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Investigating the Effectiveness of Algorithmic Interventions in Health Decision Making

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INVESTIGATING THE EFFECTIVENESS OF ALGORITHMIC INTERVENTIONS IN HEALTH DECISION MAKING

BY

JUNG MIN LEE

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ACCEPTANCE

This dissertation was prepared under the direction of the *Jung min Lee*'s Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

INVESTIGATING THE EFFECTIVENESS OF ALGORITHMIC INTERVENTIONS IN HEALTH DECISION MAKING

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JULY 31, 2023

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Algorithms and AI are playing an ever-growing role in healthcare and health-related decision making. Algorithmic tools in healthcare have the potential to support preventive care and also have the potential to enable better access to healthcare. As these tools continue to shape and transform the healthcare landscape, it is important to understand how individuals interact with algorithms and the output or recommendations that they provide. Failure to anticipate human reactions to algorithms and their outputs may lead to unintended consequences, and as a result, promoting such algorithms as a means of improving health-related decisions could backfire. Essay 1 investigates how a risk assessment algorithm affects individuals' health-protective behavior, showing that men and women respond differently. For men, the CRC risk score increased intentions to undergo CRC screening, while for women, it reduced intentions due to lowered perceived susceptibility. Essay 2 explores the link between algorithm literacy and algorithm aversion in medical decision-making. Contrary to expectations, higher algorithm literacy actually leads to greater aversion behavior. Essay 3 uses AI-generated age progression videos to encourage future health decisions. It increases willingness to engage in various future decisions but decreases the perception of connectedness to one's future self. The three essays of this dissertation explores the outputs of algorithms in healthcare and the mechanisms by which the use of algorithms affects individuals' health decisions. The essays collectively emphasize that encouraging people to embrace algorithmic tools to improve decision-making about the future may produce counter-intuitive results and operate through mechanisms that are, as yet, not well understood. This highlights the need for further research in the field of human-algorithm interaction, understanding how humans react to algorithms and the advice or outcomes they provide, and uncovering the underlying mechanisms behind these reactions.

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INTRODUCTION

Healthcare expenditures in the United States are among the highest in the world. According to the 2021 United States National Health Expenditure Fact Sheet published by the Centers for Medicare & Medicaid Services (CMS), national health spending in the United States reached $4.3 trillion, or $12,914 per person in 2021, accounting for 18.3% of the nation's gross domestic product (GDP). At the individual level, nearly one in five Americans have medical debt (Kluender et al., 2021) and out-of-pocket spending for health care exceeded $433 billion in 2021. The per capita cost of healthcare in the United States is almost three times more than the OECD average of $4,087 per capita (OECD, 2021).

Early detection and prevention of serious diseases is a powerful lever for reducing costs. For example, regular screening which enables early detection of disease often allows the use of less complex care, less invasive treatment, and more timely care processes. Such preventive care has the potential to save significant healthcare expenditures in the United States by reducing the need for more costly medical interventions in the future. A study by Maciosek et al. (2010) found that increasing the use of preventive services could result in savings of around $3.7 billion per year on medical care and reductions in hospitalization and emergency department visits. The Centers for Disease Control and Prevention (CDC) estimates that for every dollar invested in certain recommended preventive services, $5.60 can be saved in medical costs (Centers for Disease Control and Prevention, 2009).

Algorithmic tools in healthcare have the potential to support preventive care. For example, algorithms can be used to evaluate a patient's risk for certain diseases and make personalized recommendations for preventive care. A personalized risk assessment may help patients understand their health risks and take proactive steps to reduce them. Algorithms can also help patients act in health-protective ways by providing their users with more accurate and personalized information about their health. Such algorithmic solutions may include symptom checkers that enable patients to learn about potential health issues and treatment options. The timely information may help patients understand their symptoms and take appropriate action, such as seeking medical attention or making lifestyle changes.

Algorithmic tools also have the potential to enable better access to healthcare. Access to care is reported to be one of the major problems with the current healthcare system (Prentice & Pizer, 2007). A review study by Batbaatar et al. (2017) identified access as a key determinant of patient satisfaction. When individuals are unable to access the information or care they need, it can lead to reduced patient satisfaction and mistrust of the healthcare system. In addition, when individuals are unable to access information or care in a timely manner, their health problems may become more severe, requiring more costly interventions in the future. The use of patient facing algorithmic tools can provide timely access to necessary healthcare information, empowering patients to make more informed decisions about their health and care.

This dissertation explores the outputs of algorithms in healthcare and the mechanisms by which the use of algorithms affects individuals' health decisions. The first essay investigates how a risk assessment algorithm may affect an individual's intention to act in health protective behavior. Health risk calculators have the potential to promote cancer awareness and improve compliance with screening tests. However, the outputs of such algorithmic tools may have the opposite effect (i.e., reducing an individual's intention to engage in health-protective behavior). This is because the output of such algorithms is often delivered as percentage probabilities of contracting a disease and the seemingly low-risk percentage outputs may signal that there is little risk, thus providing a false sense of security. In addition, as men and women are found to react differently to risk, gender may be an important factor when studying the effect of risk calculator outputs on health behavior intention. In the context of colorectal cancer (CRC) risk calculator, we investigate how perceived susceptibility to CRC mediates the effect of CRC risk results. We also examine how the mechanism may differ according to gender with the following research questions:

RQ 1: How does providing an individualized risk score via a risk calculator influence an individual's intention to undergo CRC screening and specifically what role does perceived susceptibility play?

RQ 2: Does gender affect the mechanism through which individuals respond to a personalized risk calculator score?

The second essay examines the algorithm aversion phenomenon in healthcare and the role of algorithm literacy in the utilization of algorithmic output. Even though algorithmic models are often more accurate than human intuition, people tend not to follow algorithmic advice (Castelo et al., 2019; Dietvorst et al., 2015; Logg et al., 2019). While most studies on the utilization of algorithmic tools in healthcare report that medical professionals display resistance to such statistical models (Esmaeilzadeh et al., 2021), Longoni et al. (2019) reported that even novice patients are hesitant to use medical algorithms. Algorithm literacy has been suggested as one of the methods to overcome this problem (Burton et al., 2019) as a better understanding of how the algorithms work and how to interpret the statistical outputs may relieve users' concerns when working with algorithmic tools. This point of view is interesting as younger generations are exposed to algorithms from an early stage and will have more education about them as well. However, there are currently no empirical studies that have investigated the role of algorithm literacy on the algorithm aversion phenomenon. This essay seeks to address this knowledge gap with the following research question:

RQ: Does algorithm literacy affect individuals' willingness to accept algorithmic advice?

The third essay in this dissertation uses algorithms to nudge people to make future health decisions. Ignoring what ought to be done for the benefit of one's own future can be explained through temporal discounting. Temporal discounting suggests that individuals prefer immediate, smaller rewards over larger but delayed rewards (Scholten et al., 2019). This can lead to behaviors that create serious health problems as one ages and decrease one's longevity. Studies on health interventions have studied various methods to reduce temporal discounting in the health context. Scholten et al. (Scholten et al., 2019), in their systematic literature review, point to the effectiveness of future-provoking manipulations that promote episodic future thinking and connectivity to the future self.

Episodic future thinking involves pre-experiencing a possible future event through vividly imagining the future. Connectivity to the future self is based on the notion that the more connected an individual feels to his/her future self, the greater their willingness to engage in health protective behaviors that will be beneficial to your future self. This study utilizes an age progression algorithm whereby a current photograph is age progressed to heighten the vividness of one's future self. When an individual sees an age progressed photograph of him/herself, literature on future self-continuity would suggest that such an image could invoke an experience similar to episodic future thinking. The vividness of the image could also help one to realize that the current self and future self are the same person, bringing their perception of connectivity to the future self closer.

This study also considers the potential differences between egocentric and altruistic future decisions. Egocentric future decisions refer to the ones that directly benefit your future self, such as practicing healthy diet habits, exercising regularly, or adhering to routine medical screening. Altruistic future decisions, however, may benefit those around you in the future, often after your death, but may not directly benefit your future self. Such examples include creating an advance medical directive, creating a charitable trust, or planning on a burial plot. This study investigates the effect of age progression treatment on temporal discounting tendencies across different types of future decisions by answering the following research questions:

RQ 1: Does seeing your future self through an age progressed algorithm influence one's tendency to engage in delay discounting?

RQ 2: Does the effect of age progression on delay discounting differ based on the type of future decision, namely egocentric and altruistic future decisions?

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1 ESSAY 1:

GENDER EFFECTS ON THE IMPACT OF COLORECTAL CANCER RISK CALCULATORS ON SCREENING INTENTIONS: AN EXPERIMENTAL STUDY

1.1 Abstract[1]

Background: According to a 2020 study by the American Cancer Society, colorectal cancer (CRC) represents the third leading cause of cancer both in incidence and death in the U.S. Nonetheless, CRC screening remains lower than other high-risk cancers such as breast and cervical cancer. Risk calculators are increasingly being used to promote cancer awareness and improve compliance with CRC screening tests. However, research concerning the effects of colorectal cancer (CRC) risk calculators on the intention to undergo CRC screening, has been limited. Moreover, some studies have found impacts of CRC risk calculators to be inconsistent, reporting that receiving personalized assessments from such calculators lowers people's risk perception.

Objective: This study's objective is to examine the effect of using CRC risk calculators on individuals' intentions to undergo CRC screening. In addition, this study aims to examine the mechanisms through which using CRC risk calculators might influence individuals' intentions to undergo CRC screening. Specifically, this study focuses on the role of perceived susceptibility to CRC as a potential mechanism mediating the effect of using CRC risk calculators. Finally, this study examines how the effect of using CRC risk calculators on individuals' intentions to undergo CRC screening may vary by gender.

[1] This essay was published in JMIR Formative Research (https://formative.jmir.org/2023/1/e37553). This journal required a structured abstract. Hence, the format of the abstract presented here is different from the format used for the other two essays which have not yet been published.

Methods: We recruited a total of 128 participants through Amazon Mechanical Turk (MTurk) who live in the U.S., have health insurance, and are in the age group of 45 to 85. All participants answered questions needed as input for the CRC risk calculator but were randomly assigned to treatment (CRC risk calculator results immediately received) and control (CRC risk calculator results made available after the experiment ended) groups. The participants in both groups completed a series of questions regarding demographics, perceived susceptibility to CRC, and their intention to get screened.

Results: We found that using CRC risk calculators (i.e., answering questions needed as input and receiving calculator results) has a positive effect on intentions to undergo CRC screening, but only for men. For women, using CRC risk calculators has a negative effect on their perceived susceptibility to CRC, which in turn reduces intention to sign up for CRC screening. Additional simple slope and subgroup analyses confirm that the effect of perceived susceptibility on CRC screening intention is moderated by gender.

Conclusions: This study shows that using CRC risk calculators can increase individuals' intentions to undergo CRC screening, but only for men. For women, using CRC risk calculators can reduce their intentions to undergo CRC screening, as it reduces their perceived susceptibility to CRC. Given these mixed results, while CRC risk calculators can be a useful source of information on one's CRC risk, patients should be discouraged from relying solely upon them to inform decisions regarding CRC screening.

Keywords: Colorectal Cancer (CRC), Risk Calculator, Perceived Susceptibility, Gender, Intention

1.2 Introduction

According to a 2020 study by the American Cancer Society, colorectal cancer (CRC) represents the third leading cause of cancer both in incidence and death in the U.S. (American Cancer Society, 2020). CRC is similar to other types of cancer in the sense that the disease can be developing for some period of time without the patient knowing it. By the time a person has developed symptoms, the disease can be difficult to treat. Regular screening for early detection is therefore important. Nonetheless, screening in the case of CRC can be more effective than other types of cancers due to the slower progress from precancerous polyps to adenomas, the invasive cancerous polyps (American Cancer Society, 2017). In fact, health research has accumulated much evidence that shows the effectiveness of CRC screening (Schroy III et al., 2011). Unfortunately, CRC screening remains lower than other high-risk cancers such as breast and cervical cancer (American Cancer Society, 2020) and an estimated 37% of Americans who should have received CRC screening have not done so (American Cancer Society, 2017). While there are multiple options for CRC screening, colonoscopy has often been regarded as the gold standard among the options available and is often recommended to patients by their physicians (Issa & Noureddine, 2017).

Health risk calculators are one form of intervention used to encourage people to undergo cancer screening. Risk calculators for CRC are now readily available to anyone with an Internet browser. While it has been suggested that "providing people with individualized risk estimates can encourage them to engage in health-promoting behaviors," (E. A. Waters et al., 2009) prior research suggests that risk calculators may not be that effective in increasing peoples' intention to undergo CRC screening (Schroy III et al., 2011). While some studies found that the use of health risk calculators increase individuals' intentions to sign up for screening (Colkesen et al., 2011; Edwards et al., 2003; Losina et al., 2017; Marcus et al., 1998), other studies reported a negative or non-significant relationship between the use of risk calculators and intentions to sign up for screening (Edwards et al., 2003; Harle et al., 2012; Schroy III et al., 2011). In addition, some studies also measured perception of risk and reported that risk calculators actually lowered participants' perceptions of risk (Harle et al., 2012; Losina et al., 2017; Weinstein et al., 2004).

Moreover, a meta-analysis by Portnoy et al. (Portnoy et al., 2014) reveals that the use of a risk calculator is a strong predictor for the perceived susceptibility of health-related outcomes and its effect size is: $B = -0.65$, 95% CI [–1.13, –0.16]. These results suggest that in general using risk calculators decreases perceived risk of health-related issues. For example, Harle et al. (Harle et al., 2012) found that on average, individuals' risk perceptions of prediabetes decreased by 2% after they received the results of individualized risk calculations (Harle et al., 2012). Moreover, Losina et al. (2017) examined the efficacy of a personalized risk calculator on risk perceptions of knee osteoarthritis. They found that after using the calculator, subjects' perceived 10-year risk decreased by 12.9 percentage points to 12.5% and perceived lifetime risk decreased by 19.5 percentage points to 28.1%. In the context of colon cancer risk, research suggests that using risk calculators does not lead to expected benefits (i.e., increasing risk perceptions). Specifically, Weinstein et al. (2004) found that correlations between actual and perceived risks of colon cancer were about the same between people who received personalized feedback and those who did not receive such feedback.

Given the inconclusive findings concerning the impact of risk calculators on intentions to sign up for CRC screening, further research is needed to probe this relationship and to shed light on the mechanism through which CRC risk calculators may influence individuals' intentions.

One possible explanation for inconsistent research findings concerning the impacts of CRC risk calculators is that users may regard the output of such calculators, usually provided in percentage terms, to be so small that they perceive themselves as having a very low susceptibility to CRC. The lifetime risk of CRC in the general population is considered to be between 5% and 6% (Siegel et al., 2015) and one study reported an average CRC risk calculator result for 10-year risk as 1.02% among a group of 509 patients undergoing colonoscopy (Ladabaum et al., 2016). Another possible explanation for the inconsistent research findings concerning CRC risk calculators is that some groups of people are likely to regard the risk as more concerning than other groups. Specifically, there is a substantial body of research indicating that women and men differ in their perceptions of risk (Gustafson, 1998). Therefore, it is deemed important to consider gender and examine its role in understanding the impacts of CRC risk calculators.

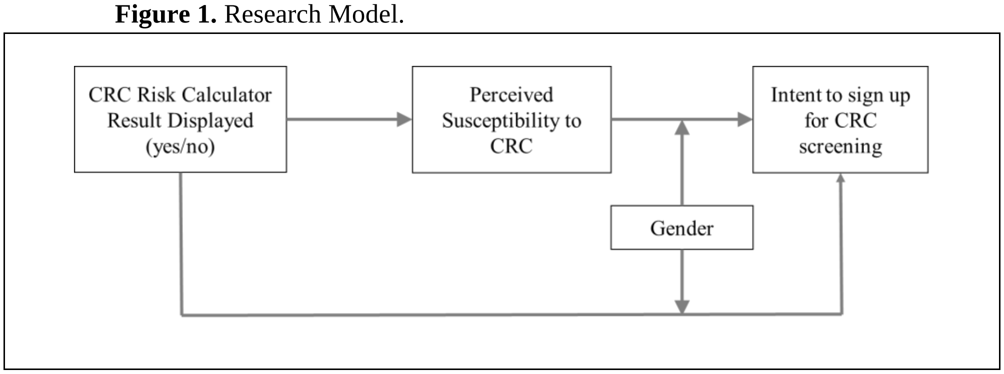
Therefore, in this study we examine the effect of using CRC risk calculators on individuals' intentions to undergo CRC screening. In addition, this study aims to examine the mechanisms through which using CRC risk calculators might influence individuals' intentions to undergo CRC screening. Specifically, this study focuses on the role of perceived susceptibility to CRC as a potential mechanism mediating the effect of using CRC risk calculators. As one of the constructs in the Theory of Planned Behavior (TPB), intention is defined as the effort one is willing to exert to reach a behavioral goal and is suggested as the "proximal antecedent to action" (Gibbons, 2006). Perceived susceptibility is an important factor in shaping risk perceptions and is defined as an individual's subjective probability that something, in this context CRC, will negatively affect him or her (Liang & Xue, 2009). Finally, this study also examines how the effect of using CRC risk calculators on individuals' intentions to undergo CRC screening may vary by gender. We note that we do not develop a priori hypotheses for two reasons: (1) prior findings regarding the effects of risk calculators have been inconsistent, and (2) existing theory does not provide us with enough information to predict the moderating effect of gender with any precision (i.e., whether it would be stronger for men or for women). In sum, we seek to address the following research questions:

RQ 1: How does providing an individualized risk score via a risk calculator influence an individual's intention to undergo CRC screening and specifically what role does perceived susceptibility play?

RQ 2: Does gender affect the mechanism through which individuals respond to a personalized risk calculator score?

Our research model is depicted as below in Figure 1.

Figure 1. Research Model.



1.3 Methods

To address our research questions and test our research model we conducted an experiment.

1.3.1 Ethical Considerations

For this study, we sought and received approval from an Institutional Review Board (IRB) at the university of the corresponding author where data collection occurred and data was managed. This study fell under the Exempt study category based on the guidelines of the IRB. Before participants could participate in this study, they were asked to read the informed consent form that was approved by IRB and indicate their willingness to participate by clicking the "Agree" button (the experiment was conducted in an online setting). The informed consent form explained the objectives of this study in layman's terms without revealing any information about the experimental design. Specifically, participants were told that we are interested in studying the effect of personalized CRC risk on intention to sign up for CRC screening. We also explained in the informed consent form that participating in this study was completely voluntary. We did not collect any personal or identifiable data. In other words, the data was completely anonymous. In addition, the data was kept in password-protected computers. Finally, the participants received $0.80 for their participation.

Table 1. Experiment Design.

	Assignment	**Pre-test**	**Manipulation**	**Post-test**
Treatment Group	R	O_1	X	O_2
Control Group	R	O_3		O_4
Note: R=random assignment; O=observation; X=treatment received				

1.3.1 Experimental Design

We employed a pretest-posttest control group design with random assignment (see Table 1) in which both perceived susceptibility and intention to sign up for CRC screening were measured before and after the manipulation. Pretest measures were used to ensure that participants in treatment vs. control groups did not differ in terms of perceived susceptibility and intention to sign up for CRC screening prior to participating in the experiment. Specifically, we conducted a t-test comparing pretest measures of perceived susceptibility to CRC and intention to sign up for CRC screening between the two groups and there was no statistically significant difference at the $P < 0.05$ significance level. Moreover, including a control group of individuals who did not learn their risk allowed us to create a tight experimental design in which the treatment and control group subjects had exactly the same experience *except* receiving the risk score. Specifically, this allowed us to be confident that any differences found between the treatment and control group were due to having received a risk calculator score and not because of having gone through the act of answering the risk calculator input questions.

While both treatment and control groups provided inputs for the CRC risk calculator after the pre-test, only the treatment group received the personalized CRC risk calculator result before the post-test. In contrast, participants in the control group received the risk calculator results at the end of the experiment (i.e., after submitting their post-test responses). This constituted the manipulation. In other words, in the post-test the control group reported their *perceived susceptibility* to CRC and their degree of *intention* to get screened for CRC right *after* the input process but before receiving the risk calculator result, whereas the treatment group was provided with the risk calculator output *before* responding to the *perceived susceptibility* and *intention* measurements. Both groups completed standard CRC risk calculator input questions. This design allowed us to examine whether receiving the CRC risk calculator results influences perceived susceptibility and intention to sign up for a colonoscopy.

1.3.2 Recruitment

The experiment was conducted through the Qualtrics survey platform, and we recruited participants through Amazon Mechanical Turk (MTurk) (see Table 2). We restricted study participation to people aged 45 to 85, who live in the U.S., and have health insurance (private health insurance or Medicare/Medicaid). Health care practices and behavior vary by country and culture and for our study we wanted to focus on the U.S. In addition, the financial burden is a major factor influencing CRC screening non-adherence (Bunn et al., 2002; Denberg et al., 2005). Therefore, to address the possible confound of financial means, we included having health insurance as a requirement for participating in our experiment.

Upon consent, participants were asked to answer questions about age, health insurance type, and whether they had ever had CRC screening. These three questions were used to filter out people who were younger than 45, who did not have any form of health insurance, and those who had already undergone CRC screening. Initially, a total of 219 MTurk users agreed to take part in the experiment but 78 of them were filtered out by the initial screening question about age, insurance, and prior CRC screening experience. In addition, 13 participants failed to pass the attention check questions and thus were removed from the study. This resulted in a total of 128 usable responses for our analysis.

Table 2. Participants.

	Men	**Women**	**Total**
Treatment Group	20	42	62
Control Group	26	40	66
Total Group	46	82	128

1.3.3 Statistical Analysis

1.3.3.1 Power

A priori, the required sample size was calculated using G*Power 3.1.9.7 (Faul et al., 2009) assuming a medium effect size (f^2 = 0.15), an α level of 0.05, and a power of 0.80, resulting in required total sample size n = 92. We based this on the meta-analysis by Portnoy et al. (Portnoy et al., 2014) which found that the use of a risk calculator is a strong predictor for the perceived susceptibility of health-related outcomes and its effect size is: B = –0.65, 95% CI [–1.13, –0.16]. In other words, –0.65 is considered a medium effect size and we used this as a guideline. Our sample size of 128 exceeded this and was deemed to give us sufficient power.

1.3.4 Risk Calculator

All participants were asked to provide the required inputs needed for a CRC risk calculator to assess their personalized risk for contracting CRC in their lifetime. To enable this process, we adapted the CRC risk calculator from the National Cancer Institute (NCI) (NCI, 2019). The calculator uses subjects' demographic, health, and lifestyle information including age, height, weight, dietary and physical activity, medical and family history to CRC, and cigarette usage for men and hormone usage for women. The calculator then provides a risk percentage expressing the lifetime chances of developing CRC.

The NCI provides the SAS code for the risk calculator. We created the calculator using the code and integrated it with the online survey. One adaptation was made regarding the age group. The original calculator was designed for the age group of 50 to 85, but our calculator was modified to also include people who are 45 to 49. We made this modification based on the current CRC screening recommendations of the American Cancer Society [23]. Participants aged 45-49 received the same outputs from the calculator that they would have received if they had entered the age of 50, as the SAS code upon which our calculator was based did not yet reflect the updated screening guideline at the time we conducted the experiment.

1.3.5 Measures

We posit in this study that *intention to sign up for CRC screening* is affected by one's *perceived susceptibility to CRC*. The two constructs were measured before and after users provided inputs for the CRC risk calculator.

1.3.5.1 Intention to sign up for CRC screening.

Measures for intention to sign up for CRC screening were adapted from previous studies (Sheeran et al., 2001; Venkatesh & Davis, 2000). Subjects were asked to respond to five measurement items, each on a seven-point Likert scale (1=Strongly Disagree; 7=Strongly Agree) (See Appendix). Behavioral intentions are commonly used in health behavior literature as the primary dependent variable and are held to be predictive of actual behavior (Mevissen et al., 2012). Cronbach's α in the current study was 0.96 for both the pre-test and post-test intention to sign up for CRC screening.

1.3.5.2 Perceived susceptibility to CRC.

Measures for perceived susceptibility were also adapted from a previous study (Chen & Zahedi, 2016). Subjects were asked to respond to three measurement items, each on a seven-point Likert scale (1=Strongly Disagree; 7=Strongly Agree) (See Appendix). Cronbach's α in the current study was 0.96 for pre-test susceptibility and 0.98 for post-test susceptibility.

1.3.5.3 Other Measures

After completing the post-test measures, participants were asked to respond to some additional questions involving demographics and control variables.

1.3.5.4 Data Analyses

A comparison of the treatment and control group means was conducted using an independent samples t-test in SPSS (version 25.0, IBM Corp., 2017). Statistical significance was defined as $P < .05$. Paired t-tests were used for comparing pre-test and post-test measures of perceived susceptibility to CRC and intention to sign up for CRC screening within each group. We used Hayes' PROCESS macro for our main analysis to conduct a regression based conditional process analysis of a moderated mediation model with 10,000 bootstrap samples (Hayes, 2017).

1.4 Results

In our assessment of random assignment, we found no significant differences between the treatment and control groups in terms of mean age, objective CRC risk (CRC risk calculator score), or BMI (Body Mass Index), at the $P < .05$ level. The descriptive statistics for the treatment and control groups and the *P*-values for the mean comparisons are shown in Table 3.

Table 3 Descriptive Statistics for Treatment and Control Groups

	Control Group (n = 66) (result not immediately received)			**Treatment Group** (n = 62) (result immediately received)			
N = 128 (men:46, women:82)	**Mean (SD)**	**Min**	**Max**	**Mean (SD)**	**Min**	**Max**	***P*-value**
Age	52.89 (7.75)	45	74	53.73 (8.00)	45	69	.55
CRC Risk Calculator Score	3.95 (1.41)	0.28	8.04	3.90 (1.57)	1.89	8.67	.86
BMI (Body Mass Index)	28.33 (8.43)	18.29	59.76	28.41 (8.02)	19.63	67.31	.95

1.4.1 Correlation Analysis

Next, we examined correlations among the key variables. We used post-test measures for the correlation analysis. As seen in Table 4, the intention to sign up for CRC screening was positively associated with perceived susceptibility to CRC (r=.30, P=.001) and subjects' BMI (r=.19, P=.04). However, it was not significantly correlated with any other variables, including age, gender, or whether the result from the risk calculator was received before the post-test measures. Age and gender did not show any significant correlation with other variables. Perceived susceptibility to CRC was negatively associated with whether the subject's CRC risk score was received (r=-0.36, $P < .001$), but not with any other variables, suggesting that participants who received their personalized CRC risk score reported lower perceived susceptibility to CRC than those who did not. In addition, the correlation between pre-test and post-test perceived susceptibility to CRC was 0.752 (P<0.001). The correlation between pre-test and post-test intention to sign up for CRC screening was 0.963 (P<0.001) (these are not shown in the table).

To determine whether participants' perceived susceptibility to CRC and intention to get screened for CRC changed after the intervention, we examined the changes in perceived susceptibility and intention to sign up in each group using pre-test and post-test measures. It was found that for each group the perceived susceptibility and intention to sign up for CRC screening decreased after the participants used the risk calculator, but to a greater extent for the treatment group (see post-pre difference in Table 5). These results indicate that receiving the risk calculator result (vs. not receiving the result) can have differing effects on both the perceived susceptibility and intention to sign up for CRC screening.

Table 4 Correlation table

	Mean (SD)	**Intention to sign up**	**Perceived susceptibility**	**Risk calculator results received (Control: 0; Treatment: 1)**	**BMI**
Intention to sign up for CRC screening	4.26 (1.66)				
Perceived susceptibility to CRC	2.71 (1.42)	0.30** (*P*=.001)			
Risk calculator result received before post-test measures (Control: 0; Treatment: 1)	0.48 (0.50)	-0.02 (*P*=.81)	-0.36** (*P*< .001)		
BMI	28.37 (8.20)	0.19* (*P*=.04)	0.06 (*P*=.51)	0.01 (*P*=.95)	
Objective risk score	3.93 (1.48)	0.16 (*P*=.07)	0.35 (*P*<.001)	-0.02 (*P*=.86)	0.35 (*P*<.001)
Age	53.30 (7.85)	-0.08 (*P*=.37)	0.17 (*P*=.06)	0.05 (*P*=.56)	0.06 (*P*=.47)
Gender (Men: 0; Women: 1)	0.64 (0.48)	-0.05 (*P*=.56)	-0.17 (*P*=.06)	0.07 (*P*=.40)	0.05 (*P*=.55)

In addition, the decreases in the perceived susceptibility and intention to sign up for CRC screening were statistically significant for the treatment group. In contrast, for the control group, the decrease in only the perceived susceptibility was statistically significant. A possible explanation for this pre- versus post- difference in perceived susceptibility, even in the control group, is that the input process associated with using the risk calculator can itself influence perceived susceptibility. As both groups responded to the input process, the act of going through a CRC risk calculator may have given them hints on the risk factors and those with no family history or who live a relatively healthy lifestyle may have felt some relief even without receiving the risk output from the calculator.

1.4.2 Main Analysis

A moderated mediation analysis using Hayes' PROCESS macro (Model 15: second stage moderated mediation) was conducted to (1) test whether perceived susceptibility mediates the relationship between the treatment (of showing the risk calculator result or not) and intention to sign up for CRC screening and (2) examine the role of gender in moderating this relationship.

Table 5 Post-Pre Differences in Perceived Susceptibility and Intention to Sign Up for CRC Screening

		Pre-test (SD)	**Post-test (SD)**	**Post-Pre difference (SD)**	***P*-value**
Treatment group (n = 62)					
	Perceived susceptibility to CRC	2.98 (1.16)	2.19 (1.26)	-0.79 (1.17)	$P < .001$
	Intention to sign up for CRC screening	4.46 (1.66)	4.23 (1.71)	-0.23 (0.47)	$P < .001$
Control group (n = 66)					
	Perceived susceptibility to CRC	3.36 (1.26)	3.20 (1.39)	-0.16 (0.53)	P=.02
	Intention to sign up for CRC screening	4.36 (1.64)	4.30 (1.61)	-0.06 (0.41)	P=.21
Note: The results reported in this table are based on a set of paired samples t-tests. As a robustness check, we also ran repeated measures ANOVAs and confirmed that the results from these analyses are consistent with the results obtained from the paired samples t-tests					

First, we examined the results from the analysis concerning the direct effect (Table 6). The results indicated that for men, receiving the CRC risk calculator result increased their intention to sign up for CRC screening (confidence interval (CI) range: 0.23 – 1.87), but this was not the case for women (CI range: -0.77 – 0.70). These results suggest that gender moderates the direct effect of the treatment on intention to sign up for CRC screening. Second, we examined the results from the analysis concerning the indirect effect (Table 6). The results indicated that for women, receiving the CRC risk calculator result reduced their perceived susceptibility to CRC, which in turn, reduced their intention to sign up for CRC screening (CI range: -0.91 – -0.21). This mediation effect was not significant among men (CI range: -0.47 – 0.18). These results suggest that gender moderates the indirect effect (via perceived susceptibility) of the treatment on intention to sign up for CRC screening. Finally, we examined both the index of moderated mediation and the results of pairwise contrasts between conditional indirect effects (the difference between indirect effects for men vs. women). The index of moderated mediation was -.43 and was statistically significant (CI range: -0.91 – -0.01). The difference between the two indirect effects was -.53 and was statistically significant (CI range: -0.91 – -0.01). These results provide further evidence supporting both the moderating role of gender and the mediating role of perceived susceptibility.

Table 6 Direct Effect and Conditional Indirect Effects of CRC Risk Calculator Output

		Effect	SE	LL BCCI	UL BCCI
Direct Effects					
	Men	1.05	0.48	0.23	1.87
	Women	-.03	0.37	-0.77	0.70
Indirect Effects (via perceived susceptibility)					
	Men	-.10	0.16	-0.47	0.18
	Women	-.53	0.18	-0.91	-0.21

Note: As a robustness check, we conducted the same analysis with the inclusion of the following covariates: age, BMI, one's belief on their likelihood of getting CRC in their lifetime, and objective risk scores of subjects provided by the risk calculator. The results from this analysis with covariates were fully consistent with those reported in this table.

1.4.3 Simple Slope and Subgroup Analyses

We used simple slope tests to further examine the moderating role of gender on the relationship between perceived susceptibility and intention to undergo CRC screening (see Figure 2 and Figure 3). Results indicated that perceived susceptibility to CRC had a significant positive effect on the intention to sign up for CRC screening for women (slope=0.53, SE=0.12, P<.001) but not for men (slope=0.10, SE=0.15, P=.51) (see Figure 2). These results provide additional insights suggesting that increased perceived susceptibility to CRC may lead to increased intention to sign up for CRC screening among women but not among men. The effect of receiving CRC risk calculator results on intention to sign up for CRC screening was also moderated by gender in that the effect was significant for men (slope=1.05, SE=0.42, P=.01) but not for women (slope=-0.03, SE =0.37, P=.93) (see Figure 3).

Figure 2 Gender difference on the relationship between perceived susceptibility and intention to undergo CRC screening

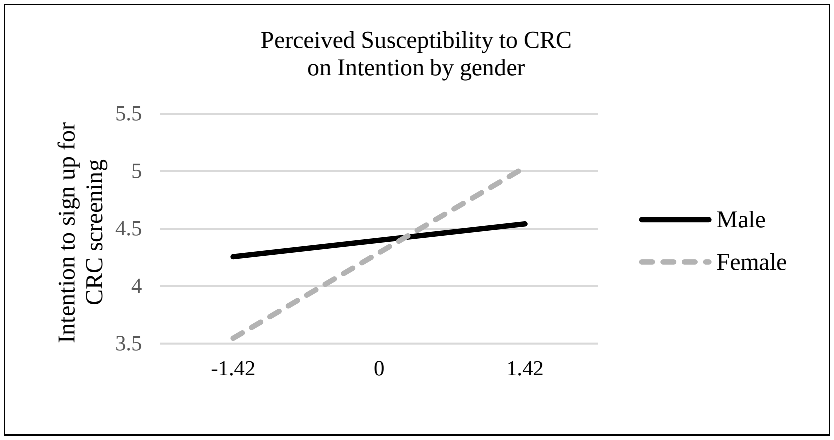
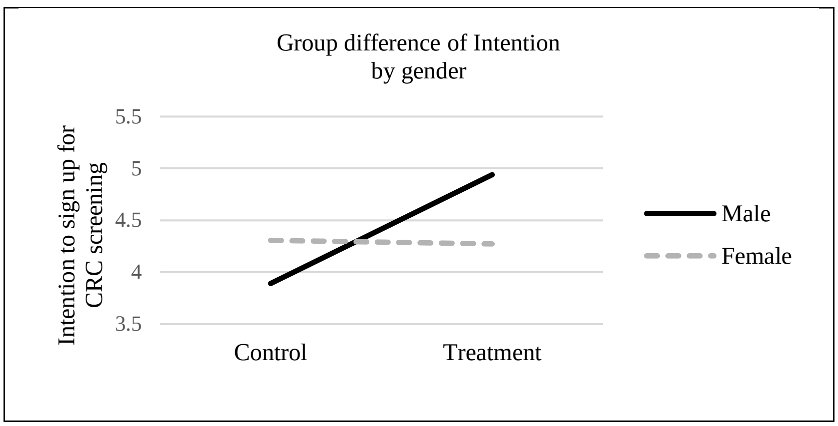


Figure 3 Gender difference on the effect of receiving CRC risk calculator result on intention to undergo CRC screening



Moreover, results of subgroup analyses (shown in Figures 4 and 5) obtained by using the PROCESS macro (model 4) clearly show that the mechanism through which the risk calculator results influence intention to undergo CRC screening differs for men and women.

1.5 Discussion

CRC screening is increasingly important, especially as CRC risk becomes greater for younger population segments, but compliance is suboptimal (DeGroff et al., 2018). CRC risk calculators have the potential to promote CRC screening as they provide individualized risk scores that may positively impact intentions to undergo CRC screening. However, prior empirical research found that providing personalized risk feedback via risk calculators decrease perceived susceptibility to CRC (Weinstein et al., 2004). Such results indicate that risk calculators may not be as useful for driving up compliance with CRC screening guidelines as one might think. In this paper, we investigated whether a CRC risk calculator can influence intention to undergo CRC screening by affecting an individual's perceived susceptibility of contracting CRC. We further probed whether gender moderates the relationship between perceived susceptibility and CRC screening intention.

Figure 4 Subgroup analysis among men (n=46)

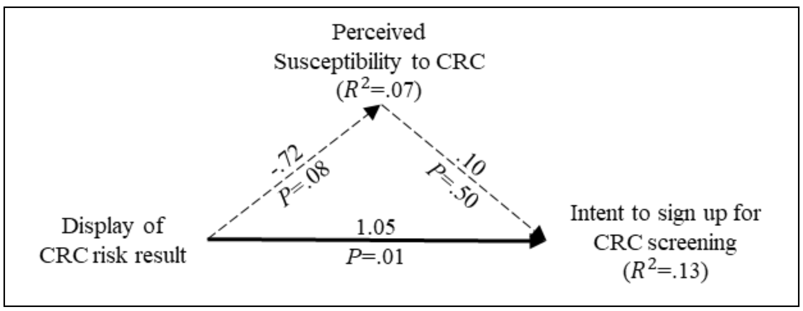
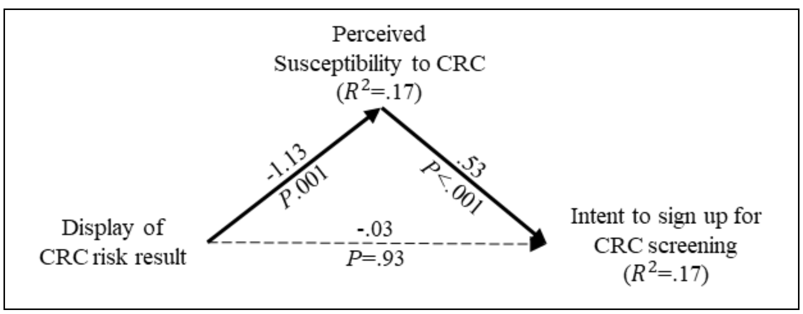


Figure 5 Subgroup analysis among women (n=82)



We found that among women, the effect of receiving CRC risk calculator results on their intention to undergo CRC screening is mediated by perceived susceptibility. Among men, the direct effect of receiving CRC risk calculator results was significant, while the mediating effect of perceived susceptibility was not. While previous research studied the impact of using a risk calculator and receiving its results on perceived susceptibility (risk perceptions) (Harle et al., 2012; Weinstein et al., 2004) or the effect of perceived susceptibility on intention (Atkinson et al., 2015; Bleiker et al., 2005), little was known about the mechanism through which receiving CRC risk calculator results affect an individual's intention to undergo CRC screening. Conditioning on gender, we show that among women, this relationship is mediated by perceived susceptibility and that among men, only the direct effect of receiving the CRC risk calculator result on their intention to sign up for screening was significant. Importantly, we also find that receiving CRC risk calculator results actually decreases CRC screening intention for women and that this is mediated through perceived susceptibility.

One interesting contribution of our study is the finding that perceived susceptibility may be central in explaining why the use of CRC risk calculators may not lead to a desired behavioral outcome. Furthermore, the finding that the risk calculator results influence men and women through different pathways and in different directions sheds light on why prior research has obtained inconsistent findings (Colkesen et al., 2011; Edwards et al., 2003; Harle et al., 2012; Losina et al., 2017; Marcus et al., 1998; Weinstein et al., 2004). Using a direct and second stage moderated mediation model, we found that gender moderates the mediating role of perceived susceptibility, such that the relationship between perceived susceptibility and intention to undergo CRC screening was significant only for women. We found that gender also moderates the direct effect of receiving risk calculator results, such that the direct effect was significant only for men. This indicates that gender differences should be considered when promoting CRC screening, suggesting that additional research is needed on how to successfully motivate CRC screening, conditional on gender.

1.5.1 *Implication for Practice*

Our primary implication for practitioners is to be cautious when implementing CRC risk calculators as a primary intervention for promoting CRC screening, as the results may not be desirable. While the individualized CRC risk scores may seem like useful information, relatively low CRC risk scores (Ladabaum et al., 2016; Siegel et al., 2015) likely cause users to perceive that their risk of contracting CRC is low, and this may cause them to forgo screening. We suggest that, at a minimum, risk calculator results should be paired with thoughtful communication from healthcare providers about the implications of the results and the importance of undergoing CRC screening.

We secondarily note that these findings have interesting implications for providing predictive model scores to individual health care consumers. In this study, we found that the effects of receiving such scores can vary by gender. The results indicated that for men, receiving the CRC risk calculator result increased their intention to sign up for CRC screening but this was not the case for women. Our results suggest that healthcare providers may need to consider gender differences when discussing CRC risk calculator results with patients.

Finally, given the easy access that patients have to calculators that are available on the web, providers should educate patients so that the results provided by these calculators do not deter patients from receiving the recommended screening. While risk calculators can be a useful source of information on one's CRC risk, patients should be discouraged from relying solely upon them to inform decisions regarding CRC screening.

1.5.2 *Limitation and Future Research*

Although we have identified a mechanism that further explains how CRC risk calculator results affect intention to undergo CRC screening, our study has limitations. First, our study measures intentions rather than behaviors. Further work is needed to verify that our findings translate to actual behaviors. Second, although we found that men and women react differently to CRC risk calculator results, further work is needed to understand more deeply why this gender difference occurs. Third, there may be other moderators that were not included in our study that could be important. Future research could include additional constructs such as masculinity, fatalism, and anxiety to probe their effect in the context of CRC screening.

Finally, while our overall sample size (N=128) was larger than the calculated required sample size (n=122) at a medium effect size (f^2=0.15), our sample exhibited gender imbalance, with almost twice the number of women (n=86) as men (n=46). Therefore, one avenue for future research would be to replicate our study with a larger and more balanced sample.

1.5.3 Conclusions

Health risk calculators have the potential to promote healthy behavior by influencing subjects' risk perception. Through this study, we found that among women, perceived susceptibility to CRC mediates the relationship between receiving CRC risk calculator results and the intention to undergo CRC screening. Among men, the direct effect of receiving CRC risk calculator results was significant while the mediating effect of perceived susceptibility was not. We also showed that the direction of the overall effect of receiving the CRC risk calculator result is positive for men and negative for women. In addition, as receiving the CRC risk calculator output was found to reduce perceived susceptibility to CRC, careful consideration on how to communicate such results is needed. Our findings suggest that interventions that influence perceived susceptibility may have unintended consequences on promoting CRC screening, underscoring the importance of communicating the result. While the use of an individualized risk assessment tool can be a good addition to one-on-one communication with a healthcare provider, the messaging provided by both the tool and the clinician may need to be tailored to account for gender differences.

1.5.4 Acknowledgements

We would like to thank for editor and reviewers for their helpful feedback on our manuscript. We would also like to thank Mahesh Boodraj who helped us during the early stages of this research project.

1.5.5 Data Availability

The dataset has been uploaded to a publicly available repository (figshare). Our data can be found at the following url: dx.doi.org/10.6084/m9.figshare.22185925

1.5.6 Conflicts of Interest

None.

1.5.7 Abbreviations

BMI: body mass index

CRC: colorectal cancer

1.6 References

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Appendix: Measures

Table A1. Measures for Perceived Susceptibility to CRC

Perceived Susceptibility	When it comes to the likelihood of getting CRC, I believe that:		
	My risk of getting CRC is high. The likelihood that I would get CRC is high.	Adapted from Chen and Zahedi, 2016 (Cronbach α=.86)	7-point Likert-type scale (1=strongly disagree; 7=strongly agree)
	The extent of my vulnerability to CRC is high.		

Table A2. Measures for Intention to undergo CRC screening

Behavioral Intention	I intend to sign-up for CRC screening if offered.	Adapted from Sheeran et al., 2001 (Cronbach α =.93)	7-point Likert-type scale (1=strongly disagree; 7=strongly agree)
	If I had the opportunity, I would sign-up for CRC screening.		
	If I was offered a CRC screening, I would try to sign-up.		
	I intend to sign-up for CRC screening.	Adapted from Venkatesh and Davis, 2000 (Cronbach α =.87)	
	I predict that I will sign-up for CRC screening in the short term.		

2 ESSAY 2:

THE EFFECT OF ALGORITHM LITERACY ON ALGORITHM AVERSION

2.1 Abstract

This study examines the relationship between algorithm literacy and algorithm aversion in a medical decision-making context. First, we replicate prior work by showing that algorithm aversion exists in a medical decision-making context; users show a greater willingness to accept advice when it comes from a human professional as opposed to an algorithm. Second, we show that contrary to what has been suggested in the literature, algorithm literacy does not reduce algorithm aversion. In fact, it has the opposite effect; higher algorithm literacy is associated with greater algorithm aversion, such that advice utilization is actually *lower* for those with higher algorithm literacy.

Keywords:

Algorithm Aversion, Algorithm Literacy, Medical AI

2.2 Introduction

The technological advances in algorithm development and the availability of data (that can be used to train the algorithmic models) have given rise to various domain-specific algorithmic solutions that have the potential to relieve barriers related to accessing expert-level domain knowledge. As evidenced by the growing number of health-related smartphone apps, there is an increased interest in the use of algorithm-based tools aimed at helping patients with their healthcare needs. These tools have the potential to provide timely access to information that can be beneficial to patients and thus represent one avenue for addressing disparity in access to healthcare which is a major issue in the U.S. healthcare system. Healthcare access is subject to the availability of medical experts, which is often tied to geographic and economic disparity. According to a 2020 National Healthcare Quality and Disparities Report from Agency for Healthcare Research and Quality (AHRQ, 2022), almost 63% of counties in the United States have reported a shortage of primary care health professionals, threatening timely access to health services. In response to the talent and resource shortage, many experts suggest a wider use of technology applications in the healthcare field (Robeznieks, 2022; Wolters Kluwer, 2022). For example, algorithmic decision support apps in healthcare have the potential to help patients by providing just-in-time medical advice as such apps can provide necessary medical advice from the symptom descriptions or pictures patients share through the app interface. However, realizing the potential benefits associated with these apps hinges on patients' willingness to accept advice from the apps.

There is considerable literature showing that people exhibit algorithm aversion and may, therefore, not be open to the advice of an algorithm-based tool. Algorithm aversion (Dietvorst et al., 2015) describes the phenomenon in which people resist advice from an algorithm and this aversion hinders the potential benefits of using algorithmic decision support tools. Across many domains, studies find that advice from algorithms is not being embraced to its full potential; users often underutilize algorithmic advice. In the healthcare context, underutilizing algorithmic advice could lead to a significant loss of potential opportunities for democratizing access to expert medical knowledge.

One possible explanation for this underutilization of algorithmic advice may be that people's general understanding of algorithms is poor. A review article by Burton et al. (2019) suggests that if people had greater algorithm literacy, they might not exhibit algorithm aversion. Drawing from Dogruel et al. (2021) and Shin et al. (2021), we define algorithm literacy as being aware of the use of algorithms and knowing how algorithms work. If a poor understanding of algorithms is the cause of algorithm aversion, it makes sense that training laypeople on "how to interact with algorithmic tools, how to interpret statistical outputs, and how to appreciate the utility of decision aids" (Burton et al., 2019, p.4) would promote the proper utilization of algorithmic decision support tools. Against this backdrop, in this research we aim to investigate the effect of algorithm literacy on individuals' responses to algorithmic advice. Specifically, we seek to address the following research question:

RQ: Does algorithm literacy affect individuals' willingness to accept algorithmic advice?

To address this research question, we draw on the emerging body of research on the utilization of algorithmic advice (Dietvorst et al., 2015; Logg et al., 2019) and the Judge Advisor Systems (JAS) literature, and by doing so we aim to extend the notion of algorithmic literacy (Burton et al., 2019) to the domain of algorithm aversion. In this paper, results of an experiment conducted with participants from Prolific are reported. These results shed new light on the influence of algorithm literacy on algorithmic advice-taking in the domain of healthcare.

2.3 Background

2.3.1 Judge-Advisor System

According to the Judge-Advisor System (JAS) literature, people rarely make decisions in isolation; they reference external resources for information or receive advice from others (Bonaccio & Dalal, 2006). JAS literature focuses on one individual's (judge) willingness to accept advice from another individual (advisor) and assumes that the judge comes up with an initial estimate and then revises their estimate after receiving advice (Logg et al., 2019). The overarching finding in the JAS literature is that people are often unreceptive to advice. Research in the JAS literature suggests that the domain expertise of the decision maker and the complexity of the decision context reduce the decision maker's willingness to accept advice. According to the JAS framework, a novice working on a highly complex decision task is most likely to utilize advice.

The JAS literature suggests various reasons for under-utilization of advice, including egocentric advice discounting (Van Swol & Sniezek, 2005), a lack of trust in advisors (Sniezek & Van Swol, 2001), and whether the decision-maker has access to the advisor's reasoning strategy (Bonaccio & Dalal, 2006). A related stream of advice utilization in decision-making research has studied cases in which advisors are algorithms, which we discuss below.

2.3.2 Algorithm Aversion

Algorithm aversion describes a phenomenon in which people exhibit a reluctance toward accepting advice from an algorithm (Dietvorst et al., 2015). This aversive behavior against advice from algorithms is exacerbated after experiencing any flaws in algorithm performance

(Dietvorst et al., 2015). But algorithmic advice is not always frowned upon. In the context of an initial encounter or single use of algorithmic advice, for example, Logg et al. (Logg et al., 2019) found that laypeople tend to rely on the advice of an algorithm over that of a human (algorithm appreciation). They also reported that algorithm appreciation behavior waned among a group with forecasting expertise. Furthermore, they found that experts tend to discount advice regardless of the advice source (human or algorithm). In contrast, laypeople tend to utilize advice from algorithms, especially when the judgment domain is objective, and the decision task deals with logical or computational problems.

Research on algorithm aversion has been studied in multiple contexts, including decisions regarding forecasting stock price (Ben David et al., 2021; Castelo et al., 2019; Önkal et al., 2009), estimating educational achievements (Dietvorst et al., 2015, 2018), online matchmaking (Logg et al., 2019; Yin et al., 2019) and medical triage (Longoni et al., 2019; Prahl & Van Swol, 2017). Several factors have been found to influence a user's decision on whether to accept advice from an algorithm. Burton et al. (2019) identified several characteristics, such as decision autonomy, false expectations users have about algorithms, and cognitive compatibility between algorithms and users. Jussupow et al. (2020) noted that the expertise of the advisor and the user's social closeness with the advisor also influence algorithm aversion when the users are faced with choosing between a human expert and an algorithm that is framed as an expert. Several task characteristics have also been linked to algorithm aversion, such as task objectivity (Castelo et al., 2019) and the complexity of the decision tasks (Schrah et al., 2006). Interestingly, healthcare is reported to be a domain in which even novice patients are averse to medical algorithms (Longoni et al., 2019) particularly when the advice utilization questions are framed as algorithmic solutions replacing human medical experts (Esmaeilzadeh et al., 2021). More generally, Cadario et al. (2021) suggested that the black-box nature of most medical AI serves as another barrier to the adoption of medical AI. This raises the question of whether having a better understanding of how modern predictive models detect and handle outliers and how such algorithms operate would help patients become more appreciative of algorithmic advice.

2.3.3 Algorithm Literacy

Burton et al. (2019) suggest algorithm literacy as one of the mitigating strategies that may overcome the underutilization of algorithms (i.e., algorithm aversion). There are currently a limited number of studies that have empirically examined algorithm literacy. Dogruel et al. (2021), in the context of personalized online content provision, developed a measure for algorithm literacy that focuses on the awareness of algorithm use and knowledge about algorithms. They did not, however, test the effect of algorithm literacy on algorithmic advice-taking. Shin et al. (2021) used FATE (fairness, accountability, transparency, and explainability) as a proxy for algorithm literacy. In the context of the adoption of media streaming platforms, they found FATE to positively affect users' trust in platforms that use algorithms to provide personalized recommendations. However, FATE taps into the operational knowledge of the organization managing the platform, not necessarily algorithm literacy per se.

Burton et al. (2019) suggested that algorithm literacy could mitigate algorithm aversion, but, to the best of our knowledge, there has been no attempt to empirically examine the effect of algorithm literacy on algorithm aversion. As one of the early review papers on algorithm aversion that suggested potential remedies for algorithm aversion, any article that empirically tested the effect of algorithm literacy on algorithm aversion would have very likely referenced Burton et al.’s (2019) paper. However, our examination of the 236 articles that have cited Burton et al.'s (2019) paper, revealed that none had empirically tested the effect of algorithm literacy on algorithm aversion. Among those 236 articles, 47 of them used the term literacy in the manuscript. Most of these articles (32) used algorithm literacy in the discussion section or in suggestions for future research. Twelve of the articles used literacy in contexts other than algorithm literacy (e.g., news literacy, risk literacy, financial literacy). We were unable to identify any articles that empirically tested the effect of algorithm literacy on algorithm aversion. Therefore, we suggest that research is warranted to enhance our understanding.

2.4 Hypotheses Development

The general findings in human-algorithm interaction research show that users are not inclined to utilize advice if it is from an algorithm. Several explanations have been offered as to why patients would be reluctant to use algorithmic advice including false expectations[2] (Burton et al., 2019), the black-box nature of medical AI models (Cadario et al., 2021), and uniqueness neglect (Longoni et al., 2019). In line with Burton et al.'s (2019) suggestion that algorithm literacy may mitigate algorithm aversion, we propose that people with a higher level of algorithm literacy will be less likely to exhibit algorithm aversion compared to those with lower levels of algorithm literacy. Our hypotheses are depicted in Figure 1a and Figure 1b.

Decisions in healthcare often require in-depth medical knowledge and are regarded as subjective tasks. The high uncertainty that is often associated with healthcare decisions suggests that patients who do not generally have medical knowledge may be more open to accepting advice. Prior studies, however, indicate that people generally do not rely on advice from

[2] Burton et al.(2019, p.18) characterized false expectations as: "A human decision maker's proclivity to utilize an algorithmic aid is influenced by that decision maker's past experiences and expectations for how the algorithm should perform; algorithms and humans are held to different standards."

algorithms in healthcare settings. Longoni et al.(2019), for example, reported algorithm aversion and suggested that this may be due to the fact that patients perceive that statistical models do not account for an individual's unique characteristics (characterized as uniqueness neglect). They explain that people view statistical predictive models as a standardized solution and thus view algorithms as advice applicable to others, but inadequate to account for their unique circumstances. Algorithm aversion exists in the healthcare domain (Longoni et al., 2019), even when the algorithms can provide advice to their users with little to no wait time (Ho & Quick, 2018). Consistent with prior literature on algorithm aversion, we posit the following replication hypothesis:

H1: Individuals show higher advice utilization in a medical context when the advice is from a human professional than when the advice is from an algorithm.

Figure 1a: H1 (Replication Hypothesis)

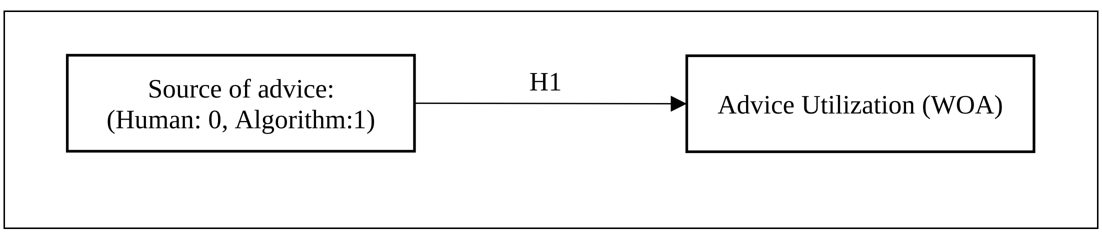
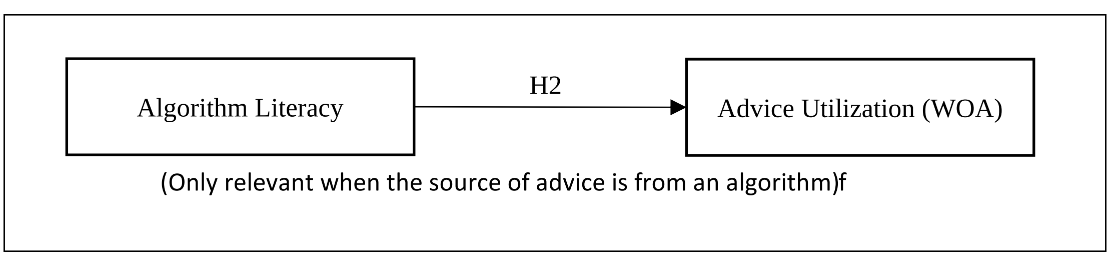


Figure 1b: H2



Next, we focus on the mitigating role of algorithm literacy on algorithm aversion behavior. As algorithm literacy deals with the statistical knowledge of predictive machine learning models and users' ability to apply such knowledge when using an algorithmic solution, people who feel more informed and empowered to use algorithms will be less likely to feel overwhelmed by them. Similarly, algorithm literacy can help users understand the black box nature of algorithmic prediction models. Those with higher algorithm literacy are more likely to better understand the factors that influence the output of an algorithm, including the data and the algorithms that drive the opaque prediction models. Thus, we posit the following hypothesis:

H2: Higher algorithm literacy will be associated with less algorithm aversion.

2.5 Research Method

We conducted an experiment to test our research model and hypotheses. We chose the experimental method to examine the causal effect of advice source (algorithm vs. doctor) on advice utilization in the context of rash diagnosis. Experiments are useful for examining causal effects; experiments can be designed to eliminate the possibility of reverse causality as the independent variable(s) can be manipulated. Further, the random assignment of study participants to different groups is one of the most effective ways to rule out endogeneity issues (Coleman, 2018). Thus, a well-designed experiment allows researchers to achieve higher internal validity than is possible with other research methods. Experiments have been widely used by scholars who study algorithm aversion and appreciation (Castelo et al., 2019; Colquitt et al., 2002; Dietvorst et al., 2015, 2018; Lim & O'Connor, 1996; Logg et al., 2019; Longoni et al., 2019).

2.5.1 Experimental Design, Task, and Procedure

The experiment involved an alternative-treatments design with pretest. The intervention was the source of the advice, either from a human doctor (human advice group) or from an algorithm (algorithm advice group). Our dependent variable, the weight of advice (WOA), was measured using both pretest (observation before the manipulation) and posttest (observation after the manipulation). Throughout this manuscript, we define *initial estimate* as the decision-maker's estimate before receiving any advice (pretest observation), and *final estimate* as the estimate after receiving the advice (posttest observation). For the experimental task, we created a skin rash diagnosis task.

After the participants agreed to participate, they were briefed about a health symptom checker mobile app (i.e., what it is and how it works). Next, participants were given a task in which they are asked to identify a rash they are hypothetically experiencing. People discount health advice when they have a higher perception of knowing about the disease (Woodcock et al. 2021), which can be explained by confirmation bias. In the context of reviewing advice from a symptom checker app, confirmation bias relates to the tendency to interpret and favor the explanation that the rash is a type they know about without giving enough consideration to other explanations. In order to avoid the possible confirmation bias towards certain more common rash types, we excluded drug rash or rashes from poison ivy or poison oak from the potential diagnosis by adding information that the participant had not taken any drugs or had any contact with plants in the last few weeks. In addition to the location of the rash in question and its picture, participants were provided with a set of information on six different types of rashes (Figure 2) that are commonly misdiagnosed (Kellawan et al., 2018). Participants were asked to provide six estimates (one per rash type) with each estimate representing their confidence (0% - 100%) that the rash type matched the rash they were hypothetically experiencing. The same questions were asked both before and after receiving advice that allegedly came from an algorithm or a medical professional.

After making the initial estimate, participants were randomly assigned to one of two groups that received the same advice but allegedly from different sources (a medical doctor or an algorithm). The advice was the likelihood that the rash corresponded to each of the six rash types, ranging from 2% to 95%. Participants in each group were then asked to re-evaluate their estimates after reviewing the advice they received from the agent (either medical doctor or algorithm). Algorithm literacy, as well as demographic information, were also collected.

Figure 2. Descriptions of rashes provided to participants

	Hidradenitis suppurativa	**Folliculitis**	**Stasis dermatitis**	**Cellulitis**	**Granuloma annulare**	**Tinea corporis**
also called	Acne inversa	Barber's itch	Venous eczema, varicose eczema		Pseudo-rheumatoid nodule	Body ringworm, athlete's foo
example picture						
Usually occurs in...	Armpits, groin, and buttocks where skin rubs together	In the arms, legs, and buttocks where body hair is present	Lower legs (ankles or shins)	Arms and legs	Hands and feet	Scalp and body
Symptoms	Lumps (pea- to marble-sized) under the skin that can be painful. Tend to enlarge and drain pus with an odor.	Small, white-headed pimples around the hair follicles. May itch or be painful.	Skin discoloration of the ankles or shins, itching, thickened skin, and open sores (ulcers).	Cellulitis may spread rapidly. Affected skin appears swollen and red and may be hot and tender.	Raised rash or bumps (lesions) in a ring pattern	Ringworm is typically scaly and may be red and itchy.

2.5.2 ***Participants***

One hundred eighty participants were recruited through the Prolific survey recruitment platform. Seven responses were filtered out based on failed attention checks[3], leaving us with 173 usable responses. The majority of participants were white, but both groups had a similar proportion of participants in terms of ethnicity (Appendix. Table A. Ethnicity by experiment groups). Table 1 summarizes the group characteristics. The two groups did not differ significantly in terms of demographics (age: p>0.05, gender), or whether they had health insurance (χ^2>0.05). The algorithm literacy cumulative score was also not significantly different between the two groups (algorithm literacy: p=.704).

Table 1. Group Characteristics

	Agent Group	**Count**	**Mean**	**SD**	**t-test *p***	X^2
Age	Human advice		33.83	12.89	0.112	
	Algorithm advice		36.87	12.10		
Algorithm Literacy	Human advice		3.85	1.04	0.704	
	Algorithm advice		3.90	0.81		
Gender	Human advice	Male: 42 Female: 42				0.941
	Algorithm advice	Male: 44 Female: 45				
Insurance	Human advice	With: 76 Without: 8				0.698
	Algorithm advice	With: 82 Without: 7				

[3] Two sets of questions were used as attention checks: "It is important that you pay attention to this survey. Select false for this response." For the second attention check, participants were asked to read a description of a telehealth app or an algorithmic app, depending on their assigned group. They were then asked the following questions "From the description above, what platform is this study about?" and "From the description above, which diagnostics category is this study about?"

2.5.3 ***Manipulations and Measures***

2.5.3.1 *Advice Source*

To test the effect associated with advice source, the two groups were provided with advice that allegedly came from either an algorithm or a human medical professional. One group was informed that the app was a telehealth service and that it connects the user with a medical professional (human-advice group). The other group was informed that the app was an algorithm that diagnoses skin rashes (algorithm-advice group).

2.5.3.2 *Algorithm Literacy*

To measure algorithm literacy, five of the true/false questions from Dogruel et al. (2021) were selected and adapted to match the context of healthcare application use. Participants responded to the following questions: “Algorithms can evolve as they interact with users and gather more data”, “Algorithms recognize when the results they provide are incomplete and can automatically correct themselves”, “An algorithm may give different results to two people who ask it the exact same question”, “Algorithms are able to think like human beings”, and “For some media companies, content that is repeated regularly (e.g., traffic reports) is already written by algorithms” (See Appendix Table B). The total number of correct answers was used to compute a score for this measure (min:0, max:5), with higher scores reflecting a higher level of algorithm literacy.

2.5.3.3 *Advice Utilization (Weight of Advice)*

We followed the JAS paradigm to measure advice utilization. The JAS paradigm assumes the participating decision-makers make a best guess for their initial estimate on matters they are not very familiar with (judgment under uncertainty) and then revise their estimate after receiving advice (Logg et al., 2019; Sniezek & Buckley, 1995) (See Appendix Figure A). Weight of

Advice (WOA) is the degree of utilizing the given advice: a WOA of 0% indicates the advice was completely ignored and a WOA of 100% suggests that the advice was fully accepted by the decision maker. WOA, the degree of taking the given advice, was calculated as the proportion of the difference between the initial estimate and the final estimate over the difference between the advice and the initial estimate (Hütter & Ache, 2016; Logg et al., 2019). F denotes the final estimate the participants (i) decided for each question (j), I is the initial estimate the participants (i) made for each question (j), and A is the advice given for each question (j).

$$WOA_{ij} = \frac{|(F_{ij} - I_{ij})|}{|(A_j - I_{ij})|}$$

2.6 Results

Table 2. shows that none of the correlations are statistically significant and that all correlation coefficients are less than 0.6, indicating multicollinearity would not be of concern.

Table 2. Descriptive Statistics and Correlations

		Mean	SD	Min	Max	1	2	3	4	5
1	**Agent Group**					-				
2	**Age**	35.39	12.54	18	4	0.12	-			
3	**Gender (m=0, f=1)**	0.50	0.50	0	1	0.01	-0.01	-		
4	**Insurance (n=0, y=1)**	0.91	0.28	0	1	0.03	0.01	-0.02	-	
5	**Algorithm Literacy Score**	3.87	0.93	1	5	0.03	0.00	-0.07	0.02	-

(no correlations are significant at p = 0.05)

2.6.1 Main analysis

All the WOAs for each rash were calculated except for the cases in which the participants' initial estimate was identical to the advice. Such cases were excluded from the analysis (2 out of 1038 cases). Also, as the WOA is highly sensitive to outliers especially when the provided advice is similar to the initial estimate, which may lead to WOA values outside 0 and 1 (Hütter & Ache, 2016), the outliers outside the 0 and 1 range were winsorized so that minimum value was set to 0 and the maximum was set to 1 (Logg et al., 2019). WOA of 0 indicates that the advice is fully discounted (fully ignored) and WOA of 1 indicates that the advice was fully taken (fully accepted). The mean WOA of the human-advice group was .44 and that of the algorithm-advice group was .37 (Table 3.WOA_t-test).

Rash #5 (Granuloma annulare) was the correct diagnosis and the between-group WOA was significant (*p*=.038) only for rash #5; WOA for other rash types did not show a statistically significant difference between groups. Participants in the algorithm-advice group expressed lower WOA (WOA_5=.65) than that of the human-advice group (WOA_5=.75).

Table 3. WOA t-test

		N	Mean	SD	Min	Max	Sig.
WOA_MEAN	Human-advice Group	4	0.44	0.26	0	1	
	Algorithm-advice Group	9	0.37	0.27	0	1	0.120
	Both Groups	73	0.40	0.27	0	1	
WOA_1	Human-advice Group		0.21	0.38	0	1	
	Algorithm-advice Group		0.17	0.36	0	1	0.571
	Both Groups		0.19	0.37	0	1	
WOA_2	Human-advice Group		0.23	0.41	0	1	
	Algorithm-advice Group		0.19	0.38	0	1	0.512
	Both Groups		0.21	0.40	0	1	
WOA_3	Human-advice Group		0.47	0.47	0	1	
	Algorithm-advice Group		0.37	0.44	0	1	0.144
	Both Groups		0.42	0.45	0	1	
WOA_4	Human-advice Group		0.38	0.42	0	1	
	Algorithm-advice Group		0.31	0.40	0	1	0.307
	Both Groups		0.34	0.41	0	1	
WOA_5	Human-advice Group		0.75	0.30	0	1	
	Algorithm-advice Group		0.65	0.34	0	1	0.038*
	Both Groups		0.70	0.32	0	1	
WOA_6	Human-advice Group		0.56	0.44	0	1	
	Algorithm-advice Group		0.54	0.43	0	1	0.680
	Both Groups		0.55	0.43	0	1	

*p<0.05
**p<0.01

A one-way analysis of variance (ANOVA) for the correct advice, rash type #5, also showed that the effect of the source (human vs. algorithm) on advice utilization was statistically significant (F(1,170) = 4.36, p = 0.038, ${\eta_p}^2$ = 0.025), supporting H1, consistent with algorithm aversion literature. We further analyzed the potential role of algorithm literacy on algorithm aversion behavior. A one-way analysis of covariance (ANCOVA) was run to examine whether algorithm aversion (regarding the correct advice, WOA of rash type #5) was still significant when including algorithm literacy as a covariate. The two assumptions on using algorithm literacy as a covariate for running ANCOVA were both met; Algorithm literacy was not different between the two groups (F(1,171) = 0.15, $p = 0.704$, ${\eta_p}^2 = 0.001$), nor were the homogeneity of regression slopes for algorithm literacy and agent types (F(1,168)=1.02, p=.313, ${\eta_p}^2$=.006). Levene's test indicated that the assumption of homogeneity of variance was not violated, F (1,170) = 1.02, p = .314. As shown in Table 4, even when including algorithm literacy as a covariate, ANCOVA shows that the effect of the treatment (advice coming from an algorithmic agent) on advice utilization (WOA) was still significant, F(1,169) = 4.13, p = .044, ${\eta_p}^2$ = .02 (further supporting H1).

Table 4. ANOVA & ANCOVA

	DV: WOA	
	ANOVA	**ANCOVA**
Treatment F-value (p-value)		
Advice Source	4.36 (*p*=0.038**)	4.13 (*p*=0.044*)
Covariate F-value (p-value)		
Algorithm Literacy		6.48 (*p*=0.012*)
Adjusted R^2	0.02	0.05
Marginal estimated means (SE)		
Human-advice group	0.75 (0.03)	0.75 (0.03)
Algorithm-advice group	0.65 (0.03)	0.65 (0.03)

*p<0.05
**p<0.01

While algorithm literacy was measured for both groups, for the purpose of hypothesis testing, the effect of algorithm literacy is only relevant for the algorithm-advice group. For the algorithm-advice group, the effect of algorithm literacy was significant but negative (β=-.24, SE=.04, p=.025) as shown in Table 5. This suggests that the more you know about algorithms (higher algorithm literacy) the less likely you are to utilize the advice from one (H2 not supported). The addition of control variables (age, gender, and insurance) did not alter the result.

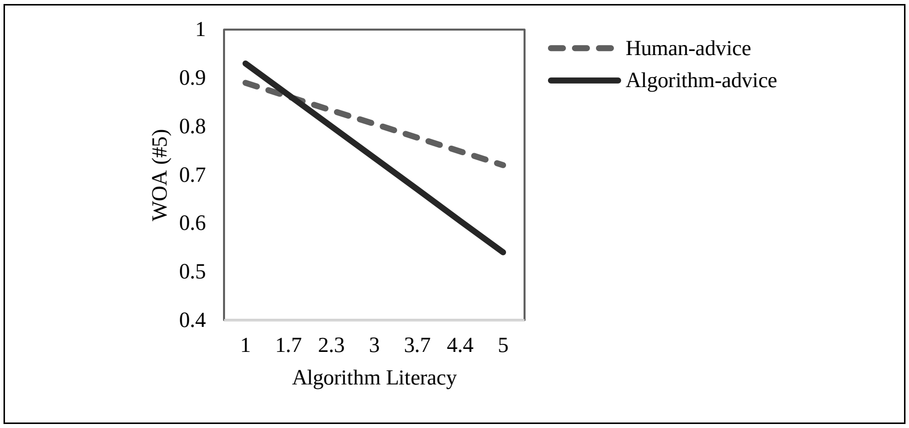
Table 5. Regression coefficients

	DV = WOA	
	Algorithm-advice group (n=88)	**Human-advice group** (n=84)
Algorithm Literacy	-0.24 (0.04) *p*=0.025*	-0.16 (0.03) *p*=0.160

Standard errors are in parentheses.
*p<0.05
**p<0.01

A simple slopes analysis, as shown in Figure 3, also revealed a significant negative slope of algorithm literacy on advice utilization among those who received advice from an algorithm (slope= -.10, SE= .04, p= .018). This suggests that advice discounting is exacerbated when the advice comes from an algorithm (algorithm-advice group) and when the individual has higher algorithm literacy. The slope associated with those who received advice from a human was not statistically significant (slope= -.05, SE=.03, p= .089).

Figure 3. Simple Slope for Algorithm Literacy by Advice Utilization (WOA)



2.7 Discussion and Conclusion

People rarely make decisions in isolation. Instead, they refer to external resources for information or receive advice from others (Bonaccio & Dalal, 2006). This is especially true in the medical field, where patients often lack relevant medical knowledge (Peng et al., 2013). Healthcare apps can be beneficial in such cases, as they can provide a diagnosis or medical advice in a timely manner.

Understanding the utilization of algorithmic-based healthcare services is becoming critical given the current surge in healthcare demand and the importance of providing affordable and high-quality healthcare (Cadario et al., 2021). Prior research had shown that algorithm aversion exists in the healthcare domain (Cadario et al., 2021; Esmaeilzadeh et al., 2021; Longoni et al., 2019). One of our aims was to see if such findings could be replicated (H1). Previous research has speculated that algorithm literacy may reduce algorithm aversion (Burton et al., 2019; Cabiddu et al., 2022; Kaufmann, 2021), but this has not been empirically tested. Therefore, in this study, we sought to answer whether higher levels of algorithm literacy may increase individuals' willingness to accept algorithmic advice in a healthcare context. We hypothesized that higher algorithm literacy would be associated with greater utilization of algorithmic advice (H2).

Our results showed that the phenomenon of algorithm aversion can indeed be replicated in the healthcare domain. Specifically, participants showed greater utilization of advice when it came from a doctor, as compared to an algorithm (supporting H1). In contrast, H2 was not supported. We hypothesized that algorithm literacy would reduce algorithm aversion, but our results showed the opposite, which contradicts what was implied in the prior literature (Burton et al., 2019; Cabiddu et al., 2022; Kaufmann, 2021). Our results indicate that greater algorithm literacy leads to more algorithm aversion, such that advice utilization is actually *lower* for those with higher algorithm literacy.

One potential explanation is that those with higher algorithm literacy may have been more cognizant of the limitations of algorithms, causing them to be more, rather than less, skeptical about accepting advice from an algorithm. For example, those with higher algorithm literacy may have been more concerned about uniqueness neglect. Longoni et al. (2019) suggested that patients are prone to algorithm aversion because they perceive that statistical models do not account for an individual’s unique characteristics (characterized as uniqueness neglect). They explain that people view statistical predictive models as a standardized solution, and thus they view algorithmic outputs as solutions applicable to others, but inadequate to account for their unique circumstances.

This study makes two contributions. First, it provides a strong empirical test of algorithm aversion in the context of rash diagnosis. Second, and more importantly, to the best of our knowledge this study provides the first empirical test of the relationship between algorithm literacy and algorithm aversion. Our findings show that, contrary to the assumptions in the literature, higher levels of algorithm literacy are actually associated with less willingness to accept advice from an algorithm. Thus, we suggest that the effects of algorithm literacy should be considered in future research on algorithm aversion.

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Appendix

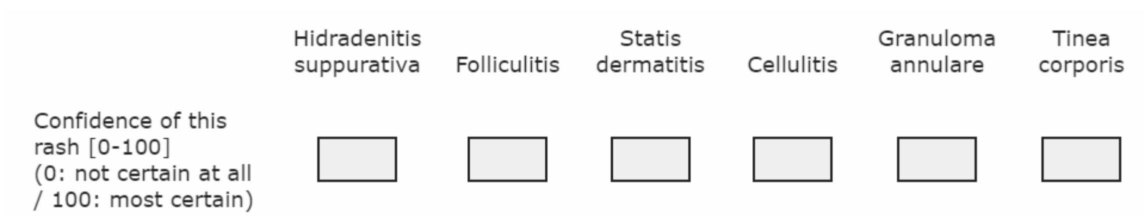
Table A. Ethnicity by experiment groups

Ethnicity	**Human-advice group**	**Algorithm-advice group**	**Total**
White	62	71	133
Black or African American	9	6	15
Hispanic or Latino	4	5	9
Asian	9	6	15
Native Hawaiian or Other Pacific Islander	0	1	1
Other	0	0	0
Total	84	89	173

Table B. Measures for Algorithm Literacy

Algorithm Literacy	Algorithms recognize when the results they provide are incomplete and can automatically correct themselves. [F → reverse coded]	Adapted from Dogruel et al., 2021 (reliability =.80)	7-point Likert-type scale (1=strongly disagree; 7=strongly agree)
	Algorithms can evolve as they interact with users and gather more data. [T]		
	An algorithm may give different results to two people who ask it the exact same question. [T]		
	Algorithms are able to think like human beings. [F → reverse code]		
	For some media companies, content that is repeated regularly (e.g., traffic reports) is already written by algorithms. [T]		

Figure A. Measures used in pretest (initial estimate) and posttest (final estimate)



3 ESSAY 3:

NUDGING WITH AGE PROGRESSION SOFTWARE IN HEALTH DECISION MAKING

3.1 Abstract

People tend to put off or avoid making decisions to engage in future oriented behaviors despite the future benefits it may bring to themselves or others. In this study, we conducted an experiment to investigate the influence of seeing one's future self on decision-making about the future. We also examined the role of decision type (egocentric or altruistic). First, we show that an AI generated personalized and realistic age progression video clip increases individuals' willingness to engage in a wide range of decisions about the future that have not been previously investigated using such an approach. Second, we show that one's perception of connectedness to their future self (i.e., future self-continuity (FSC)) mediates this relationship. As with previous studies conducted in other contexts, we found that FSC increased the willingness to engage in decisions about the future. However, we found that the age progression treatment decreased FSC, which led to a negative indirect effect of the treatment through FSC. The total effect of the treatment was positive as the magnitude of the indirect effect was smaller than that of the direct effect. Lastly, we tested whether decision type (i.e., egocentric vs. altruistic) moderates the mediation relationship. The conditional indirect effect revealed that the indirect effect was significant for the egocentric decision type, but not for the altruistic decision type.

3.2 Introduction

A common theme in many life decisions is that one must sacrifice in the present in order to reap greater rewards in the future. Decision-making about one's health is no different. The problem is that many people prefer instant gratification and are unwilling to sacrifice in the present to enrich their future well-being. Thus, decisions to engage in healthy behaviors can be challenging because of the temptation for instant gratification rather than foregoing such temptations and investing in one's long-term health.

3.2.1 Delay discounting in healthcare

Delay discounting refers to the tendency for individuals to value immediate rewards more highly than those that are delayed (Scholten et al., 2019). In the context of healthcare, delay discounting refers to the tendency to put off decisions about engaging in healthier behaviors despite the long-term benefits that could result from such behaviors (Chapman, 2005). This could include decisions to adopt a healthy diet, quit smoking, undergo recommended health screenings, or get vaccinated. Because unhealthy behaviors often have delayed effects on health, delay discounting can be a major barrier to effective health management, which can contribute to negative health outcomes over time.

3.2.2 The cost implication of delay discounting in healthcare in the U.S.

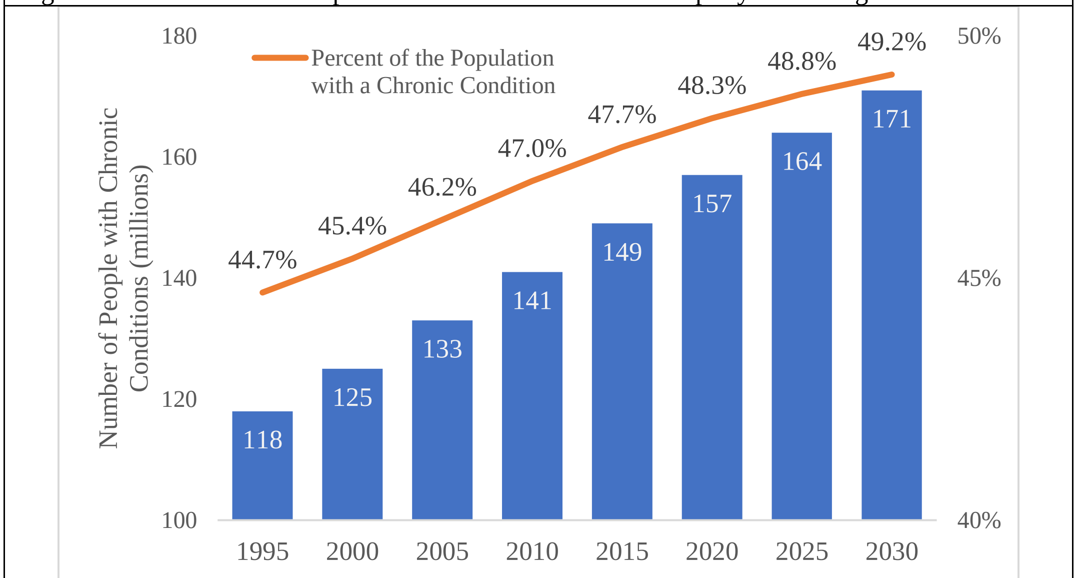
According to the Centers for Medicare & Medicaid Services (CMS, 2021)), national health spending in the United States reached $4.3 trillion, accounting for 18.3% of the nation's gross domestic product (GDP). Approximately 13% of personal healthcare expenditure is devoted to end-of-life care (Aldridge & Kelley, 2015), the care that often results in managing complications of chronic disease (Lynn & Adamson, 2003). For example, 47.1% of chronic disease costs were attributed to obesity in 2016, amounting to $1.72 trillion, or 9.3% of the U.S. GDP in that year. Obesity is the leading risk factor for chronic diseases in the U.S., having steadily risen since the

'60s. (Waters & Graf, 2018). Similarly, O'Connell and Manson (2019) reported that diabetes alone costs the U.S. over $403 billion annually, an expenditure that is expected to grow to a projected $825 billion by 2030 (Williams et al., 2020). Further, approximately 8.7% of healthcare spending in the U.S. can be attributed to chronic disease that results from cigarette smoking and exposure to secondhand smoke (Waters & Graf, 2018). Much of the costs that are currently spent managing chronic diseases could be avoided, or at least reduced, if people engaged in healthier behaviors.

The Centers for Disease Control and Prevention (CDC) identified four risk factors that contribute to preventable chronic disease: lack of physical activity, poor nutrition, tobacco use, and excessive alcohol consumption (Schmidt et al., 2016). Their findings suggest that many chronic diseases can be prevented, minimized, or delayed if people take better care of themselves. But at the current pace, the number of Americans with chronic conditions is expected to grow as the population's life expectancy increases (Raghupathi & Raghupathi, 2018). Wu and her colleagues (2000) projected that approximately 171 million Americans will have chronic health conditions by 2030, a steady increase from 157 million in 2020 (Figure 1). This will lead to an increase in healthcare expenditure related to chronic health conditions, underscoring the need for interventions that encourage people to adopt a more health-protective lifestyle.

Chronic diseases are illnesses that usually last a long time. They tend to progress slowly and are often caused by genetics, environment, or unhealthy habits. The best strategies to deal with chronic diseases are to prevent and detect them early for efficient treatment. Unfortunately, many people put off decisions to engage in health-protective behaviors (Allegrante et al., 2019) despite the long term economic and health benefits. Such a tendency results in decisions that are not in the best interest of your future self. This is an example of a broader phenomenon known as delay discounting.

Figure 1. The Number of People with Chronic Conditions is Rapidly Increasing



Source: (Wu & Green, 2000)

3.2.3 Strategies for reducing delay discounting

Strategies to reduce delay discounting in healthcare, and thus encourage people to engage in health-protective behaviors sooner may involve helping people to connect with their future selves. Prior research has suggested various ways to try and reduce delay discounting. Scholten et al. (2019), in their systematic literature review, summarized training-based and manipulation-based approaches that aimed to reduce delay discounting. They found that the manipulation-based approaches were more effective in reducing delay discounting. While the training-based approaches focused on increasing the salience of future rewards, the manipulation-based approaches heightened one’s connectivity to the future self. An example of this approach is showing someone an age progressed photograph which may affect their future self-continuity (i.e., the degree to which people feel connected with their future selves). Hershfield et al. (2011)

suggest that future self-continuity is associated with behaviors that would benefit oneself in the future. Individuals with a low future self-continuity may perceive their future self as being almost a total stranger (i.e., psychologically distant) and therefore they may be less willing to engage in behaviors that would benefit themselves in the future.

Research has shown that people who have a strong sense of future self-continuity tend to have better long-term outcomes in areas such as financial planning (Hershfield, 2011), health (Blouin-Hudon & Pychyl, 2015; Reinhard et al., 2020), and overall well-being (Bixter et al., 2020). Interventions that aim to increase future self-continuity by encouraging people to think about their future selves, such as visualizing exercise activities or journaling, have been shown to be effective in improving decisions that result in larger long-term benefits.

3.2.4 Future decision type

Decision context may also influence delay discounting in healthcare. Odum et al. (2020) found that delay discounting is steeper for decisions regarding nonmonetary as opposed to monetary outcomes. People also show steeper delay discounting for health outcomes as compared to monetary outcomes (Baker et al., 2003). Contextual factors can also influence egocentric and altruistic future decisions. For example, Yi et al. (2011) found that people are more likely to make altruistic future decisions when rewards are further in the future. Bartels et al. (2013) found that feeling less connected to one's future self is associated with altruistic behaviors.

Egocentric future decisions refer to the ones that directly benefit your future self, such as practicing healthy diet habits, exercising regularly, or adhering to routine medical screening.

Altruistic future decisions, however, may benefit those around you in the future, often after your death, but may not directly benefit your future self. Such examples include creating an advance medical directive, creating a charitable trust, or planning on a burial plot.

This study investigates the effect of age-progression algorithms on delay discounting tendencies across egocentric and altruistic decisions:

> *RQ1: Does seeing your future self through an age-progressed algorithm influence one's tendency to engage in delay discounting?*

> *RQ2: Does the effect of age progression on delay discounting differ based on the type of future decisions, namely egocentric and altruistic future decisions?*

3.3 Background

3.3.1 Delay Discounting

Ignoring what ought to be done for the benefit of one's own future can be explained through delay discounting. People make numerous suboptimal decisions as most individuals do not act in a purely rational manner as traditional economics once assumed (Thaler & Sunstein, 2009). Instead, humans are affected by heuristics and biases and thus are prone to making suboptimal choices (Bazerman & Moore, 2012). Time and cost constraints also limit the available information, such that we tend to give greater weight to present concerns than to future concerns (Thaler, 2000). Pronin (2008) extends this view, suggesting that the human mind is comprised of multiple selves and that people perceive their future selves as being so distant that individuals may treat their own future selves like other people.

Discounting the future, which involves delaying actions that can affect the future, may lead to dire consequences as some future events require immediate action (Lewis Jr & Oyserman, 2015). Delay discounting has been studied in many contexts including finance, education, career management, and health (Urminsky, 2017). Ho et al. (2006) note that delay discounting is often found for decisions that involve either immediate costs with delayed benefits (e.g., regular exercise, health screenings) or immediate benefits with delayed costs (e.g., smoking, food obsession). Hershfield et al. (2011) expand this view, suggesting that delay discounting also occurs when immediate benefits are traded off against long-term ones.

The perspective that their future self can always take action later often leads to failure to sufficiently engage in preventive health behaviors. Notably, delay discounting is found to be steeper particularly for health outcomes than in other contexts such as monetary ones (Odum et al., 2020). Such delay discounting tendencies are often observed even among those who are health conscious (Urminsky, 2017). One explanation for such biased behavior is that the long-term benefits of health decisions are harder to quantify and may take more time to be realized. As preventive health behaviors typically require a long-term commitment for the benefits to be realized, interventions that focus on the future events are often not effective enough to motivate action today (Rutchick et al., 2018). Some scholars suggest that shifting individuals' temporal perspective to increase the psychological relevance of the future self for the current self could reduce delay discounting and encourage health-protective behavior. Scholten et al. (2019) found that future-provoking manipulations that promote episodic future thinking and connectivity to the future self can help reduce delay discounting.

3.3.2 *Future Self-Continuity*

Hershfield and colleagues (2011) describe future self-continuity as the sense of similarity and connection people feel with their future selves. Such psychological connection (with their future selves) influences the degree of delay discounting. Future self-continuity provides a way to understand how people perceive their future selves in relation to their current selves and how this perception affects their decisions, behaviors, and outcomes. When the psychological connections between one’s present and future self are strong (Hershfield, 2011), the long-term benefits of a decision may be clearer. Greater future self-continuity is associated with promoting behavior that would benefit oneself in the future, such that the closer you feel to your future self the more you will engage in behaviors that will benefit your future (i.e., less delay discounting). Conversely, the further away you feel from your future self (i.e., lower future self-continuity), the more delay discounting one will engage in, resulting in decisions that are less beneficial to your future self. In other words, when people perceive their future self as very different from the present self, they will care less about the welfare of that future, less connected self (Hershfield, 2011; Urminsky, 2017).

Several perspectives also support the influence of future self-continuity on delay discounting. The *multiple selves* perspective (Bazerman et al., 1998) describes internal conflicts as negotiations between current and future selves. Under the *multiple selves* perspective, future selves are seen as separate persons, rather than the same self at different points in time. The *failure of imagination* perspective focuses on the difficulty that people may have in projecting themselves to future selves (Blouin-Hudon & Pychyl, 2015; Hershfield, 2011).

3.3.3 Egocentric and Altruistic Future Decisions

As described in delay discounting, future decisions are choices we make in the present that impact the future. Future decisions are often characterized by their potential long-term impact, and such impact may not be immediately felt or apparent. The consequences of future decisions often accumulate over time, resulting in larger rewards or penalties in the future. The decisions that benefit one's future can be categorized into two types: egocentric and altruistic future decisions (Yi et al., 2011). Both involve future decisions that have larger long-term rewards. The main difference between the two is the intended beneficiary of the future rewards, either self or others. Batson (2002) defines altruism as the motivation to increase others' welfare, and egocentric as the motivation to increase the welfare of the future self.

Egocentric future decisions are often motivated by a desire to achieve personal satisfaction or gain. When thinking about healthcare needs, people are more likely to focus on their own personal health concerns. Such egocentric future decisions, motivated by a desire to improve one's own health and well-being, may include engaging in healthy exercise and diet, choosing to maintain a low-stress work-life balance, or engaging in preventive health (e.g., cancer screening). Conversely, altruistic future decision-making refers to the act of making choices that prioritize the well-being of others in the future. Such altruistic future decisions, motivated by a desire to improve the outcomes of others even at the cost of current discomfort or investment, may include charitable giving and decisions that could relieve the burden from your family after one's death (e.g., creating a funeral plan, advance medical directive, or writing a will).

3.4 Research Model and Hypotheses

We introduce our research model in Figure 2, followed by the theoretical logic that underpins our hypotheses.

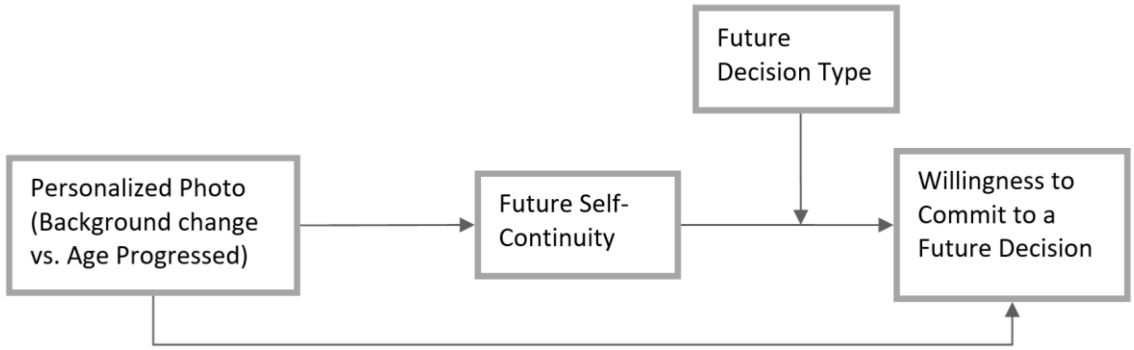


Figure 2. Research model.

3.4.1 Effect of Age-Progressed Photo on Delay Discounting

Scholten et al. (2019) found that manipulation-based approaches were more effective than training-based approaches in reducing delay discounting in the healthcare context. Manipulation-based approaches typically involve exercises that ask participants to vividly imagine the future or efforts that prime participants with thought exercises or photos of older people or their older selves. The growing interest in artificial intelligence (AI) supported tools has led to the emergence of innovative applications including apps that generate highly realistic images that depict individuals in an aged state. Apps such as AgingBooth, FaceApp, Snapchat, and TikTok (using the aging filter) have become a source of entertainment and self-expression, enabling individuals to engage in an imaginative exploration of their potential aging journey. By leveraging the power of AI, these apps provide individuals with a vivid and interactive experience that may encourage self-reflection and foster a deeper appreciation of what they will look like as they grow older.

Experiencing one's future self through age-progressed photos could provide people with a window into the future, which in turn, influences them to feel more connected to their future selves. In line with research that shows people may fail to identify with their future selves because of a lack of belief or imagination, Hershfield et al. (2011) propose that age-progressed renderings will encourage individuals to allocate more resources to that future. Age progression as a manipulation-based intervention has been studied in many contexts including personal savings (Hershfield, 2011), delinquent behavior (Van Gelder et al., 2013), alcohol dependency (Owen et al., 2019), UV skin care (Blashill et al., 2018; Persson et al., 2018; Williams et al., 2013), and smoking (Burford et al., 2013; Song et al., 2013). The collective findings suggest that this type of manipulation can reduce delay discounting. Thus, consistent with prior literature, we posit the following replication hypothesis:

H1: People presented with an age-progressed photo of themselves will show greater willingness to commit to a future decision compared to those who are presented with a non-age-progressed photo.

3.4.2 Underlying Mechanism of Age Progression: Future Self-Continuity

Hershfield et al. (2011) identified three research approaches that aim to reduce delay discounting through manipulation-based interventions. One approach utilizes precommitment strategies to constrain future behavior, using remedies that would appeal to long-term planners. Studies using this approach conceptualize problems with intertemporal decision-making as conflicts between different selves; long-term planners and short-sighted doers. The second approach seeks to increase the appeal of future benefits that can be realized by investing in one's future early. Studies using this approach assume people have difficulties in appreciating the future benefits in the present time. A third approach that Hershfield et al. (2011) suggested focuses on the temporal selves rather than the current or delayed rewards. This approach is in line with the notion that neglecting the future self may be due to a lack of imagination (Parfit, 1984). The connectedness of the current self to the future self represents the degree to which the current self acknowledges that the future self is indeed the same self. Hershfield et al. (2011) suggest that a vivid image of the future self may help one to imagine what the future holds, which in turn, would reduce delay discounting tendency.

People engage in future-supporting decisions (i.e., less delay discounting) when the future self is experienced as more connected to the current self (Ersner-Hershfield et al., 2009; Lewis Jr & Oyserman, 2015). Rutchick et al. (2018) cite Pronin & Ross (2006) and Wakslak et al. (2008) as examples of attributional thinking to support the idea that feeling closer to your future self (i.e., higher future self-continuity) requires effort as people tend to think of their future self as a totally different person, like a stranger. The influence of future self-continuity on reducing delay discounting has been studied in many domains, including retirement savings (Bartels et al., 2013; Hershfield, 2011; Zhang & Aggarwal, 2015), exercising for better health (Rutchick et al., 2018) and academic achievements (Adelman et al., 2017; Blouin-Hudon & Pychyl, 2015). Thus, consistent with prior literature, we posit the following replication hypothesis:

H2: Future self-continuity will mediate the relationship between seeing an age-progressed photo of oneself and willingness to commit to a future decision.

3.4.3 Moderating Role of Future Decision Type

We posit that the type of future decision (e.g., egocentric or altruistic) is also an important factor for studying delay discounting using future self-continuity. We therefore investigate the type of future decision as a factor moderating the mediating effect of future self-continuity on the relationship between seeing an age-progressed photo of oneself and delay discounting tendency. As suggested earlier, the motivation for decisions that lead to future rewards can be categorized as egocentric and altruistic (Yi et al., 2011), depending on the intended beneficiary of the decision. The key difference between these two types of decisions for the future is the perspective from which the decision is made. Altruistic decision-making takes a broader view, considering the well-being of all those who will be affected by the decision. Egocentric decision-making, on the other hand, focuses solely on the individual who makes the decision and their personal goals and desires.

As the age progression video clip influence one's FSC, the degree of connectedness one has with their future self, this may evoke a stronger sense of self-awareness; individuals who experience a more pronounced effect on their FSC may make egocentric future decisions. Since FSC does not help people to understand the future needs of others, any elevation of FSC induced by seeing an age-progressed photo of oneself would not be expected to influence to make altruistic future decisions. Thus, we hypothesize that future decision type (altruistic or egocentric) will moderate the effect of seeing an age progressed photo of oneself on delay discounting tendency such that:

H3: Altruistic or egocentric future decision type will moderate the extent to which future self-continuity mediates the indirect effect of seeing an age progressed photo of oneself on willingness to engage in future decisions. More specifically, the indirect effect of future self-continuity will be greater when the future decision type is egocentric than when the future decision type is altruistic.

3.5 Method

3.5.1 Research Design and Participants

Following previous studies that used vivid photos to influence people’s future self-continuity (Burford et al., 2013; Hershfield, 2011; Lee et al., 2020; Song et al., 2013), we use a highly suggestive age progressed photo of oneself as the intervention in this study. The study employed a mixed design with one between subject factor (age progression vs. no age progression) and one within subject factor (future decision type: egocentric / altruistic). Participants were randomly assigned to treatment or control groups and were asked to respond to two sets of decisions (one set of altruistic decisions and one set of egocentric decisions). The contexts of the egocentric future decisions were (a) ‘healthy exercise’, (b) ‘work-life balance’, and (c) ‘get screened for colorectal cancer’. The contexts of the altruistic future decisions were (d) ‘body donation for medical research’, (e) ‘fill out advance medical directives’, and (f) ‘create charitable trust’. The altruistic and egocentric decision type questions were displayed in a random sequence to remove any order effects.

The study used the Qualtrics survey platform to record participants' responses and the participants were recruited through the Prolific survey recruiting platform. The study was conducted in two phases: headshot photo collection (stage 1) and the main study (stage 2). One hundred seventy-two participants completed stage 1, and the final sample size of this study who completed stage 2 was 156. We assumed a medium effect size for power analysis following previous studies that used age progression as a treatment (Blashill et al., 2018; Burford et al., 2013; Williams et al., 2013). We calculated the required sample size using G*Power, which yielded a sample size of N=128 with a power of .80 and α =.05.

3.5.2 Procedure, Treatment, and Measurements

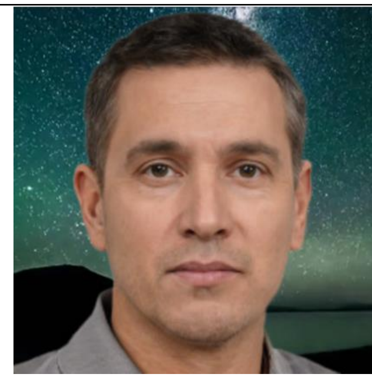
In stage 1 of the study, after the participants agreed to participate by submitting the informed consent, they were asked to provide their age and whether they have a webcam or a camera to take a photo of themselves. On the following page, participants were asked to upload a headshot photo using their webcam or their mobile device. After uploading their photo, participants were asked about their experience regarding certain lifestyle choices and decisions. The questions included whether they (a) exercise regularly, (b) maintain a work-life balance, (c) have already had CRC screening, (d) have signed up to donate their body for medical research, (e) have completed an AMD, and (f) have created a charitable trust (see Appendix B for questions and responses). As the dependent variable that was collected in the second stage asked about their willingness to commit to the items (a-f) above, these questions were later used to filter out participants who had already had CRC screening, already signed up to donate their body for medical research, already completed an AMD, or already created a charitable trust. In addition to the questions on lifestyle choices and decisions, we collected participants' future orientation using the consideration of future consequences (CFC) scale, measures adapted from Enzler et al. (2019) (see Appendix F for items and scale). Participants were then informed that they would be invited to a follow-up study, which would be scheduled within a week. In the follow-up study, participants were randomly assigned to one of two groups in which they saw either a short video of the photo they provided against an animated background (control group, i.e., no age progression) or a short video clip of the photo they provided being age progressed to appear as an 80-year-old person (treatment group).

Building a realistic and personalized video clip, which would enable the participants to meet their older selves was particularly important in this research to understand the effectiveness of age progression treatments, as people tend to perceive their future selves as complete strangers in behavioral studies (Hershfield, 2011; Hershfield et al., 2011; Pronin et al., 2008). We used an implementation of Alaluf et al. (2021)'s Style-based Age Manipulation (SAM) algorithm to enable age progression. SAM is an implementation of style-based generative adversarial networks (StyleGAN) that generate highly suggestive portraits based on input attributes including a photo to be used as a source. Background change was implemented using the MoviePy Python library. Figure 3 is an example of what the subjects saw depending upon whether they were in the treatment or control group.

The experiment design was a basic randomized design comparing treatment to control. After being randomly assigned to one of the two groups, participants were shown one of the two video clips. Those in the control group saw an animated clip with a background change, while those in the treatment group saw themselves growing old, from their current age to age 80 (see Figure 3). After seeing the video clip of the assigned group, participants were asked to respond to future decisions (Appendix D). A greater willingness to engage in each future decision indicates lower levels of delay discounting.

The next section of the survey measures participants' perception of connectedness to their future self (future self-continuity: Hershfield et al., 2009) by selecting one of the images with two circles, with varying degrees of overlap. One circle is labeled as the current self and the other circle is labeled as the future self at age 80. The degree of overlap of the circle indicates how close you (current self) consider yourself to be to your future self (Figure 4, see Appendix E for the exact instructions used). We also measured the temporal distance to your future self (see appendix G for measure for the items and scale). The experiment concluded with manipulation check questions (Appendix H) to assess whether participants correctly identified the age of the person in the age progressed video clips as much older than they currently are.

Figure 3. Original photo[4], a screenshot of age progressed video clip, and a screenshot of background changed video clip

Original photo	Age Progressed	Background changed
		

In addition to the main study, we also conducted a separate independent manipulation check to verify whether participants correctly recognized each decision about the future as an altruistic or an egocentric one. As introducing a manipulation check prior to the decision task might have created demand effects, an independent manipulation check was employed. A separate group of participants (N=40) were recruited and responded to questions that asked their perception on the degree to which each future decision (a-f) benefits the self (egocentric) or others (altruistic). The seven-point scale items were presented in random order (see Appendix I for questions and scale).

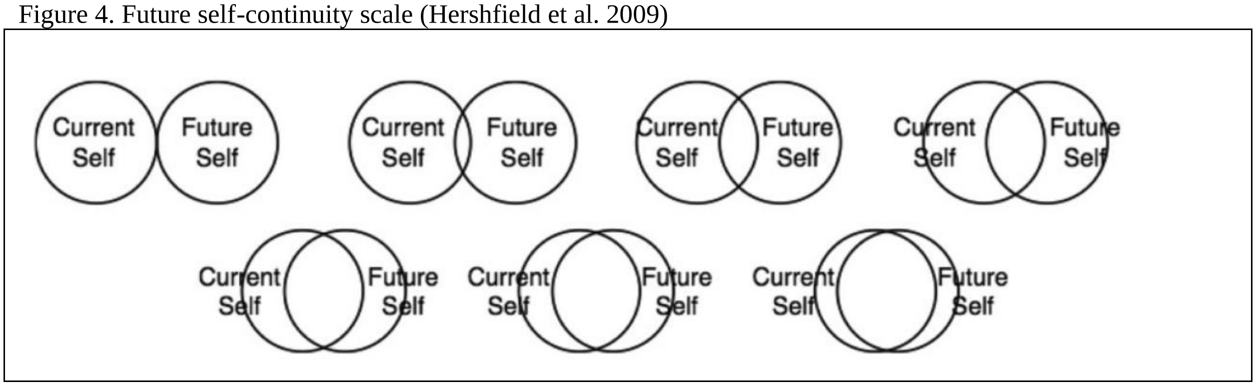
3.6 Analysis

Data for the experiment were first analyzed using mixed design ANOVA in SPSS (version 25.0, IBM Corp., 2017). The participants were randomly assigned to either the treatment group (i.e., age progressed video clip condition) or the control group (i.e., background changed video

[4] The person in this photo does not exist; the image is AI-generated. Due to privacy concerns, the photo in this table was picked from a pool of randomly generated photos from the https://generated.photos service that uses a generative adversarial network (GAN) method to create a realistic portrait.

clip with no age progression). Participants were also asked about their willingness to engage in both altruistic and egocentric future decisions. Mixed ANOVA assesses the mean differences of the groups with respect to two factors: the within-subjects factor, which in our case is the altruistic and egocentric future decisions, and the between-subjects factor, which was whether or not the subject received the age progression treatment. A mixed design ANOVA also enabled us to probe for possible interaction between these two factors on participants' willingness to engage in future decisions.

Figure 4. Future self-continuity scale (Hershfield et al. 2009)



In order to test the research model and associated hypotheses, I use the Hayes PROCESS macro (Hayes, 2017) in SPSS. The PROCESS macro enables path analysis using bootstrapped regression, a widely used method to test research mediation models. As the research model involves a second-stage moderation, the moderated mediation analysis will be based on Model 14 of the PROCESS macro with 10,000 bootstrap samples. The significance of the direct and indirect relationship as well as that of the interaction with the moderator will be critical in determining whether our hypotheses are supported.

3.7 Results

Table 2 shows descriptive statistics for the participants in the study. Age, gender, insurance, and participants' future orientation did not differ across groups ($p > .05$). The proportion of those who did not have any existing medical condition, however, was different between the two groups (X^2(1, N=156) = 5.82, *p*=.016). Therefore, subsequent analyses will include the existing medical condition as a control variable.

Table 2. Descriptive Statistics and Tests to Determine if Randomization was Successful

Items	**Control group (n=78)**			**Treatment group (n=78)**			**t-test**	**Sig.**
	Mean (SD)	Min	Max	Mean (SD)	Min	Max		
Age	37.58 (5.86)	30	50	38.55 (5.81)	30	50	t(154)=-1.04	.299
Future orientation	4.62 (.75)	3	6.67	4.50 (.60)	2.33	6.00	t(147)=1.10	.275
Items	**Control group (n=78)**			**Treatment group (n=78)**			**Chi − square test X^2(1,N=156)**	**Sig.**
Gender	Male: 36, Female:42			Male: 44, Female: 34			1.64	.200
Insurance	Uninsured: 9, Insured: 69			Uninsured: 10, Insured 68			.06	.807
Existing medical condition	Don't have: 50, Have: 28			Don't have: 35, Have: 43			5.82	.016

An independent manipulation check (N=40, Table 3) confirmed that the participants view exercising, CRC screening, and work-life balance as egocentric future decisions that benefit the future self (mean: 5.58), and that they view body donation for medical research, completing an advance medical directive, and creating a trust for charity as altruistic future decisions (mean: 1.83).

Table 3. Independent manipulation check

Items (N=40)	**Mean (SD)**	**Decision Type**	**Mean (SD)**	**t**	**Sig.**
Exercising	1.30 (.69)	Egocentric future decisions	1.83 (.89)	15.80	*p*<.001
CRC	2.18 (1.75)				
Work-life balance	2.03 (1.54)				
Body donation	6.28 (1.30)	Altruistic future decisions	5.58 (1.20)		
AMD	4.65 (2.13)				
Charity	5.80 (1.49)				

Table 4 shows the age progression manipulation check result. The seven-point scale question asked the relative age of the provided video clip compared with the current self, from much younger to much older (see Appendix H). Participants in the age progression treatment group rated the person in the video clip as much older than they currently are (mean: 6.51), while those in the control group (background changed only; no age progression) rated the person in the video clip as similar to their current age (mean: 3.97).

Table 4. Manipulation Check

Manipulation check items	Treatment Mean (SD)	Control Mean (SD)	T-test result [t (sig.)]
Relative age[5]	6.51 (.75)	3.97 (.60)	-23.276 (p<.001)

To test Hypothesis 1, we conducted a one-way MANOVA with the age progression treatment as the between-subjects factor and a MANCOVA with existing medical conditions as a covariate. Participants' responses about their lifestyle and experience were used as filters[6], resulting in n=109. Table 5 presents the MANOVA and MANCOVA results. MANOVA results revealed a significant effect of the age progression treatment on participants' decisions about the future (F(6,102)=2.36, *p*=.035). In addition, the willingness to engage in decisions about the future was higher for those who received the age progression treatment for each of the six decisions (Appendix C), supporting H1. The MANOVA results showed a medium-large (Cohen, 2013) effect size (η_p^2=.122) of age progression treatment, with a power of .79. The main effect of age progression treatment, however, was not significant at the p<0.05 level (F(6,101)=2.08, *p*=.062) in the MANCOVA where existing medical condition was introduced as a covariate (F(6,101)=1.53, *p*=.176). Thus, ANCOVA[7] was used for further univariate analysis of each decision about the future (Table 6).

Table 5. MANOVA and MANCOVA

Between-subject factor	Method	Pillai's Trace	F	Sig.	Partial η^2	Power
Treatment	MANOVA	.122	F(6,102)=2.364	.035	.122	.790
Treatment	MANCOVA	.110	F(6,101)=2.081	.062	.110	.727
Existing condition		.083	F(6,101)=1.531	.176	.083	.569

[5] Another manipulation check question, 'Help me imagine', also showed consistent results (Appendix A).
[6] For example, the individual analysis on willingness to sign up for CRC screening only included those who responded no to CRC screening experience. The different sample sizes in Tables 4, 5, 7a, 7b,8a, and 8b are the result of applying each filter for each decision about the future.
[7] For the sake of completeness, the ANOVA result of each decision about the future is displayed in Appendix C.

The covariate, the existing medical condition, was not significantly related to participants' decisions about the future except for the case of work-life balance (F(1,153)=4.46, *p*=.036). There were significant effects of the treatment (i.e., age progression) on all decisions about the future except those involving body donation for medical research (F(1,124)=1.071, *p*=.303) and completing an advance medical directive (F(1,138)=1.236, *p*=.268). These two decisions represent altruistic future decisions. In contrast, the treatment was found to have significant effects on all three egocentric decisions.

Table 6. ANCOVA result

Items	**Treatment**		**Control**			**F**	**Sig.**	**Partial η^2**	**power**
	Mean (SD)	**n**	**Mean (SD)**	**n**					
a. Exercise (n=156)	5.83 (1.273)	78	5.27 (1.625)	78	Treatment	F(1,153)=7.121	.008	.044	.755
					Covariate	F(1,153)=2.271	.134	.015	.322
b. Work-life balance (n=156)	5.56 (1.429)	78	4.82 (1.807)	78	Treatment	F(1,153)=5.858	.017	.037	.672
					Covariate	F(1,153)=4.463	.036	.028	.555
c. CRC screening (n=137)	5.97 (1.106)	68	5.59 (1.428)	69	Treatment	F(1,134)=4.337	.039	.031	.543
					Covariate	F(1,134)=3.585	.060	.026	.468
d. Body donation (n=127)	4.23 (1.731)	60	3.88 (1.674)	67	Treatment	F(1,124)=1.071	.303	.009	.177
					Covariate	F(1,124)=.520	.472	.004	.110
e. AMD filled out (n=141)	5.25 (1.481)	71	4.89 (1.528)	71	Treatment	F(1,138)=1.236	.268	.009	.197
					Covariate	F(1,138)=2.275	.134	.016	.322
f. Charity set up (n=155)	3.90 (1.648)	78	3.25 (1.778)	78	Treatment	F(1,152)=4.543	.035	.029	.563
					Covariate	F(1,152)=1.011	.316	.007	.170

Using aggregate measures for the two decision types (a linear average of the three egocentric decisions (1-3) and a linear average of the three altruistic decisions (4-6)), a mixed-design ANCOVA (Table 7) revealed that there was a positive and significant main effect of the treatment (F(1,106)=7.67, *p*=.007), while the covariate was not significant. There was also a significant main effect of decision type on participants' willingness to engage in decisions about the future (F(1,106)=93.47, *p*<.001) such that participants were more willing to engage in egocentric decisions than altruistic ones. There was no significant interaction between decision type and the age progression treatment (F(1,106)=.90, p=.345), and the covariate (F(1,106)=1.54, *p*=.218) was not significant. The insignificant interaction (future decision type * age progression treatment) indicates that the effect of the age progression treatment did not vary depending upon whether the decisions were egocentric or altruistic.

Table 7. Mixed design ANCOVA

		F (1,106)	**Sig.**	**Partial η^2**	**power**
Between-subjects	Age progression treatment	7.67	.007	.067	.783
	existing_condition (covariate)	.02	.899	<.001	.052
Within-subjects	Future decision (FD) type	93.47	<.001	.469	1.000
	FD_type * age progression treatment	.90	.345	.008	.156
	FD_type * existing_condition (covariate)	1.54	.218	.014	.233

FD_type: future decision type

Continuing to use the aggregate measures for the two decision types, we performed separate mediation analyses for the two decision types using Hayes' PROCESS macro (model 4). Table 8a summarizes whether future self-continuity (FSC) mediates the effect of the age progression treatment on decisions about the future. The results show that the indirect effect through FSC is significant (-.13, LLCI=-.285, ULCI=-.012), supporting H2. However, while the age progression treatment negatively and significantly lowered FSC for both decision types, the indirect effect was significant only for altruistic decisions. Existing medical condition was not a significant covariate for any of the paths (Table 8b).

Table 8a. Mediation analysis results (M: FSC)

Items	**Direct effect (c' path)**		**X→ M (a path)**		**M→Y (b path)**		**Indirect effect**			**Total effect (c path)**	
	c'	*sig.*	a	*sig.*	b	*sig.*	a*b	LLCI	ULCI	c	*sig.*
Both future decision types (n=109)	.64	.001	-1.02	.003	.12	.021	-.13	-.285	-.012	.51	.007
Egocentric future decisions (n=136)	.54	.017	-.99	.002	.11	.107	-.11	-.301	.018	.43	.065
Altruistic future decisions (n=117)	.74	.002	-1.07	.002	.15	.012	-.16	-.325	-.029	.57	.010

Table 8b. Covariate results for mediation analyses						
Items	**Outcome: M**		**Outcome: Y**		**Total effect model**	
	cov	*sig.*	cov	*sig.*	cov	*sig.*
Both future decision types (n=109)	.10	.782	.01	.947	.02	.899
Egocentric future decisions (n=136)	-.23	.467	.23	.345	.20	.407
Altruistic future decisions (n=117)	-.00	.994	.04	.870	.04	.874

Table 9a summarizes the six individual mediation results. The analysis included existing medical condition as a covariate; the effect and its significance are shown in Table 9b. The age progression treatment negatively and significantly affected future self-continuity (a-paths, $p<.05$) for all six future decisions. The effect of the mediator (FSC) on willingness to engage in decisions about the future was significant for most cases, except for exercise (.09, p=.175) and body donation (-.01, p=.905). This led to the insignificance of the indirect effect for both cases, the significance of which is indicated by the fact that zero is not contained within the lower-level (LLCI) and upper-level confidence intervals (ULCI). For the other four decisions, FSC partially mediated the relationship between the age progression treatment and willingness to engage in decisions about the future.

Table 9a. Individual mediation analyses (M: FSC)											
Items	**Direct effect (c' path)**		**X→ M (a path)**		**M→Y (b path)**		**Indirect effect**			**Total effect (c path)**	
	c'	*sig.*	a	*sig.*	b	*sig.*	a*b	LLCI	ULCI	c	*sig.*
a. Exercise (n=156)	.72	.004	-.90	.002	.09	.175	-.80	-.251	.013	.63	.008
b. Work-life balance (n=156)	.81	.003	-.90	.002	.20	.008	-.12	-.412	-.050	.64	.017
c. CRC screening (n=137)	.62	.007	-.97	.001	.16	.011	-.16	-378	-042	.46	.039
d. Body donation (n=127)	.32	.303	-.77	.019	-.01	.905	.01	-.154	.176	.32	.303
e. AMD filled out (n=141)	.51	.058	-1.13	<.001	.20	.008	-.22	-.484	-.062	.29	.268
f. Charity set up (n=155)	.74	.010	-.90	.002	.18	.023	-.16	-.431	-.024	.58	.041

Table 9b. Covariate results for each individual mediation						
Items	**Outcome: M**		**Outcome: Y**		**Total effect model**	
	cov	*sig.*	cov	*sig.*	cov	*sig.*
a. Exercise (n=156)	-.23	.418	-.34	.158	-.36	.114
b. Work-life balance (n=156)	-.23	.418	.60	.021	.56	.036
c. CRC screening (n=137)	-.21	.482	-.39	.079	-.43	.061
d. Body donation (n=127)	-.30	.373	.22	.481	.22	.472

e. AMD filled out (n=141)	-.01	.985	.39	.124	.39	.139
f. Charity set up (n=155)	-.25	.394	.33	.239	.28	.316

Using the aggregate measures for the two decision types, we performed a second stage moderated mediation analysis using Hayes' PROCESS macro (model 14). As all participants responded to all six decisions about the future, a new dataset was created by merging (stacking) the existing dataset. Two new variables were created to make use of the stacked dataset. One of those variables stored the mean of participants' willingness to commit to egocentric or altruistic decisions about the future. The other indicated which decision type the new variable was storing. For example, if a response (row) had 6 as the mean of the dv for the egocentric items (a,b,c) and 4 for the altruistic ones (d,e,f), the stacked dataset would have two rows; one that has 6 as the newly created dv and decision type as egocentric, and the other that has 4 as the newly created dv and decision type as altruistic. The stacked dataset doubled the size of the original dataset (N=156), resulting in N=312. We excluded (listwise deletion) those who already had CRC screening, already signed up to donate their body for medical research, already completed an AMD, or already created a charitable trust. The final sample size for this analysis was n=218.

Figure 5 depicts the result of the moderated mediation analysis. Existing condition was included as a covariate, but was not found to be significant. The direct effect of the age progression treatment was significant and positive. The a-path was negative and significant, (-1.02, *p*<.001) and the b-path was positive and significant (.16, *p*=.008). However, the second-state moderated mediation was not significant, as indicated by the interaction (-.73, *p*=.406) of decision type and FSC on the dv, as well as the index of moderated mediation not being significant (.075, LLCI: -.112, ULCI: .254). The conditional indirect effect revealed that the indirect effect was significant for egocentric decision type (-.16, LLCI: -.315, ULCI: -.042), but not for altruistic decision type (-.09, LLCI: -.248, ULCI: .040). The difference between the conditional indirect effect (egocentric and altruistic) was not significant (Index of moderated mediation: .07, LLCI: -.114, ULCI: .251). Thus, H3 was not supported.

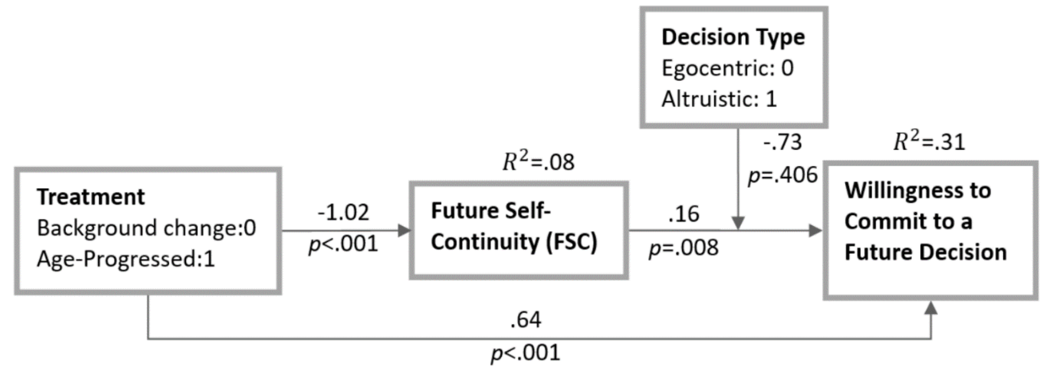


Figure 5. Second-stage moderated mediation.

Switching back to the original dataset (N=156), we also tested an alternative mediator, temporal distance, with results shown in Tables 10a-11. Using the aggregate measures for egocentric and altruistic decision types, we found that temporal distance did not mediate the relationship between the age progression treatment and the future decision (Table 9a). When we examined the individual decisions, we found that none of them showed any significant mediation effect associated with temporal distance (Table 11).

Table 10a. Mediation by decision types using aggregate measures (M: Temporal Distance)

Items	**Direct effect (c' path)**		**X→ M (a path)**		**M→Y (b path)**		**Indirect effect**			**Total effect (c path)**	
	c'	*sig.*	a	*sig.*	b	*sig.*	a*b	LLCI	ULCI	c	*sig.*
Egocentric future decisions (n=137)	.58	.004	.16	.395	.12	.295	.02	-.021	.128	.60	.004
Altruistic future decisions (n=117)	.35	.140	.10	.629	.05	.661	.01	-.028	.093	.35	.127

Table 10b. Covariate results from mediation analysis by decision type

Items	**Outcome: M**		**Outcome: Y**		**Total effect model**	
	cov	*sig.*	cov	*sig.*	cov	*sig.*
Egocentric future decisions (n=137)	-.36	.076	-.16	.295	-.20	.370
Altruistic future decisions (n=117)	-.43	.045	.28	.303	.25	.311

Table 11. Individual mediation analyses (M: Temporal Distance)											
Items	**Direct effect (c' path)**		**X→ M (a path)**		**M→Y (b path)**		**Indirect effect**			**Total effect (c path)**	
	c'	*sig.*	a	*sig.*	b	*sig.*	a*b	LLCI	ULCI	c	*sig.*
a. Exercise (n=156)	.63	.009	.04	.822	.06	.561	.00	-.031	.077	.63	.008
b. Work-life balance (n=156)	.64	.017	.04	.822	.03	.825	.00	-.042	.062	.64	.017
c. CRC screening (n=137)	.43	.054	.16	.401	.22	.030	.03	-.023	.204	.46	.039
d. Body donation (n=127)	.31	.308	.03	.890	.32	.023	.01	-.093	.196	.32	.303
e. AMD filled out (n=141)	.30	.243	.07	.719	-.20	.088	-.01	-.135	.051	.29	.268
f. Charity set up (n=155)	.60	.035	.02	.929	-.01	.908	-.00	-.058	.046	.60	.035

3.8 Discussion

In this research, we investigated the effect of an age progression treatment on people's decisions about the future (RQ1) and whether the effect would vary depending upon the type of decision (egocentric or altruistic) (RQ2). Our research shows that a personalized and realistic age progression video clip increases individuals' willingness to engage in decisions about the future (H1). Our findings show that one's perception of connectedness to their future self (i.e., future self-continuity (FSC)) mediates this relationship (H2). Lastly, we tested whether decision type (i.e., egocentric vs. altruistic) moderates the mediation relationship (H3). While the direct and indirect effects were significant (a: -1.02, p<.001; b: .16, p=.008; c`: .64, p<.001), the index of moderated mediation was not significant (.8, LLCI= -.112, ULCI= .254). However, the conditional indirect effect revealed that the indirect effect was significant for the egocentric decision type (-.16, LLCI= -.315, ULCI= -.042), but not for the altruistic decision type (-.09, LLCI= -.248, ULCI= .040).

Of particular note is that contrary to previous studies that that implied age progression treatments may serve to increase FSC (Ganschow et al., 2021; Hershfield, 2011; Rutchick et al., 2018), our results indicate that the age progression treatment actually decreases FSC.

Specifically, the path coefficient from X→M (where M=FSC) in our mediation model was -1.02 (p=.003). As in previous studies conducted in other contexts, we found that FSC increased the willingness to engage in decisions about the future (.12, p=.021). However, the indirect effect of the age progression treatment through FSC was negative (-.13, LLCI=-.285, ULCI=-.012). Furthermore, the size of the indirect effect was small compared to the direct effect (.64, p=.001) such that the total effect was positive (.51, p=.007). This suggests that contrary to prior theorizing (Hershfield et al., 2011; Van Gelder et al., 2013), FSC is not a good explanatory mechanism for the positive effect of age progression treatment on one's willingness to engage in decisions about the future. Thus, we explored perceived temporal distance as an alternative mechanism. However, there were no significant indirect effects with perceived temporal distance as a mediator.

3.8.1 Implication for Research

This study provides support for the effectiveness of age progression treatments in promoting individuals' willingness to make decisions about the future. This finding aligns with previous studies suggesting that visual representations of one's future self can enhance future-oriented behavior. However, our results challenge the assertion that future self-continuity (FSC) serves as an explanatory mechanism for this effect. Contrary to previous studies (Ganschow et al., 2021; Hershfield, 2011; Rutchick et al., 2018), we did not find that age progression treatments increased FSC. Indeed, we found the opposite (i.e., that the age progression treatment decreased FSC). This challenges the assumption that individuals' perceived connection with their future selves (FSC) is the primary driver behind the effectiveness of age progression treatments and suggests the need for further exploration of alternative mechanisms that may account for the observed effects.

3.8.2 Limitations and Future Research

As is always the case, our study is not without limitations. These limitations include: (1) our assumption regarding a medium effect size, (2) the use of stacked data for the moderated mediation analysis, (3) questions that remain regarding the explanatory mechanism for the effect of the age progression treatment on decisions about the future, and (4) testing only one possible age progression manipulation. First, we assumed a medium effect size based on the prior literature and this drove our sample size calculation. However, our empirical results revealed a small to medium effect size in some of our analyses. While the overall sample size provided sufficient power to detect effects on the aggregate measures used for our dependent variables, the effect sizes of individual ANCOVA analyses were small and our power to detect effect of this magnitude was low. This suggests that the sample size may not have been sufficient in some cases. For example, based on the WebPower calculator, a sample size of more than 670 participants would have been necessary to have sufficient power to rigorously test the effect of age progression treatment on exercise intentions.

Secondly, our mixed design necessitated the use of stacked data when analyzing moderated mediation, which was not ideal as it could introduce bias in detecting significance. Specifically, the used of stacked data inflated the sample size and could have produced a false positive. However, since we did not detect a significant second stage moderated mediation, any bias introduced through the analysis was not consequential.

In addition, despite testing future self-continuity (FSC) and future orientation as potential mediators, neither of them provided explanations for the effect of age progression treatment observed in this study. These findings raise questions about the underlying processes involved in age progression effects and highlight the need for future research to explore other potential mediators that may provide a better understanding of the underlying mechanisms at play.

Lastly, we used an age progressed video clip, but there are other ways that we could have manipulated individuals' connection their future selves. One such manipulation, for example, is to have participants imagine themselves as an older self. Our age progression treatment was delivered as an external stimulus and did not require deep thinking on the part of the individual receiving the stimulus. Other manipulations (i.e., internal) such as writing a letter to your future self might have produced a stronger or different psychological response. This differentiation between external and internal mechanisms emphasizes the importance of considering the specific processes involved in age progression treatments and the potential differential effects they may have on future-oriented decision-making.

3.9 Conclusion

In this research, we conducted an experiment to investigate the influence of seeing one's future self on decision-making about the future. We also examined the role of decision type (egocentric or altruistic). Our findings demonstrate that a personalized and realistic age progressed video clip increases individuals' willingness to engage in decisions about the future. This supports the effectiveness of age progression treatments in promoting future-oriented behavior.

However, contrary to previous studies, our findings suggest that seeing one’s future self actually decreases FSC, and that FSC does not explain the positive effect of age progression on individuals’ willingness to engage in decisions about the future.

In conclusion, while age progression treatments show promise in encouraging future-oriented behavior, our results emphasize the importance of considering alternative mediators and exploring the complexity of the underlying mechanisms involved. By addressing these research gaps, future studies can contribute to the development of effective interventions and strategies aimed at promoting individuals' engagement in decisions about their future.

3.10 Appendix

Appendix A. Manipulation Check

Manipulation check items	**Treatment Mean (SD)**	**Control Mean (SD)**	**T-test result [t (sig.)]**
Relative age	6.51 (.75)	3.97 (.60)	-23.276 (p<.001)
Help imagine[8]	4.83 (1.68)	2.05 (1.22)	-11.857 (p<.001)

Appendix B. Experience with DV items

	Yes	No
Do you exercise [9]regularly?	99	57
Have you ever been screened for colorectal cancer (e.g., colonoscopy)?	18	137
Are you maintaining a healthy work-life balance?	99	57
Have you signed up to donate your body after your death for medical research?	29	127
Have you ever filled out an Advance Medical Directives form to communicate your end-of-life care preference with your family members and healthcare professionals?	15	141
Have you ever set up a charitable trust to leave all or a portion of your estate to charity when you die?	1	155

Appendix C. ANOVA result

Items	**Treatment Mean(SD)**	**Treatment n**	**Control Mean(SD)**	**Control n**	**F**	**Partial η^2**	**power**
1. Exercise (n=156)	5.83 (1.273)	78	5.27 (1.625)	78	F(1,154)=5.824, *p*=.017	.036	.669
2. Work-life balance (n=156)	5.56 (1.429)	78	4.82 (1.807)	78	F(1,154)=8.126, *p*=.005	.050	.809
3. CRC screening (n=137)	5.97 (1.106)	68	5.59 (1.428)	69	F(1,135)=2.969, p=.087	.022	.402
4. Body donation (n=127)	4.23 (1.731)	60	3.88 (1.674)	67	F(1,125)=1.361, p=.246	.011	.212
5. AMD filled out (n=141)	5.25 (1.481)	71	4.89 (1.528)	71	F(1,139)=2.107, p=.149	.015	.302
6. Charity set up (n=155)	3.90 (1.648)	78	3.25 (1.778)	78	F(1,153)=5.584, p=.019	.035	.651

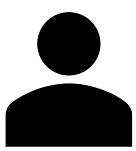
[8] Alternative manipulation check, as mentioned in footnote #5.
[9] Items (a) Exercise and (c) work-life-balance were measured on 7-point scales that were later converted to dichotomous scales by recoding 1-4 as no and 5-7 as yes.

3.10.1 Measures

Appendix D. Dependent Variables (Willingness to engage in decisions about the future)

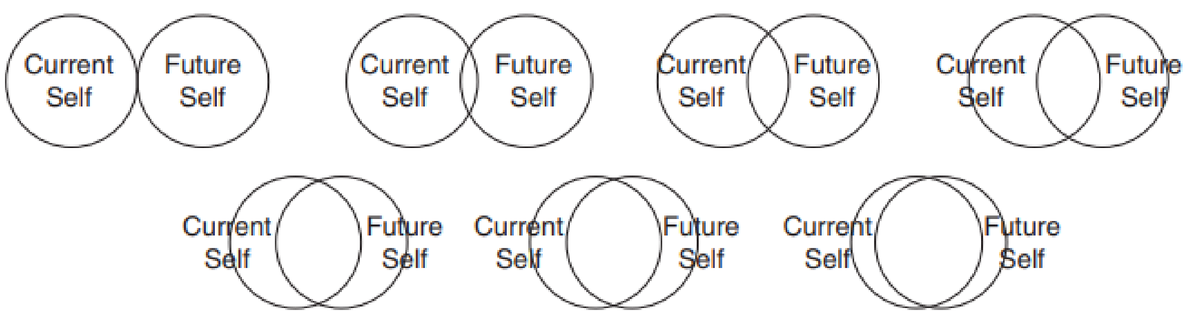
Please indicate how likely or unlikely you are to commit to each of the following questions:						
Extremely unlikely	Moderately unlikely	Slightly unlikely	Neither likely nor unlikely	Slightly likely	Moderately likely	Extremely likely
Exercising						
Sign up for colorectal cancer (CRC) screening when I become eligible.						
Work-life balance						
Register to donate my body for medical research						
Creating Advance Medical Directives that communicate the end-of-life care preferences to my family members and healthcare professionals.						
Creating a charitable trust to leave all or portion of my estate to charity when I die.						

Appendix E. Future Self Continuity



Click on the picture below that best describes how **similar** you feel with your future self.

Current self = you now
Future self = you in the future



Appendix F. Consideration of Future Consequences – short (Future Orientation)

Extremely uncharacteristic of me	Moderately uncharacteristic of me	Slightly uncharacteristic of me	Neither characteristic nor uncharacteristic of me	Slightly characteristic of me	Moderately characteristic of me	Extremely characteristic of me
I consider how things might be in the future.						
I am willing to sacrifice now in order to achieve future outcomes.						
I think it is important to take warnings about negative outcomes seriously even if the negative outcome will not occur for many years.						
I mainly act to satisfy my immediate concerns, figuring the future will take care of itself.*						
I think that sacrificing now is usually unnecessary since problematic future outcomes can be dealt with at a later time.*						
I only act to satisfy immediate concerns, figuring that I will take care of future problems that may occur at a later date.*						

(* denotes reverse coded items. The asterisk mark was not visible to the study participants.)

Appendix G. Temporal Distance

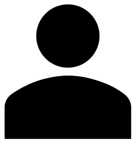
Is the length of time that will pass between your current age and when you are 80 years old short or long?

Extremely short	Very short	Short	Neither short nor long	Long	Very long	Extremely long

How far away in time does becoming 80 years old feel to you?

Extremely close	Very close	Close	Neither close nor far	Far	Very far	Extremely far

Appendix H. Manipulation check



Compared to your current self, how much younger or older do you think the person in the above image is?

Very much younger than me	Moderately younger than me	Slightly younger than me	Very close to my age	Slightly older than me	Moderately older than me	Very much older than me

The short clip above helps me to imagine myself at age 80.

Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree

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4 CONCLUSION

Algorithms and AI are playing an ever-growing role in healthcare and health related decision making. As these tools continue to shape and transform the healthcare landscape, it is important to understand how individuals interact with algorithms and the output or recommendations that they provide. Failure to anticipate human reactions to algorithms and their outputs may lead to unintended consequences, and as a result, promoting such algorithms as a means of improving health-related decisions could backfire. This dissertation consists of three essays that shed light on cases in which the use of algorithms to improve health-related and future-oriented decisions has produced counter-intuitive results that may not align with the intended goals promoting health protective behaviors and future-oriented decision-making.

The first essay examined the use of colorectal cancer (CRC) risk calculators and their influence on individuals' intention to undergo CRC screening and found that it actually decreased individuals' perceived susceptibility to CRC. Consequently, this decrease in perceived susceptibility resulted in a reduction in individuals' intention to participate in CRC screening. The findings also revealed that the effect of receiving CRC risk calculator results on screening intention differed between men and women. For women, perceived susceptibility to CRC mediated the relationship between receiving risk calculator results and screening intention. In contrast, the direct effect of receiving risk calculator results on screening intention was significant among men. These results highlight the importance of considering gender differences in promoting CRC screening and emphasize the need for tailored interventions that address perceived susceptibility.

The second essay focused on algorithm aversion in the healthcare domain and the role of algorithm literacy in individuals’ willingness to accept algorithmic advice. The study replicated the phenomenon of algorithm aversion, showing that participants exhibited greater utilization of advice from human doctors compared to algorithms. Contrary to belief that algorithm literacy would mitigate algorithm aversion, our findings indicated the opposite, indicating that individuals with greater algorithm literacy were more skeptical about accepting advice from algorithms. These results suggest the need for further exploration of the effects of algorithm literacy on algorithm supported decision-making.

The third essay explored the influence of an AI generated age progression treatment on decision-making about the future and the role of decision type (egocentric or altruistic) in delay discounting. Although the treatment showed a positive influence, our results provided some results that ran counter to the established literature regarding the proposed mediating role of future self-continuity. Specifically, we found that the age progression video clip, contrary to our theorizing, actually diminished individuals' perceived connectedness to their future selves. Thus, the indirect effect of age progression through future self-continuity was negative, working against the effect of the age progression treatment, suggesting the need for further research to identify if there are alternative explanatory mechanisms at play. The study also examined decision type and found that the indirect effect of age progression on decisions about the future was significant for egocentric decisions but not for altruistic decisions.

These essays collectively emphasize that encouraging people to embrace algorithmic tools to improve decision-making about the future may produce counter-intuitive results and operate through mechanisms that are, as yet, not well understood. This highlights the need for further research in the field of human-algorithm interaction, understanding how humans react to algorithms and the advice or outcomes they provide, and uncovering the underlying mechanisms behind these reactions. These studies provide a foundation that can inform future research aimed at developing and applying algorithmic interventions and strategies to promote decisions that are aligned with positive healthcare intentions and behaviors. By gaining a deeper understanding of human-algorithm interactions, we can harness the potential of these tools in healthcare and ensure their effectiveness in promoting health protective behaviors and facilitating future-oriented decision-making.