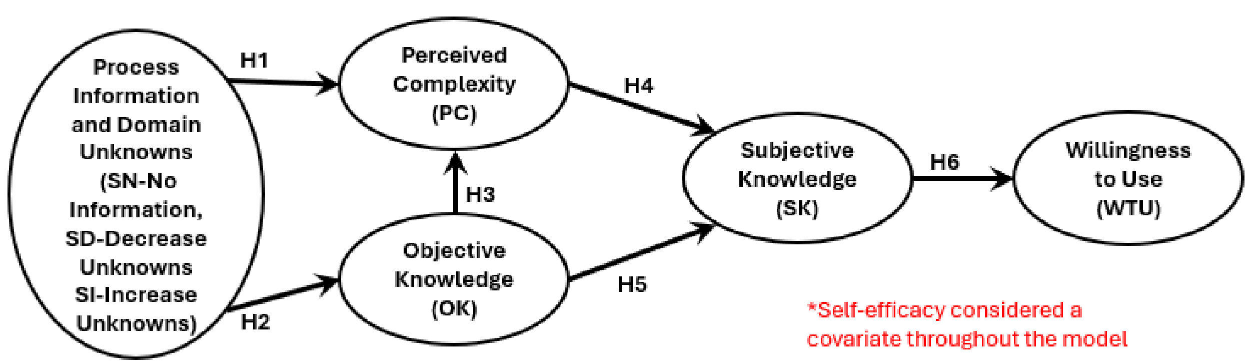
## Discussion

Overall, our initial model received less than satisfactory support. In thinking through these unexpected results, we focused on the possibility that we may have construed too limited a role for self-efficacy in this initial model. We had limited this critical construct to only a moderating role in the link between subjective knowledge (SK) and willingness to use the algorithm (WTU). In retrospect, we felt that self-efficacy may play a role in each of the paths linking  our constructs and conducted an exploratory reanalysis in which we controlled for the role of self-efficacy on each of the model pathways. Moreover, we also removed self-efficacy as a moderator of the link from SK to WTU. Thus, we examined the overall process model using SE as a covariate in order to control its effects on each model path.

**Alternative Model Analysis-Controlling for Self-Efficacy**

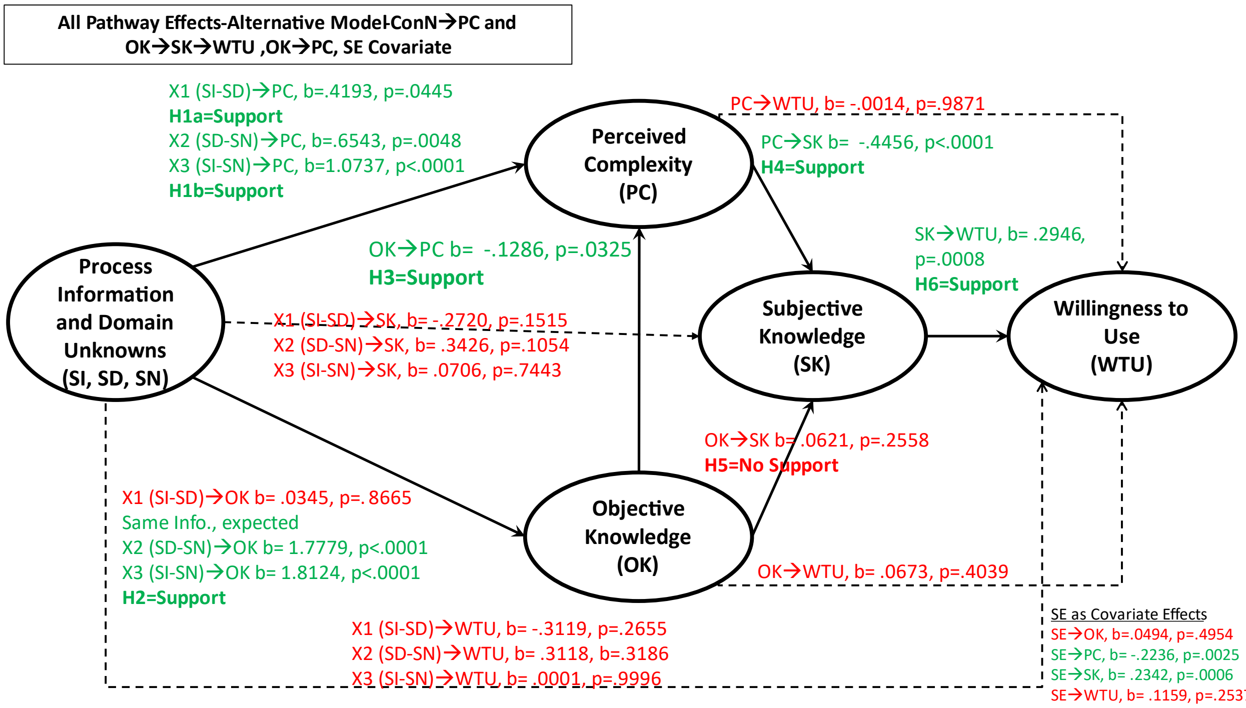
The revised exploratory model specification model is shown in Figure 3. We dropped H7 (the moderating role of self-efficacy, SE on the link between SK and WTU). Also, we control for the effects of self-efficacy by including it as a covariate on all the pathways in the process model. As before, the data were analyzed using a variant of Hayes 2018 Parallel Serial Moderated Mediation in PROCESS SPSS, baseline model 80 with customized syntax that reflected the changes describe above. The complete details of the analysis are presented in CH3-Appendix E.

*Figure 3-Alternate Model Path-Diagram*



## Alternate Model Results

*Figure 4-Alternative Model-Controlling for Self-efficacy*




The results of the new analysis are shown in Figure 4 above and the relevant path coefficients are shown below in Table 2.

*Table 2-Alternative Model-Controlling for Self-efficacy*

| Outcome | Source | | | | | | |
|---|---|---|---|---|---|---|---|
| | X1 (SI-SD) | X2 (SD-SN) | X3 (SI-SN) | OK | PC | SK | SE Covariate |
| OK | b= .0345, p=.8665 | b= 1.7779, p<.0001 | b= 1.8124, p<.0001 | | | | b= .0494, p=.4954 |
| PC | b= .4193, p=.0445 | b= .6543, p= .0048 | b= 1.0737, p<.0001 | b= -.1286, p=.0325 | | | b= -.2236, p=.0025 |
| SK | b= -.2720, p=.1515 | b= .3426, p=.1054 | b= .0706, p=.7443 | b= .0621, p=.2558 | b= -.4456, p<.0001 | | b= .2342, p=.0006 |
| WTU | b= -.3119, p=.2655 | b= .3118, b=.3186 | b= .0001, p=.9996 | b= .0673, p=.4039 | b= -.0014, p=.9871 | b= .2946, p=.0008 | b= .1159, p=.2537 |

*Self-Efficacy as a Covariate.* Removing self-efficacy (SE) as a moderator of the relationship between subjective knowledge (SK) and willingness to use (WTU) variables and controlling for its effects on all the model paths produced a dramatic change in support for the core hypotheses that comprised the alternate model shown in Figure 3. In this new model, self-efficacy (SE) has direct and significant impacts on perceived complexity (PC: b= .2236, p=.0025) and subjective knowledge (SK: b= .2342, p=.0006). However, it had no significant impact on objective knowledge (OK) and willingness to use (WTU) .

*Effects on Perceived Complexity.* After controlling for self-efficacy, the process information manipulations had statistically significant effects on perceived complexity. The estimated parameters showed a significant impact of the contrast X1 (SI – SD) on perceived complexity (PC: b= .4193, p=.0445). This result shows that when process information domain unknowns increased (versus decreased) the decision domain was perceived as having higher perceived complexity and is consistent with Hypothesis H1a.

Next, we compared the impact on perceived complexity of both the process information (domain unknowns) conditions, SD and SI, respectively, relative to the control condition. The results show that (a) both X2 (SD – SN) had a significant impact on perceived complexity (PC: b= .6543, p = .0048); and that (b) X3 (SI – SN) also had a significant impact (PC: b=1.0737, p<.0001). These results are consistent with H1b and are intriguing in that providing process information, relative to no information (control), actually increases the perceived complexity of the decision domain, regardless of whether the perceptions of domain unknowns was prompted as increased or decreased. However, as one would expect, the impact was smaller in the SD (versus the SI) condition where the prompt suggested a decrease (versus an increase) in domain unknowns.

This analysis also allowed us to examine the effect of objective knowledge (OK) on perceived complexity of the decision domain. We find that objective knowledge significantly and negatively affects perceived complexity (PC: b= -.1286, p=.0325). Consistent with the original

Hypothesis H3, individuals with higher levels of objective knowledge perceived the decision domain as less complex.

*Effects on Objective Knowledge.* In line with our original predictions, SD and SI, the two process information (domain unknowns) conditions had significant effects on participants' objective knowledge (OK) levels, relative to the SN (control, no information) condition. Thus X2 (SD -SN) had a significant impact on objective knowledge (OK: b=1.7779, p<.0001) as did X3 (OK: b=1.8124, p<.0001). This is consistent with Hypothesis H2. However, the two process information conditions did not differ in their impact on objective knowledge. Thus, the effect of X1 (SI -SD) on objective knowledge was not significant (OK: b=.0345, p=.8865). This is consistent with expectations as the objective content of the provided process information was identical in the two conditions. Overall, these results show that process information has the expected positive impact on objective knowledge.

*Effects on Subjective Knowledge.* Although we did not hypothesize any direct differential effects of providing process information on subjective knowledge, our analyses reported a check for such direct effects. Consistent with our conceptual model, we find no significant evidence of such direct effects. The p values associated with the tests for X1 (SI – SD), X2 (SD – SN), and X3 (SI-SN) all exceed .10). Also, contrary to H5, we did not find a direct effect of objective knowledge on subjective knowledge (SK: b = .0621, p = .2558). On the other hand, perceived complexity had a significant and negative effect on subjective knowledge (SK: b= -. 4456, p<.0001). This is consistent with Hypothesis H4. We note that these results show that objective knowledge has an impact on subjective knowledge that works through perceived complexity. This indirect path fully mediates the OK-SK relationship and explains the lack of support for the direct effect posited in Hypothesis H5.

*Effects on Willingness to Use the Algorithm.* Our results now show a strong and significant positive relationship between subjective knowledge (SK) and the willingness to use the algorithm (WTU: b=.2946, p=.0008). This result is consistent with Hypothesis H6 and shows that an individual's subjective knowledge level (as directly or indirectly determined by a series of antecedent factors, including the provided process information) increases willingness to use the decision algorithm. Removing the moderating effect of self-efficacy on the SK-WTU relationship (the original Hypothesis H7) and <u>controlling for the role of self-efficacy in each of the model paths</u> produces a pattern of effects consistent with the alternative process model that was hypothesized.

<u>Discussion</u>

We acknowledge that the results reported here stem from an exploratory analysis that was informed by the estimation results for the original model. Thus, removing the moderating role of self-efficacy originally posited, and controlling for self-efficacy effects on each model path by using it as a covariate, reveals a pattern of effects that is largely consistent with the effects posited in the original conceptual model (Hypotheses H1 through H6). This reflects a learning that the initially postulated role of self-efficacy in H7 (as a moderator of the SK-WTU relationship) was too limiting. Self-efficacy plays a strong role in the determination of both perceived complexity (b= -.2236, p=.0025) and subjective knowledge (b= .2342, p= .0006). Our initial failure to account for these effects masked important relationships.

Notably, the lack of support for H5 can be attributed to the full mediation of the direct link from objective to subjective knowledge by the implied indirect path through perceived complexity as a mediator. This indirect effect is determined as a product of the path coefficients linking OK to PC (b = -.1286) and PC to SK (b = -.4456) and computes as a positive indirect effect (b = .0573) of OK on SK.  We provide a summary comparison in Table 3 below of the results from the analyses of the original model that we had conceptually posited and the exploratory model that we examined after reconceptualizing the role of self-efficacy.

*Table 3-Summarized Results of Initial vs. Alternate Models*

| Hypothesis # | Hypothesis Summary | Results | |
|---|---|---|---|
| | | Initial Model | Alternate Model |
| 1a | Relative to decision makers in the SD condition, perceived complexity (PC) will be higher for those in the SI condition. | (b= .3236, p=.1214) | (b=.4193, p=.0445) |
| 1b | Relative to decision makers in the SN condition, perceived complexity (PC) will be higher for decision makers in both the SD and SI conditions. | SD-SN, (b= .6943, p=.003)<br>SI-SN, (b= 1.0179, p<.0001) | SD-SN, (b= .6543, p=.0048)<br>SI-SN, (b= 1.0737, p<.0001) |
| 2 | The process information manipulation (both domain unknowns decrease SD; domain unknowns increase SI) will raise the decision maker's objective knowledge (OK) level relative to the SN (control no information) condition. | SD-SN, (b= 1.7719, p<.0001)<br>SI-SN, (b= 1.8276, p<.0001) | SD-SN, (b= 1.7779, p<.0001)<br>SI-SN, (b= 1.8276, p<.0001) |
| 3 | Increases in the level of objective knowledge (OK) will lower the decision maker's level of perceived complexity (PC) of the decision (algorithm and task) domain. | (b= -.1359, p=.0258) | (b= -.1286, p=.0325) |
| 4 | Higher levels of perceived complexity (PC) will lower subjective knowledge (SK). | (b= -.4786, p<.0001) | (b= -.4456, p<.0001) |
| 5 | Higher levels of objective knowledge (OK) will increase subjective knowledge (SK). | (b= .0653, p=.2409) | (b= .0621, p=.2558) |
| 6 | Higher (lower) levels of subjective knowledge (SK) will raise (lower) a decision maker's willingness to use the algorithm (WTU). | (b= .3473, p=.3028) | (b= .2946, p=.0008) |
| 7 | Self-Efficacy (SE) will moderate the relationship between subjective knowledge (SK) and willingness to use the decision algorithm (WTU). The effect of subjective knowledge (SK) will be smaller for higher levels of self-efficacy. | (b=-.0102, p=.8713) | |

The reconceptualized model provides important insights regarding how subjective knowledge may play into a decision maker's willingness to algorithms for decision making. Our results suggest (subject to confirmatory replication) that this feeling of confidence as determined by a series of antecedents, and  can provide insights into the circumstances that might explain when decision makers may display either algorithm aversion or algorithm appreciation (Dietvorst 2015; Logg at al 2019).  The results also suggest that when decision domains involve significant complexity, simple provision of process information may produce greater objective knowledge (what is known), but may also  enhance perceptions of what remains unknown about the decision domain (algorithm and task) and enhance perceived complexity. . In our study, we directly prompted these alternative inferences to examine how they may influence perceptions of complexity, objective knowledge and subjective knowledge. Future research may focus on examining situations where such inferences occur unprompted. The results should shed light on how both decision makers and decision targets respond to domain information and the mental mechanisms that drive responses (aversion or appreciation) not only to algorithmic decision aids, but to AI support in general.

Finally, self-efficacy may also play a significant role in these situations. In the present work, we controlled for the effect of self-efficacy by using it as a covariate on each model path. However, it stands to reason that it may play a larger and more focal role in how provided process information is interpreted, and how it affects complexity perceptions and subjective knowledge (confidence). Clearly, this individual difference construct can play a large role in determining how managers as decision makers trust and adopt algorithms and related AI support tools. Similarly, consumers, whether in decision maker or decision target roles, may also respond differently to the AI "black box" depending on their self-efficacy levels. These are important future research issues for managerial and consumer decision researchers.

## CH3-Appendix A-Study Walkthrough and Manipulation

All participants (n=291) were introduced into the study and assumed the role of a loan manager at a local bank (specific details on right). They were provided with information on FICO scores and related calculation components. The participant was told they could choose to use a reliable software algorithm or an experienced human appraiser to calculate the FICO score.

**General Instructions-Please Read Carefully**

Imagine you are a loan manager at a local bank, and you are responsible for approving personal loans. One key approval criterion is an applicant's FICO score which is a measure of the person's creditworthiness. Applicant FICO scores are calculated using either a reliable software algorithm or an experienced human appraiser. FICO scores range from 300-850 (below 580 is Poor, 670-739 is Good, and above 800 is Exceptional) and consider the six technical weighted data inputs listed in the table below.

| Input | Weight |
|---|---|
| Debts/Amounts Owed | 30% |
| Payment History | 17.5% |
| Significant Negative Events | 17.5% |
| Age of Credit | 15% |
| New credit/Inquiries | 10% |
| Account Mix | 10% |

As a loan manager, you may choose either method for processing the applications, but will be ultimately responsible for the scores provided by either the reliable algorithm or the experienced human appraiser.

You have arrived at the office, just sat down at your desk, and you receive the following notice.

Participants were then provided either additional process information on the algorithm and how it accomplishes the task or provided non-relevant information regarding COVID.

## Algorithm Information-Process Information Present

This notice is from your Finance department. They are providing the following information about the computer algorithm named Algo that was created to calculate FICO Scores based on personal credit information. Please read the following information carefully. We will ask you a few questions about it.

**Computer Algorithm-Definition**-Algo is a computer program that contains carefully defined computer instructions that take a set of inputs (data) about loan applicants and manipulate them to create an index that signals the applicant's creditworthiness.

**Computer Algorithm-Programming**- Good programming involves creating algorithms that are relatively compact, simple, and fast. All programming languages contain grammar rules, characters, symbols, and words, that specify the instructions. One basic element is iteration, which is repeating instructions until the applicant's entire profile has been processed and a FICO score calculated.

**Computer Algorithm-Process Instructions**- Algo's process instructions include criteria for performing FICO score calculations accurately. Algo calculates FICO scores using carefully specified operating, termination, and error minimization rules that treat each applicant on a case-by-case basis.

**Computer Algorithm-Input, Output Variables, and Interactions**-For algorithms, like Algo, the total number of instruction steps depend on the number of input variables and the relationships among them. The higher the number of variables and their interrelationships, the more data manipulation needed to determine an accurate and valid FICO score.

## COVID Information-Process Information Absent (Control)

This notice is from your HR department indicating a recent upsurge on COVID-19 cases in the area. They are providing the following information about COVID-19 to protect yourself and others. Please read the following information carefully. We may ask you a few questions about it.

**What Is COVID-19?** COVID-19 is a coronavirus that has spread throughout the world. Symptoms can range from mild (or no symptoms) to severe illness and is primarily spread from person to person.

**How COVID-19 Is Spread**- You can become infected from coming within 6 feet of a person who has COVID-19, from respiratory droplets when they cough, sneeze or talk, and/or by touching a surface/object that has the virus on it and then by touching your mouth, nose, or eyes.

**Protect Yourself and Others From COVID-19**- There are currently several vaccinations for COVID-19 and the best way to protect yourself and others is to get vaccinated on a regular basis. If you have a weakened immune system, or when there is an outbreak, wear a mask that covers your nose and mouth and practice social distancing. Clean and disinfect frequently touched surfaces. Wash your hands often with soap and water for at least 20 seconds or use an alcohol-based hand sanitizer that contains at least 60% alcohol.

**Prevent the Spread of COVID-19 If You Are Sick**- Stay home if you are sick, except to get medical care. Avoid public transportation, ridesharing, or taxis. Separate yourself from other people and pets in your home. If you need medical attention, call ahead.

Participants in the process information present group then received either the Domain Unknowns Decrease or Domain Unknowns Increase manipulation information (specifics below).

The participants in the control group did not receive any algorithm related information nor domain unknowns manipulation information.

Domain Unknowns Decrease-

The information you just read is very useful knowledge to have. This knowledge will help you understand how algorithms perform their designated tasks. This understanding can result in higher quality decisions that result in good loans and decrease default rates

Domain Unknowns Increase-

The information you just read is very basic knowledge. However, in order to understand how algorithms perform their designated tasks there are quite a few complex nuances that must be understood. An incomplete understanding can result in lower quality decisions that result in bad loans and increase default rates

Summary-Process Information Conditions-

1. Process Information and Domain Unknowns Decrease Information (SD)
2. Process Information and Domain Unknowns Increase Information (SI)
3. Control-No Process Information and No Domain Unknowns Information (SN)

We then measured participant levels of the following (in the order indicated below to avoid adjacency concerns for the model constructs to the extent possible):

1. Willingness to Use (WTU) an algorithm (vs. experienced human appraiser)
2. Objective knowledge (OK)
3. Perceived Complexity (PC)
4. Self-efficacy (SE)

Lastly, participant demographic information was collected, and they were thanked for their voluntary participation.

**CH3-Appendix B-Construct Manipulation Check and Measurement-Scales and Internal Consistencies**

Manipulation check-Domain Unknowns (SD, SI)

The "domain unknowns" manipulation was checked separately using three 7-point Likert items.

1=Disagree to 7=Agree

- I have much more to learn about algorithms.
- I have adequate knowledge of algorithms. (Reverse Score)
- I feel that what I know about algorithms is small relative to what I do not know.

Cronbach alpha = .76 indicating acceptable internal consistency.

The manipulation check for domain unknowns shows significant difference ($M_{Increase}$=5.66; $M_{Decrease}$ =5.22; $F(1, 146) = 5.7$, $p$ =.018).

Measure-Perceived Complexity (PC)

Perceived Complexity of the decision algorithm/task was measured using three 7-point Likert items.

1=Disagree to 7=Agree

- Computer algorithms used to calculate credit scores are complex.
- Computer algorithms used to calculate credit scores developed are difficult to understand.
- Computer algorithms that process multiple inputs and provide FICO score output are hard to follow.

Cronbach alpha = .90 indicating high internal consistency.

Measure-Objective Knowledge (OK)

Following Brucks (1985) we used a 7-item MC questionnaire to measure objective knowledge of the algorithm and how it works.

Mean accuracy (# correct out of 7):

Control-No Information (SN) =3.76
Domain Unknown Increase (SI) =5.59
Domain Unknown Decrease (SD) = 5.53

*Objective Measure Scale Items* (answers in italics)

1. Algo is a-

*computer program*
storage device
compute dataset
mathematical formulas

2. An algorithm's programming language uses grammar rules, characters, symbols and words to specify-

*Instructions*
Classifications
Redundancies
Outputs

3. For algorithms, the total number of instruction steps depends on the-

Length of code
Formatting types
*Number of input variables and relationships among them*
Processing speed

4. Iteration is a program element that involves-

selecting information
*repeating instructions*
deletion
specifying details

5. An algorithm should include specified rules regarding-

Codes of conduct
Length of the program
*Operating, termination, and error minimization*
Predictive conditions

6. Good programming involves creating algorithms that are relatively-

Innovative
Sophisticated and multilayered
*Compact, simple, and fast*
Robust

7. Data manipulation of an algorithm increases when-

*The number of input variables increase*
The number of input variables decrease
The number of interrelationships decrease
There are no interrelationships

---

Objective knowledge showed no difference between the two conditions where process information was provided.

($M_{SI}=5.59$; $M_{SD}=5.53$, $p=.783$)

Objective knowledge was significantly different between the conditions where process information was present or absent.

($M_{SD}=5.53$; and $M_{SN}=3.76$, $p<.001$)
($M_{SI}=5.59$; and $M_{SN}=3.76$, $p<.001$)

Measure-Subjective Knowledge (SK)

Subjective knowledge was measured on a scale adapted from Flynn and Goldsmith (1999). We used three 7-point Likert items.

1=Disagree to 7=Agree

- I am confident that I understand how a computer algorithm develops the credit score.
- I know better than most people how the computer algorithm computes a credit score.
- I am confident that I can explain how computer algorithm arrives at the output, if asked.

Cronbach alpha = .915 indicating high internal consistency.

Measure-Willingness to Use (WTU)

Willingness to use the algorithmic model of the decision algorithm/task was measured using three 7-point Likert items.

1=Disagree to 7=Agree

- I prefer to use this computer algorithm over the human appraiser.
- I feel more confident using this computer algorithm versus the human appraiser.
- I am more comfortable having the computer algorithm, versus the human appraiser, make the loan decision.

Cronbach alpha = .975 indicating high internal consistency.

Measure-Self-Efficacy

Self-Efficacy was a modified New General Self Efficacy Scale (NGSE-Chen et al, 2001). We used six 7-point Likert items.

1=Disagree to 7=Agree

- I am able to achieve most of the goals that I set for myself.
- Compared to other people, I do most tasks very well.
- I perform effectively on many different tasks.
- I can solve challenging analytical problems.
- I am good at thinking analytically.
- I do not need help from other people to solve analytical problems.

Cronbach alpha = .905 indicating high internal consistency.

**CH3-Appendix C-Model Constructs Discriminant Validity**

Discriminant Validity-Process Information (Domain Unknowns) vs. Perceived Complexity

Table of inter-item correlations shows no correlation above .36 between domain unknowns and perceived complexity scale items. Additionally, bivariate correlations test shows a mean correlation of .243; 95% CI [.12, .36]. These data indicate discriminant validity between measures of domain unknowns and perceived complexity.

Domain Unknowns Scale Items-

- I have much more to learn about algorithms.
- I have adequate knowledge of algorithms. (Reverse Score)
- I feel that what I know about algorithms is small relative to what I do not know.

Perceived Complexity Scale Items-

- Computer algorithms used to calculate credit scores are complex.
- Computer algorithms used to calculate credit scores developed are difficult to understand.
- Computer algorithms that process multiple inputs and provide FICO score output are hard to follow.

**Inter-Item Correlation Matrix**

| | DS1 | DS2R | DS3 |
|---|---|---|---|
| PC1 | .356 | .189 | .299 |
| PC2 | .310 | .213 | .247 |
| PC3 | .314 | .179 | .150 |

Formal discriminant validity assessment (Pieters, 2017)-

- Average Correlation= .243; Average Shared Variance = .059
- AVE (λ^2)/N) for domain unknowns= .79; perceived complexity= .72
- **AVE domain unknowns (.79) and AVE perceived complexity (.72) > Average Shared Variance (.059)**

Discriminant Validity-Process Information (Domain Unknowns) vs. Subjective Knowledge

Table of inter-item correlations shows no correlation above -.15 between domain unknowns and subjective knowledge scale items. Additionally, bivariate correlations test shows a mean correlation of -.115; 95% CI [-.24, .02]. These data indicate discriminant validity between measures of domain unknowns and subjective knowledge.

Domain Unknowns Scale Items-

- I have much more to learn about algorithms.
- I have adequate knowledge of algorithms. (Reverse Score)
- I feel that what I know about algorithms is small relative to what I do not know.

Subjective Knowledge Scale Items-

- I am confident that I understand how a computer algorithm develops the credit score.
- I know better than most people how the computer algorithm computes a credit score.
- I am confident that I can explain how computer algorithm arrives at the output, if asked.

**Inter-Item Correlation Matrix**

| | DS1 | DS2R | DS3 |
|---|---|---|---|
| SK1 | -.016 | -.128 | -.103 |
| SK2 | -.040 | -.141 | -.101 |
| SK3 | -.062 | -.146 | -.123 |

Formal discriminant validity assessment (Pieters, 2017)

- Average Correlation= -.115; Average Shared Variance = .013
- AVE (λ^2)/N) for domain unknowns= .80; subjective knowledge= .85
- **AVE domain unknowns (.80) and AVE subjective knowledge (.85) > Average Shared Variance (.013)**

Discriminant Validity-Perceived Complexity and Subjective Knowledge

Table of inter-item correlations shows no correlation above -.49 between perceived complexity and subjective knowledge scale items. Additionally, bivariate correlations test shows a mean correlation of -.466; 95% CI [-.551, -.370]. These data indicate discriminate validity between measures of perceived complexity and subjective knowledge.

Perceived Complexity Scale Items-

- Computer algorithms used to calculate credit scores are complex.
- Computer algorithms used to calculate credit scores developed are difficult to understand.
- Computer algorithms that process multiple inputs and provide FICO score output are hard to follow.

Subjective Knowledge Scale Items-

- I am confident that I understand how a computer algorithm develops the credit score.
- I know better than most people how the computer algorithm computes a credit score.
- I am confident that I can explain how computer algorithm arrives at the output, if asked.

Inter-Item Correlation Matrix

| | PC1 | PC2 | PC3 |
|---|---|---|---|
| SK1 | -.269 | -.490 | -.486 |
| SK2 | -.276 | -.407 | -.392 |
| SK3 | -.309 | -.459 | -.431 |

Formal discriminant validity assessment (Pieters, 2017)

- Average Correlation= -.466; Average Shared Variance = .217
- AVE (λ^2)/N) for perceived complexity= .78; subjective knowledge= .81
- **AVE perceived complexity (.78) and AVE subjective knowledge (.81) > Average Shared Variance (.217)**

Discriminant Validity-Perceived Complexity and Self-efficacy

Table of inter-item correlations shows no correlation above -.25 between perceived complexity and self-efficacy scale items. Additionally, bivariate correlations test shows a mean correlation of -.153; 95% CI [-.26 to -.04]. These data indicate discriminant validity between measures of perceived complexity and self-efficacy.

Perceived Complexity Scale Items-

- Computer algorithms used to calculate credit scores are complex.
- Computer algorithms used to calculate credit scores developed are difficult to understand.
- Computer algorithms that process multiple inputs and provide FICO score output are hard to follow.

Self-efficacy Scale Items-

- I am able to achieve most of the goals that I set for myself.
- Compared to other people, I do most tasks very well.
- I perform effectively on many different tasks.
- I can solve challenging analytical problems.
- I am good at thinking analytically.
- I do not need help from other people to solve analytical problems.

Inter-Item Correlation Matrix

| | PC1 | PC2 | PC3 |
|---|---|---|---|
| SE1 | .033 | -.118 | -.055 |
| SE2 | .029 | -.110 | -.065 |
| SE3 | -.018 | -.113 | -.064 |
| SE4 | -.108 | -.243 | -.125 |
| SE5 | -.098 | -.248 | -.149 |
| SE6 | -.150 | -.247 | -.177 |

Formal discriminant validity assessment (Pieters, 2017)

- Average Correlation= -.153; Average Shared Variance = .023
- AVE (λ^2)/N) for perceived complexity= .82; self-efficacy = .68
- **AVE perceived complexity (.82) and AVE self-efficacy (.68) > Average Shared Variance (.023)**

Discriminant Validity-Subjective Knowledge and Self-Efficacy

Table of inter-item correlations shows no correlation above .3 between subjective knowledge and self-efficacy scale items. Additionally, bivariate correlations test shows a mean correlation of .245; 95% CI [.13, .35]. These data indicate discriminant validity between measures of subjective knowledge and self-efficacy.

Subjective Knowledge Scale Items-

- I am confident that I understand how a computer algorithm develops the credit score.
- I know better than most people how the computer algorithm computes a credit score.
- I am confident that I can explain how computer algorithm arrives at the output, if asked.

Self-efficacy Scale Items-

- I am able to achieve most of the goals that I set for myself.
- Compared to other people, I do most tasks very well.
- I perform effectively on many different tasks.
- I can solve challenging analytical problems.
- I am good at thinking analytically.
- I do not need help from other people to solve analytical problems.

Inter-Item Correlation Matrix

| | SK1 | SK2 | SK3 |
|---|---|---|---|
| SE1 | .073 | .119 | .109 |
| SE2 | .122 | .181 | .230 |
| SE3 | .048 | .118 | .148 |
| SE4 | .174 | .233 | .284 |
| SE5 | .202 | .259 | .292 |
| SE6 | .181 | .271 | .288 |

Formal discriminant validity assessment (Pieters, 2017)

- Average Correlation= .245; Average Shared Variance = .06
- AVE (λ^2)/N) for subjective knowledge = .84; self-efficacy = .68
- **AVE subjective knowledge (.84) and AVE self-efficacy (.68) > Average Shared Variance (.06)**

Discriminant Validity-Subjective Knowledge and Willingness to Use

Table of inter-item correlations shows no correlation above .28 between subjective knowledge and willingness to use scale items. Additionally, bivariate correlations test shows a mean correlation of .255; 95% CI [.14, .36]. These data indicate discriminant validity between measures of subjective knowledge and willingness to use.

Subjective Knowledge Scale Items-

- I am confident that I understand how a computer algorithm develops the credit score.
- I know better than most people how the computer algorithm computes a credit score.
- I am confident that I can explain how computer algorithm arrives at the output, if asked.

Willingness to Use Scale Items-

- I prefer to use this computer algorithm over the human appraiser.
- I feel more confident using this computer algorithm versus the human appraiser.
- I am more comfortable having the computer algorithm, versus the human appraiser, make the loan decision.

Inter-Item Correlation Matrix

| | WTU_1 | WTU_2 | WTU_3 |
|---|---|---|---|
| SK1 | .259 | .274 | .268 |
| SK2 | .195 | .227 | .206 |
| SK3 | .177 | .233 | .228 |

Formal discriminant validity assessment (Pieters, 2017)

- Average Correlation= .255; Average Shared Variance = .065
- AVE (λ^2)/N) for subjective knowledge = .84; willingness to use = .94
- **AVE subjective knowledge (.84) and AVE willingness to use (.94) > Average Shared Variance (.065)**

## CH3-Appendix D-Initial Model Test

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

Written by Andrew F. Hayes, Ph.D.       www.afhayes.com

Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************

Model  : CUSTOM

Y  : WTU_Avg

X  : ConN

M1  : OKScore

M2  : PC_Avg

M3  : SK_Avg

W  : SEAllAvg

Sample

Size:  291

Coding of categorical X variable for analysis:

| ConN | X1 | X2 |
|---|---|---|
| 1.000 | .000 | .000 |
| 2.000 | 1.000 | .000 |
| 3.000 | .000 | 1.000 |

**************************************************************************

OUTCOME VARIABLE:

OKScore

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .5237 | .2743 | 1.9554 | 54.4287 | 2.0000 | 288.0000 | .0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 5.5319 | .1442 | 38.3552 | .0000 | 5.2480 | 5.8158 |
| X1 | .0557 | .2024 | .2753 | .7833 | -.3426 | .4541 |
| X2 | -1.7719 | .2009 | -8.8204 | .0000 | -2.1673 | -1.3765 |
| X3 | -1.8276 | .1993 | -9.1712 | .0000 | -2.2199 | -1.4354 |

**************************************************************************

OUTCOME VARIABLE:

PC_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .2508 | .0629 | 2.0712 | 6.4239 | 3.0000 | 287.0000 | .0003 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 5.4220 | .3669 | 14.7793 | .0000 | 4.6999 | 6.1440 |
| X1 | .3236 | .2083 | 1.5534 | .1214 | -.0864 | .7336 |
| X2 | -.6943 | .2330 | -2.9798 | .0031 | -1.1530 | -.2357 |
| X3 | -1.0179 | .2331 | -4.3664 | .0000 | -1.4768 | -.5591 |
| OKScore | -.1359 | .0606 | -2.2407 | .0258 | -.2553 | -.0165 |

OUTCOME VARIABLE:

SK_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .4852 | .2354 | 1.7092 | 22.0188 | 4.0000 | 286.0000 | .0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 5.1893 | .4423 | 11.7337 | .0000 | 4.3188 | 6.0598 |
| X1 | -.1611 | .1900 | -.8479 | .3972 | -.5352 | .2129 |
| X2 | -.3236 | .2149 | -1.5057 | .1333 | -.7466 | .0994 |
| X3 | -.1625 | .2187 | -.7429 | .4581 | -.5929 | .2680 |
| OKScore | .0653 | .0556 | 1.1752 | .2409 | -.0441 | .1747 |
| PC_Avg | -.4786 | .0536 | -8.9247 | .0000 | -.5841 | -.3730 |

**************************************************************************

OUTCOME VARIABLE:

WTU_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .2810 | .0789 | 3.5805 | 3.4649 | 7.0000 | 283.0000 | .0014 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 2.5898 | 1.3223 | 1.9586 | .0511 | -.0129 | 5.1925 |
| X1 | -.3134 | .2802 | -1.1185 | .2643 | -.8650 | .2381 |
| X2 | -.3105 | .3127 | -.9929 | .3216 | -.9260 | .3050 |
| X3 | .0029 | .3195 | .0092 | .9927 | -.6259 | .6318 |
| OKScore | .0694 | .0817 | .8496 | .3963 | -.0914 | .2301 |
| PC_Avg | -.0010 | .0880 | -.0114 | .9909 | -.1742 | .1722 |
| SK_Avg | .3473 | .3364 | 1.0324 | .3028 | -.3149 | 1.0095 |
| SEAllAvg | .1446 | .2037 | .7099 | .4784 | -.2563 | .5455 |
| Int_1 | -.0102 | .0627 | -.1622 | .8713 | -.1337 | .1133 |

Product terms key:

Int_1 : SK_Avg x SEAllAvg

Test(s) of highest order unconditional interaction(s):

| | R2-chng | F | df1 | df2 | p |
|---|---|---|---|---|---|
| M3*W | .0001 | .0263 | 1.0000 | 283.0000 | .8713 |

----------

Focal predict: SK_Avg (M3)

Mod var: SEAllAvg (W)

Data for visualizing the conditional effect of the focal predictor:

Paste text below into a SPSS syntax window and execute to produce plot.

```
DATA LIST FREE/
  SK_Avg     SEAllAvg   WTU_Avg    .
BEGIN DATA.
    1.6515    3.8005    3.7760
    3.1363    3.8005    4.2343
    4.6211    3.8005    4.6926
    1.6515    4.9507    3.9230
    3.1363    4.9507    4.3639
    4.6211    4.9507    4.8048
    1.6515    6.1010    4.0700
    3.1363    6.1010    4.4935
    4.6211    6.1010    4.9170
END DATA.
GRAPH/SCATTERPLOT=
 SK_Avg   WITH    WTU_Avg  BY      SEAllAvg .
```

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Relative direct effects of X on Y

| | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| X1 | -.3134 | .2802 | -1.1185 | .2643 | -.8650 | .2381 |
| X2 | -.3105 | .3127 | -.9929 | .3216 | -.9260 | .3050 |
| X3 | .0029 | .3195 | .0092 | .9927 | -.6259 | .6318 |

Omnibus test of direct effect of X on Y:

| R2-chng | F | df1 | df2 | p |
|---|---|---|---|---|
| .0051 | .7897 | 2.0000 | 283.0000 | .4550 |

----------

Relative conditional and unconditional indirect effects of X on Y:

INDIRECT EFFECT:

ConN -> OKScore -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0039 | .0210 | -.0406 | .0485 |
| X2 | -.1229 | .1498 | -.4247 | .1641 |
| X3 | -.1268 | .1519 | -.4336 | .1666 |

INDIRECT EFFECT:

ConN -> PC_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | -.0003 | .0361 | -.0707 | .0850 |
| X2 | .0007 | .0689 | -.1571 | .1266 |
| X3 | .0010 | .0969 | -.2135 | .1751 |

INDIRECT EFFECT:

ConN -> SK_Avg -> WTU_Avg

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X1 | 3.8005 | -.0497 | .0709 | -.2094 | .0769 |
| X1 | 4.9507 | -.0478 | .0623 | -.1791 | .0712 |
| X1 | 6.1010 | -.0460 | .0616 | -.1821 | .0695 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0016 | .0201 | -.0386 | .0470 |

-----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X2 | 3.8005 | -.0999 | .0936 | -.3195 | .0377 |
| X2 | 4.9507 | -.0961 | .0811 | -.2795 | .0342 |
| X2 | 6.1010 | -.0923 | .0824 | -.2824 | .0355 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0033 | .0301 | -.0582 | .0730 |

----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X3 | 3.8005 | -.0501 | .0836 | -.2557 | .0793 |
| X3 | 4.9507 | -.0482 | .0748 | -.2239 | .0740 |
| X3 | 6.1010 | -.0463 | .0732 | -.2210 | .0711 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0017 | .0209 | -.0418 | .0520 |

INDIRECT EFFECT:

ConN -> OKScore -> PC_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0000 | .0028 | -.0060 | .0062 |
| X2 | -.0002 | .0252 | -.0418 | .0621 |
| X3 | -.0002 | .0254 | -.0448 | .0605 |

INDIRECT EFFECT:

ConN -> OKScore -> SK_Avg -> WTU_Avg

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X1 | 3.8005 | .0011 | .0055 | -.0092 | .0146 |
| X1 | 4.9507 | .0011 | .0050 | -.0089 | .0126 |
| X1 | 6.1010 | .0010 | .0048 | -.0088 | .0116 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0000 | .0013 | -.0033 | .0023 |

-------------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X2 | 3.8005 | -.0357 | .0396 | -.1272 | .0340 |
| X2 | 4.9507 | -.0344 | .0347 | -.1084 | .0319 |
| X2 | 6.1010 | -.0330 | .0351 | -.1113 | .0303 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0012 | .0122 | -.0243 | .0289 |

------------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X3 | 3.8005 | -.0368 | .0403 | -.1302 | .0318 |
| X3 | 4.9507 | -.0354 | .0353 | -.1128 | .0290 |
| X3 | 6.1010 | -.0340 | .0352 | -.1118 | .0279 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0012 | .0118 | -.0224 | .0292 |

------------

INDIRECT EFFECT:

ConN -> PC_Avg -> SK_Avg -> WTU_Avg

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X1 | 3.8005 | -.0478 | .0411 | -.1457 | .0145 |
| X1 | 4.9507 | -.0460 | .0359 | -.1313 | .0120 |
| X1 | 6.1010 | -.0442 | .0377 | -.1358 | .0114 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0016 | .0142 | -.0290 | .0315 |

-----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X2 | 3.8005 | .1026 | .0656 | .0068 | .2604 |
| X2 | 4.9507 | .0987 | .0532 | .0200 | .2257 |
| X2 | 6.1010 | .0948 | .0572 | .0121 | .2326 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | -.0034 | .0269 | -.0607 | .0498 |

-----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X3 | 3.8005 | .1504 | .0872 | .0110 | .3568 |
| X3 | 4.9507 | .1447 | .0680 | .0402 | .3059 |
| X3 | 6.1010 | .1390 | .0744 | .0269 | .3156 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | -.0050 | .0383 | -.0806 | .0751 |

-----------

INDIRECT EFFECT:

ConN -> OKScore -> PC_Avg -> SK_Avg -> WTU_Avg

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X1 | 3.8005 | .0011 | .0053 | -.0072 | .0142 |
| X1 | 4.9507 | .0011 | .0048 | -.0069 | .0126 |
| X1 | 6.1010 | .0010 | .0046 | -.0071 | .0120 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0000 | .0011 | -.0028 | .0020 |

----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X2 | 3.8005 | -.0356 | .0269 | -.0993 | .0012 |
| X2 | 4.9507 | -.0342 | .0234 | -.0924 | -.0020 |
| X2 | 6.1010 | -.0329 | .0252 | -.0948 | -.0005 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0012 | .0100 | -.0202 | .0216 |

----------

| | SEAllAvg | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|---|
| X3 | 3.8005 | -.0367 | .0288 | -.1099 | .0010 |
| X3 | 4.9507 | -.0353 | .0246 | -.0962 | -.0018 |
| X3 | 6.1010 | -.0339 | .0257 | -.0986 | -.0010 |

Index of moderated mediation:

| | Index | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| SEAllAvg | .0012 | .0102 | -.0202 | .0219 |

------------

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

W values in conditional tables are the mean and +/- SD from the mean.

------ END MATRIX -----

## CH3-Appendix E-Alternative Model Test-Controlling for Self-Efficacy

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.0 *****************

       Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2022). www.guilford.com/p/hayes3

**************************************************************************
Model  : CUSTOM
    Y  : WTU_Avg
    X  : ConN
   M1  : OKScore
   M2  : PC_Avg
   M3  : SK_Avg

Covariates:
 SEAllAvg

Sample
Size:  291

Coding of categorical X variable for analysis:
  ConN     X1     X2
 1.000   .000   .000
 2.000  1.000   .000
 3.000   .000  1.000
**************************************************************************
```

OUTCOME VARIABLE:

OKScore

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .5249 | .2755 | 1.9590 | 36.3738 | 3.0000 | 287.0000 | .0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 5.2965 | .3738 | 14.1685 | .0000 | 4.5607 | 6.0323 |
| X1 | .0345 | .2049 | .1682 | .8665 | -.3689 | .4379 |
| X2 | -1.7779 | .2013 | -8.8336 | .0000 | -2.1740 | -1.3817 |
| X3 | -1.8124 | .2007 | -9.0295 | .0000 | -2.2074 | -1.4173 |
| SEAllAvg | .0494 | .0724 | .6827 | .4954 | -.0930 | .1918 |

***************************************************************************

OUTCOME VARIABLE:

PC_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .3039 | .0924 | 2.0132 | 7.2757 | 4.0000 | 286.0000 | .0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 6.4468 | .4940 | 13.0497 | .0000 | 5.4744 | 7.4192 |
| X1 | .4193 | .2078 | 2.0181 | .0445 | .0104 | .8283 |
| X2 | -.6543 | .2301 | -2.8438 | .0048 | -1.1072 | -.2014 |
| X3 | -1.0737 | .2306 | -4.6566 | .0000 | -1.5275 | -.6198 |
| OKScore | -.1286 | .0598 | -2.1483 | .0325 | -.2463 | -.0108 |
| SEAllAvg | -.2236 | .0734 | -3.0455 | .0025 | -.3680 | -.0791 |

**************************************************************************

OUTCOME VARIABLE:

SK_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .5162 | .2665 | 1.6455 | 20.7098 | 5.0000 | 285.0000 | .0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 3.9370 | .5642 | 6.9787 | .0000 | 2.8266 | 5.0475 |
| X1 | -.2720 | .1892 | -1.4380 | .1515 | -.6444 | .1003 |
| X2 | -.3426 | .2109 | -1.6243 | .1054 | -.7579 | .0726 |
| X3 | -.0706 | .2162 | -.3265 | .7443 | -.4962 | .3550 |
| OKScore | .0621 | .0545 | 1.1386 | .2558 | -.0452 | .1694 |
| PC_Avg | -.4456 | .0535 | -8.3361 | .0000 | -.5509 | -.3404 |
| SEAllAvg | .2342 | .0674 | 3.4736 | .0006 | .1015 | .3670 |

**************************************************************************

OUTCOME VARIABLE:

WTU_Avg

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .2808 | .0789 | 3.5682 | 4.0519 | 6.0000 | 284.0000 | .0006 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 2.7469 | .8989 | 3.0557 | .0025 | .9774 | 4.5163 |
| X1 | -.3119 | .2796 | -1.1157 | .2655 | -.8623 | .2384 |
| X2 | -.3118 | .3121 | -.9991 | .3186 | -.9261 | .3025 |
| X3 | .0001 | .3184 | .0005 | .9996 | -.6267 | .6270 |
| OKScore | .0673 | .0805 | .8359 | .4039 | -.0912 | .2257 |
| PC_Avg | -.0014 | .0878 | -.0162 | .9871 | -.1742 | .1714 |
| SK_Avg | .2946 | .0872 | 3.3776 | .0008 | .1229 | .4663 |
| SEAllAvg | .1159 | .1014 | 1.1437 | .2537 | -.0836 | .3155 |

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Relative direct effects of X on Y

| | Effect | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| X1 | -.3119 | .2796 | -1.1157 | .2655 | -.8623 | .2384 |
| X2 | -.3118 | .3121 | -.9991 | .3186 | -.9261 | .3025 |
| X3 | .0001 | .3184 | .0005 | .9996 | -.6267 | .6270 |

Omnibus test of direct effect of X on Y:

| R2-chng | F | df1 | df2 | p |
|---|---|---|---|---|
| .0051 | .7906 | 2.0000 | 284.0000 | .4546 |

----------

Relative indirect effects of X on Y

ConN -> OKScore -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0023 | .0207 | -.0423 | .0469 |
| X2 | -.1196 | .1477 | -.4245 | .1597 |
| X3 | -.1219 | .1486 | -.4185 | .1642 |

ConN -> PC_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | -.0006 | .0439 | -.0858 | .0964 |
| X2 | .0009 | .0640 | -.1413 | .1203 |
| X3 | .0015 | .1041 | -.2270 | .1863 |

ConN -> SK_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | -.0802 | .0616 | -.2152 | .0253 |
| X2 | -.1009 | .0813 | -.2929 | .0260 |
| X3 | -.0208 | .0716 | -.1834 | .1064 |

ConN -> OKScore -> PC_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0000 | .0026 | -.0054 | .0057 |
| X2 | -.0003 | .0236 | -.0408 | .0580 |
| X3 | -.0003 | .0246 | -.0431 | .0614 |

ConN -> OKScore -> SK_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0006 | .0051 | -.0108 | .0122 |
| X2 | -.0325 | .0353 | -.1101 | .0336 |
| X3 | -.0332 | .0352 | -.1073 | .0354 |

ConN -> PC_Avg -> SK_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | -.0551 | .0359 | -.1390 | -.0004 |
| X2 | .0859 | .0489 | .0157 | .2013 |
| X3 | .1410 | .0650 | .0412 | .2933 |

ConN -> OKScore -> PC_Avg -> SK_Avg -> WTU_Avg

| | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| X1 | .0006 | .0042 | -.0072 | .0109 |
| X2 | -.0300 | .0214 | -.0842 | -.0016 |
| X3 | -.0306 | .0215 | -.0812 | -.0015 |

********************** ANALYSIS NOTES AND ERRORS ***********************

Level of confidence for all confidence intervals in output:

95.0000

Number of bootstrap samples for percentile bootstrap confidence intervals:

5000

------ END MATRIX -----

**CH3-References-Essay 2**


Alexander, V., Blinder, C., & Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior*, *89*, 279–288.

Bandura, A. (1994). Self-efficacy. In V. S. Ramachaudran (Ed.), Encyclopedia of human behavior (Vol. 4, pp. 71-81). New York: Academic Press.

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research, 12.* 1-16.

Chakravarti, D., Mitchell, A., & Staelin, R. (1979). Judgment Based Marketing Decision Models: An Experimental Investigation of the Decision Calculus Approach. *Management Science*, *25*(3), 251.

Chakravarti, D., Mitchell, A., & Staelin, R. (1981). Judgment Based Marketing Decision Models: Problems and Possible Solutions. *Journal of Marketing*, *45*(4), 13.

Chen, G., Gully, S.M., & Eden, D. (2001). Validation of a New General Self-Efficacy Scale. *Organizational Research Methods*, 4; 62.

Dawes, R. M., Faust, D., & Meehl, P. E. (1989). Clinical versus actuarial judgment. *Science, 243*(4899), 1668–1674.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114-126.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science*, (3), 1155.

Flynn, L. R., & Goldsmith, R. E. (1999). A Short, Reliable Measure of Subjective Knowledge. *Journal of Business Research*, *46*(1), 57–66.

Goldstein, J. (1988). A far-from-equilibrium systems approach to resistance to change. *Organizational Dynamics*, *17*, 16-26.

Koopmans, M. (2017), Perspectives on Complexity, Its Definition and Applications in the Field. *Complicity: An International Journal of Complexity and Education*, Volume 14, Number 1, pp. 16-35.

Ladyman, J., Lambert, J., & Wiesner, K. (2013). What is a complex system?. *European Journal for Philosophy of Science*, *3*, 33-67.

Little, J. D. C. (1970). Models and Managers: The Concept of a Decision Calculus. *Management Science*, *16*(8), B466.

Little, J. D. C. (1979). Aggregate Advertising Models: The State of the Art. *Operations Research*, *27*, 4, (July-August), 629-667.

Logg, J., Minson, J., & Moore, D. A. (2018). Algorithm Appreciation: People Prefer Algorithmic To Human Judgment. *Organizational Behavior and Human Decision Processes*, 151, 90-103.

Nicolis, G., & Prigogine, I. (1989). *Exploring complexity: An introduction*. New York: Freeman.

Park, C. W., & Lessig, V. P. (1981). Familiarity and its impacts on consumer decision biases and heuristics. *Journal of Consumer Research, 8*, 223-230.

Piaget, J. (1971). *Biology and knowledge: An essay on the relations between organic regulations and cognitive processes.* Chicago: University of Chicago Press.

Pieters, R. (2017). Meaningful Mediation Analysis: Plausible Causal Inference and Informative Communication. *The Journal of Consumer Research*, *44*(3), 692–716.

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal*, *27*, 279-423.

von Berthalanffy, L. S. (1969). *General system theory*. New York: George Braziller.

Weng, G., Bhalla, U., & Iyengar, R. (1999). Complexity in Biological Signaling Systems. *Science, 284*(5411), 92-96.

Wierenga, B., Van Bruggen, G. H., & Staelin, R. (1999). The success of marketing management support systems. *Marketing Science*, *18*(3), 196-207.

Yeomans, M, Shah, A, Mullainathan, S, Kleinberg, J. (2019). Making sense of recommendations. *Journal Behavior Decision Making*, 1– 12.

# Chapter 4-Algorithms, Decision Makers and Decision Targets-Conclusions and Future Research

Algorithmic models as parts of AI-based decision support are becoming increasingly familiar fixtures in contemporary society. They impinge on our lives in professional settings where they are important decision-making tools that we must learn to use as decision makers. They are also becoming a pervasive presence in personal consumption settings where they are deployed in service settings or where we are decision targets (i.e., recipients of decisions that are influenced to different degrees by algorithmic models). Yet, the popular press and academic researchers report that that these algorithms encounter mixed receptivity from both user decision makers as well as decision targets. Whereas some researchers report that decision makers and targets evidence "algorithm appreciation," (Logg et al 2018), a large corpus of work reports widespread "algorithm aversion." In other words, people prefer to rely on human experts versus "machine algorithms" in a wide variety of decision making and consumption contexts (see e.g., Dietvorst et al, 2018; Jussupow et al, 2020; Mahmud et al 2022).

This dissertation presents two empirically based essays that explore factors that influence preference for algorithm-based recommendations versus those provided by human experts in business decision contexts. Both essays focus on the decision maker (as opposed to the decision target) using experimental psychological methods to examine managerial decision settings (specifically a loan officer making loan approval/denial decisions ) in which decision makers choose between algorithmic and human expert recommendations. We examine situations in which the algorithm and the human expert are presented as competing (versus complementary) resources for the decision maker, exhibit varying performance levels (Essay 1), and when different levels of process information are provided about the algorithm.

## Essay 1 Findings

Essay 1 presents three studies that examine the extent to which a decision maker's final decision aligns with a recommendation from an algorithm versus a human expert, when the two recommendations explicitly conflict. Study 1 examines this issue along with the potential moderating roles of task complexity (complex/simple) and the conflict configuration (algorithm approve/human expert deny the loan and vice-versa). Study 1 found no main or interactive effects involving task complexity, but conflict configuration had a significant effect. Although a significant majority of the participants approved (versus denied) the loan in all four conditions, approval levels were higher when the human expert (versus the algorithm) recommended approval. Thus, although participants did override the recommendation of both the algorithm and the human expert, the algorithm's' denial recommendations were overridden more often than those of the human experts (suggesting a preference for the latter).

Study 2 examined decision outcomes under conflict configuration and the moderating role of the accuracy levels of the human expert/algorithm. As in Study 1, the majority of participants chose to approve the loan, and approval levels were higher when the human expert recommended approval (the algorithm recommended denial) relative to when the algorithm recommended approval (the human recommended denial). Moreover, this effect of conflict configuration was moderated by the accuracy level of the human expert/algorithm. Thus, we see evidence of algorithm aversion, but contingent upon the accuracy levels of the algorithm and the human expert. Participants tended to align with the higher accuracy source. However, the effects are asymmetric – the alignment is stronger for the human expert than for the algorithm. The decision likelihood data tend to mirror the decision data. There is evidence of algorithm aversion, but as in the decision data, it is contingent upon the relative accuracy of the algorithm and the human expert. Notably, there is a dissociation between the actual decision and the decision likelihood judgments. The asymmetry that is observed in the decision data is absent in the decision likelihood data.

In Study 3, we examine whether the participants' final decision is influenced by the degree to which the algorithm (human expert) recommendation aligns with the decision maker's (participant) predisposition to approve/deny the loan. Not surprisingly, the presence of a predisposition moderated (and weakened) the effects observed in Study 2. First, predisposition moderated (weakened) the tendency for participants' decisions to be more aligned to the human expert's recommendation (versus the algorithm) when both sources had similar accuracy levels (high-high or low-low). Second, predisposition attenuated the degree to which decisions aligned with the recommendations from the lower accuracy source when the two sources had unequal accuracy levels (high-low or low-high). Third, predisposition also attenuated the asymmetry in the extent to which participant decisions aligned more with the human expert's (versus the algorithm's) recommendation as a function of accuracy variations (high vs. low).

The results also showed that participants' decisions aligned with the recommendations from the source that corresponded to the decision maker's predispositions. The main effect of predisposition persisted across the accuracy level manipulation for the two sources (but with variations influenced by the specific configuration of the accuracy level of the recommendation source). However, we also observed an interaction between predisposition and source accuracy levels. The results suggest that participants were more likely to approve a loan when predisposed to approve but not when predisposed to deny. Interestingly, participants' decisions did not align more with the human expert (versus the algorithm) when it corresponded to the decision maker's predisposition to deny. As such, the predisposition deny effect was similar whether the recommendation came from a human expert or an algorithm.

Our studies have several novel features including (a) head-to-head competition stemming from conflicting recommendations from the algorithm versus human expert, (b) the effect of matching as well as differential accuracy levels for the two sources, and (c) decision maker predisposition. Prior work on algorithm aversion/appreciation has not examined these contingencies. The results of Studies 1 -3 provide consistent support for algorithm aversion. Study 1, set in a consumer loan decision context, showed that recommendations had greater impact when they came from a "human expert," (vs. an algorithm) and more so when they recommended loan approval (versus denial). However, in our head-to-head conflict situations, we consistently find that decision makers align to recommender sources that they perceive as more accurate. At the same time, decision makers align asymmetrically with the high accuracy human expert (vs. the high accuracy algorithm).

The predisposition manipulation in Study 3 allowed us to examine if recommendations from a human expert or an algorithm successfully countered or reinforced decision maker predispositions. The results (detailed in the preceding section) showed basic effects similar to those found in Study 2. However, predisposition moderated the interactive effects of conflict configuration and source accuracy and attenuated the effects observed in Study 2. However, decisions across varying accuracy levels showed greater alignment with the human expert (vs. the algorithm) for recommendations consistent with the decision maker's predisposition to approve. However, the predisposition deny effect was similar irrespective of the source of the recommendation (human or algorithm).

## Essay 2 Findings

Essay 2 develops a model of how providing process information regarding the decision domain (the inner working of an algorithm and task) influences a decision maker's willingness to use an algorithm (versus a human appraiser/expert). The setting, again, is a consumer loan context and the study participant plays the role of a loan officer considering the use of a decision algorithm versus a human appraiser to determine a FICO score as an input to the loan approval decision. We contrast the effects in three information conditions in which participants are assigned respectively to a baseline (control) condition where no process information is provided; or conditions in which the algorithm information provided respectively decreases or increases what is unknown about the decision domain.

The model describes how such process information influences participants' perceived complexity of the problem domain both directly and indirectly through its effect on objective knowledge. The model also examines how perceived complexity and objective knowledge together drive the decision maker's subjective knowledge (confidence) about the algorithm as a decision support tool. and how subjective knowledge affects the decision maker's willingness to use the algorithmic model (versus the human expert) for the decision task. These model relationships are presented as a set of formal hypotheses that we test using data collected in an empirical study set in the consumer loan context, using participants from the Prolific web platform. In an initial version of the process model, we had proposed a relatively limited role of self-efficacy as a moderator of the relationship between subjective knowledge and willingness to use the model. Based on an initial analysis, we reconceptualized the role of self-efficacy in the process model and conducted an exploratory reanalysis in which we used self-efficacy as a covariate in each relationship in the model to control for its effects.

The revised exploratory analysis showed results that provide strong support for the process model. The process information manipulation influences both perceived complexity and objective knowledge. However, only perceived complexity (but not objective knowledge) mediates the information effect on subjective knowledge. We find, as expected, that subjective knowledge, as determined via the preceding pathways, influences willingness to use the algorithm. The study also suggests alternative propositions regarding how self-efficacy may influence the model's constituent relationships. The model presents a novel conceptual framework and a process perspective that sheds light on the circumstances under which decision makers may display algorithm aversion and versus algorithm appreciation. We plan to replicate these analyses in a future research study.

## Future Research

We conclude the dissertation by outlining our future research agenda in this exciting research domain. First, we propose to extend Essay 1 by examining how algorithm appreciation and aversion is manifested as a function of the decision maker's cognitive and emotional profiles. Here we plan to develop a set of studies that would examine the impact of variables such as prior domain knowledge, privacy concerns, self-efficacy and control orientation.

Second, the performance gap between the human and the algorithm may also play a role in establishing boundary conditions for algorithm aversion. The magnitude of performance differences may be relevant in this regard. Relatedly, the performance accuracy measures that were provided were fairly simplistic and did not involve more sophisticated presentations of performance accuracy that speak to issues of the specificity and sensitivity rates that are common descriptors of performance quality in medical diagnosis. Tangible and intangible differences in penalty functions for the parties involved may also make a difference in the preferred source.

Third, future research may shed light  shed light on whether these such  performance differences matter in different ways to decision makers in their professional capacity (e.g., a physician) and decision targets (e.g., a patient). This would allow us to examine situations where managers and their customers may have similar or different orientations or predispositions toward algorithms and how this impacts the service provider's relationship with the customer. Recent reviews of the algorithm aversion literature (e.g.,  Jussupow et al., 2020; Mahmud et al., 2022)  point to this difference as a potentially important factor that influences receptivity to algorithmic decision aids. While this may relate to level of understanding, differences in personal investment levels may also influence receptivity (Beck et al., 2009). Notably, the Dietvorst et al. (2015) and Logg et al. (2019) studies involved choosing between individual's own estimates versus that of the algorithm. This suggests a possible confound where apparent algorithm aversion actually stems from differences in the sense of ownership or a status quo bias (Samuelson and Zeckhauser, 1988).

We also anticipate conducting research that extends Essay 2. Apart from a confirmatory replication of the process model, one obvious extension is to focus on a different application domain (specifically healthcare and medical diagnostics). One specific application is reviewing and interpreting mammograms and use of human expert or an algorithmic diagnostic tools to assist in making a final determination (Cheng et al., 2006; Gardezi et al., 2019; Rana et al., 2015; Gharibdousti et al., 2019; and Tosin et al., 2017).

Among representative papers on algorithm aversion in healthcare contexts (e.g., Castelo et al., 2019; Longoni et al., 2019; Shaffer et al., 2013), only  Longoni et al. (2019) tested preferences for human experts versus algorithms and included varying performance (accuracy). Their findings show algorithm aversion even when the algorithm exhibits superior accuracy relative to the human. We note two issues that may have made their results context specific. First, they used a situation involving "high agency interaction" (i.e., high interaction with the human or algorithm) which may have stimulated a need to ask additional questions. Moreover, the decision maker in this context was also the decision target (i.e., the party directed affected by the decision). This contrasts with situations where the identities of the decision maker (e.g., a physician soliciting diagnostic support) and the decision target (a patient affected by the diagnosis) differ.

The "black box" nature of algorithmic decisions may be a deterrent to adoption not merely because of poor comprehension, but also because opacity makes it difficult to assess fairness, establish accountability, and generate trust. Such opacity also makes decision targets less receptive to decisions, e.g., denied by an "unexplainable" algorithm. Such research build on recently advanced teleological explanations for algorithm aversion (Tomaino et al. 2022). These issues are attracting both managerial attention from the standpoint of customer satisfaction and regulatory scrutiny focused on consumer protection. The need for justification to self and others is an important decision driver (Simonson 1989; Simonson and Nowlis 2000) and examining the extent to which this motivates choices between algorithmic decision aids and human experts is also an important issue for future research.

## Conclusion

The studies reported in this dissertation contribute to our understanding of the factors that influence algorithm aversion and appreciation. Our findings may inform the design of algorithms that are more user-friendly and transparent and build user trust and acceptance. The insights that result from the present and planned work should help create strategies to break down resistance to algorithms, particularly in situations where they may benefit decision makers and consumers in decision maker or decision target roles. Importantly, our research points  to situations where algorithms and human experts play complementary roles that build on each other's strengths and circumvent weakness. Our hope is that this research contributes to a better understanding of the role of algorithms in decision making and facilitate beneficial social impact.

## References-Chapter 4


Beck, H. P., J. B. McKinney, M. T. Dzindolet and L. G. Pierce. (2009). "Effects of human-machine competition on intent errors in a target detection task." Human Factors, 51(4), 477–486.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, 144(1), 114-126.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them. *Management Science*, (3), 1155.

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-dependent algorithm aversion. Journal of Marketing Research, 56(5), 809-825.

Cheng, H. D., Shi, X. J., Min, R., Hu, L. M., Cai, X. P., & Du, H. N. (2006). Approaches for automated detection and classification of masses in mammograms. Pattern recognition, 39(4), 646-668.

Gardezi, S. J. S., Elazab, A., Lei, B., & Wang, T. (2019). Breast cancer detection and diagnosis using mammographic data: Systematic review. Journal of medical Internet research, 21(7), e14464.

Gharibdousti, M. S., Haider, S. M., Ouedraogo, D., & Susan, L. U. (2019). Breast cancer diagnosis using feature extraction techniques with supervised and unsupervised classification algorithms. Applied Medical Informatics., 41(1), 40-52.

Jussupow, E., Benbasat, I., & Heinzl, A. (2020). Why are we averse towards algorithms? A comprehensive literature review on algorithm aversion.

Logg, J. M., J. A. Minson and D. A. Moore. (2019). "Algorithm appreciation: People prefer algorithmic to human judgment." Organizational Behavior and Human Decision Processes, 151, 90–103.

Longoni, C., Bonezzi, A., & Morewedge, C. K. (2019). Resistance to medical artificial intelligence. Journal of Consumer Research, 46(4), 629-650.

Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. Technological Forecasting and Social Change, 175, 121390.

Rana, M., Chandorkar, P., Dsouza, A., & Kazi, N. (2015). Breast cancer diagnosis and recurrence prediction using machine learning techniques. IJRET: International Journal of Research in Engineering and Technology eISSN, 2319-1163.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. Journal of risk and uncertainty, 1, 7-59.

Shaffer, Victoria A., C. Adam Probst, Edgar C. Merkle, Hal R. Arkes, and Mitchell A. Medow (2013), "Why Do Patients Derogate Physicians Who Use a Computer-Based Diagnostic Support System?" Medical Decision Making, 33 (1), 108–18.

Simonson, I. (1989). Choice based on reasons: The case of attraction and compromise effects. Journal of consumer research, 16(2), 158-174.

Simonson, I., & Nowlis, S. M. (2000). The role of explanations and need for uniqueness in consumer decision making: Unconventional choices based on reasons. Journal of Consumer Research, 27(1), 49-68.

Tomaino, G., Teow, J., Carmon, Z., Lee, L., Ben-Akiva, M., Chen, C., ... & Zhao, J. (2020). Mobility as a service (MaaS): The importance of transportation psychology. *Marketing Letters*, *31*, 419-428.

Tosin, A. T., Morufat, A. T., Aladejobi, S. A., Oyedepo, O. M., Olusayo, O. E., & Olatude, O. S. (2017). Feature Extraction Techniques for Mass Detection in Digital Mammogram. Journal of Scientific Research and Reports, 1-11.