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Predicting the Avoidance of Body Weight Information Using Novel Measures of Trait Information Avoidance

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Abstract

Information avoidance is a growing topic of study in the field of behavioral economics. It has been conceptualized as a form of psychological threat management, is suggested to be a generally stable trait. Moreover, trait information avoidance has been shown to predict real-world information decisions. This study aims to explore the phenomenon of body weight information avoidance, which remains poorly understood. 836 participants completed an online survey containing measures of constructs related to suggested information avoidance mechanisms. Notably, this survey included two measures of trait information avoidance, the Information Avoidance Scale and the recently-developed Information Preferences Scale, that previously demonstrated predictive abilities. Participants later chose between obtaining or avoiding weight information in the form of a body fat percentage estimate. Using a series of logistic regression and Lasso regularization models, this study finds a strong effect for predicting information avoidance using the Information Avoidance Scale, and a moderate effect for predicting information avoidance using the Information Preferences Scale.

Keywords

information avoidance, health information avoidance, information preferences, body weight, self-beliefs, body image, avoidance, psychological threat, decision-making, behavioral economics

Disciplines

Behavioral Economics | Other Public Health

PREDICTING THE AVOIDANCE OF BODY WEIGHT INFORMATION USING NOVEL MEASURES OF TRAIT INFORMATION AVOIDANCE

By

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ABSTRACT

Information avoidance is a growing topic of study in the field of behavioral economics. It has been conceptualized as a form of psychological threat management, is suggested to be a generally stable trait. Moreover, trait information avoidance has been shown to predict real-world information decisions. This study aims to explore the phenomenon of body weight information avoidance, which remains poorly understood. 836 participants completed an online survey containing measures of constructs related to suggested information avoidance mechanisms. Notably, this survey included two measures of trait information avoidance, the Information Avoidance Scale and the recently-developed Information Preferences Scale, that previously demonstrated predictive abilities. Participants later chose between obtaining or avoiding weight information in the form of a body fat percentage estimate. Using a series of logistic regression and Lasso regularization models, this study finds a strong effect for predicting information avoidance using the Information Avoidance Scale, and a moderate effect for predicting information avoidance using the Information Preferences Scale.

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INTRODUCTION

Obesity is an incredibly complex public health issue in the modern world. Although it is influenced by various social, economic, and physiological factors, individual behavior is a key determinant of obesity, and sustainable behavioral change is often necessary for its management. Accordingly, many weight management interventions rely on giving people information that they can use to make healthier lifestyle decisions. No matter how well-designed these interventions are, however, they are only effective if the people they target actually obtain and apply the information. It may seem irrational that people would actively avoid weight-related information that could improve decision-making and long-term health. Nevertheless, information avoidance is a well-documented phenomenon in the field of behavioral economics. If one feels psychologically threatened by information to the extent that its objective benefits are outweighed, information avoidance theory predicts that one would choose to avoid it.

The goal of this project was to further our understanding of information avoidance using a specific illustration from the domain of weight and obesity. 836 participants completed an online behavioral study centered around the avoidance of body fat percentage information. In the first phase, participants completed a survey that measured various constructs related to the self-belief threat mechanism of information avoidance. One week later, participants made an active decision to obtain or avoid information about their estimated body fat percentage from an online calculator. Notably, the first phase also included two measures of trait information avoidance: the Information Avoidance Scale (IAS; Howell and Shepperd 2016), and the Information Preferences Scale (IPS; Ho, Hagmann, and Loewenstein 2020). These measures of trait information avoidance, along with the other self-belief threat measures administered in the study, were then used to model the information decision and predict avoidance.

Understanding the mechanisms between weight information avoidance and using them to predict real-world decisions has important implications for addressing the obesity epidemic. Behavioral economics researchers, healthcare providers, and public health officials are designing weight management interventions that give people more ownership over their health information. If self-view threat plays a significant role in weight information avoidance, these interventions may need to be modified to mitigate this threat. As this project was one of the first uses of the Information Preferences Scale, the results are also of interest to researchers studying information avoidance in other domains.

LITERATURE REVIEW

Information Avoidance

Classical economic theory assumes that the utility of information depends on the extent to which it can increase the utility of a decision outcome. Conversely, behavioral economists argue that information itself can have inherent utility or disutility. This argument is based on the observation that some people actively choose to avoid information, even when it is beneficial to decision-making and nominally costless to obtain (Loewenstein 2006). Information avoidance thus arises when the inherent disutility of information outweighs the expected utility of an informed decision outcome.

Measuring Information Avoidance

In the behavioral economics literature, information avoidance is generally defined and measured in two different ways. First, it can be conceptualized as a behavioral outcome. Given an opportunity to access information, people can choose to obtain or avoid it. In some domains (e.g. health), researchers measure real information decisions in field studies or lab experiments

(Dwyer, Shepperd, and Stock 2015; Katapodi et al. 2009). More commonly, surveys are used to measure self-reported intentions to obtain or avoid information, especially when the information (e.g. cancer risk information) is sensitive or impractical to obtain for experimental purposes (Woolley and Risen 2018; Emanuel et al. 2015; Taber et al. 2015). Additionally, studies that force participants to make an active decision to either obtain or avoid information (e.g. by indicating "yes" or "no" on a survey) have the advantage of distinguishing active information avoidance (i.e. a conscious decision to avoid the information) from passive information avoidance or study dropout.

Second, information avoidance can be conceptualized as a relatively stable behavioral trait that is moderated by internal and external factors and differs across domains. A number of instruments measure psychological constructs related to trait information avoidance, including the Cognitive Avoidance Questionnaire (Sexton and Dugas 2008), the Levine Denial of Illness Scale (Levine et al. 1987), and a questionnaire that measures monitoring and blunting styles of information seeking (Miller 1987).

As noted by Howell and Shepperd (2016), these instruments are limited because they primarily measure defensive emotional responses to threatening information rather than assessing avoidance itself, and because they cannot be applied to specific domains. The Howell and Shepperd Information Avoidance Scale (IAS) attempts to address these concerns. It includes eight items in the form of "I would rather not know _____" or "even if it will upset me, I want to know _____." Experimenters fill in the blanks with the specific type of information relevant to the study (e.g. "my body fat percentage"). The IAS can measure differences in information avoidance as a predictor measure, or act as a proxy for situation-specific avoidance behavior as an outcome measure. However, it does not assume or assess any particular motivation for information avoidance. The IAS has been used in a number of health information avoidance studies to date (Dwyer et al. 2014; Heck and Meyer 2019; Price et al. 2019).

An alternative tool, the Information Preferences Scale (IPS), was developed by Ho, Hagmann, and Loewenstein (2020). Each of the thirteen IPS items describes a hypothetical scenario involving an opportunity to learn information about health, personal finance, or personal characteristics. For each scenario, respondents indicate the degree to which they would want to know (or not know) the information. In a series of studies, the IPS was able to predict information decisions in scale-related domains (e.g. health), out-of-sample domains (e.g. politics), and across time points. The IPS authors note that their scale measures information avoidance as a more general psychological trait, in contrast to the scenario-specific avoidance behavior measured by the Howell and Shepperd IAS. Furthermore, the IPS directly measures information decision outcomes, instead of more abstract attitudes that may not align with actual behavior. In a study assessing predictive validity, the IPS (but not the Howell and Shepperd IAS) was able to predict real-world information decisions, even when administration of the scale and the information decision were separated by a two-week time lag.

Self-Belief Threat as a Mechanism of Information Avoidance

Information avoidance is often conceptualized as a form of psychological threat management. In an extensive literature review, Sweeny, Melnyk, Miller, and Shepperd (2010) summarize common information-derived threats under three broad mechanisms of information avoidance. First, information can threaten to challenge closely-held beliefs about the self, others, or the world. Second, information can threaten to obligate unwanted action or behavior change. Third, information can threaten to cause unpleasant emotions. These threats can increase the inherent disutility of information, leading to avoidance.

The self-belief threat mechanism is interesting to study because of its very individualized nature. A single piece of information may pose very different types of threats to different people, depending on the strength and valence of their beliefs, and how closely these beliefs align with reality. This mechanism is therefore related to hedonic motivations such as optimism maintenance and confirmation bias (Golman, Hagmann, and Loewenstein 2017). People are inclined to avoid information that threatens to disconfirm positive self-beliefs. Conversely, people are inclined to avoid information that threatens to confirm negative self-beliefs.

Self-Belief Threat and Health Information Avoidance

Studies on the role of self-belief threat in the domain of health information avoidance appear to show conflicting results. Greater perceived disease risk is a consistent predictor of information-seeking behavior such as disease screening (Hay, McCaul, and Magnan 2006). However, people with high perceived disease risk are also known to avoid disease-related information. This result is more common among people who have greater disease worry, suggesting that the threat of confirming negative beliefs is more salient to them (Persoskie, Ferrer, and Klein 2014).

Information avoidance is also more prevalent in the context of life-threatening or untreatable diseases such as cancer and Huntington's Disease (Emanuel et al. 2015; Taber et al. 2015; Oster, Shoulson, and Dorsey 2013). This is related to findings that low self-efficacy (i.e. low confidence in one's ability to exert control over life events) increases cancer information avoidance (Case, Andrews, Johnson, and Allard 2005). However, health-related self-beliefs can also be positive. Consistent with optimism maintenance theory, people frequently underestimate their disease risk, especially if they are asymptomatic or believe themselves to be "healthy". This has been associated with lower screening rates for diseases such as cancer (Katapodi, Dodd, Lee, and Facione 2009).

Self-Belief Threat and Weight Information Avoidance

Despite the overall wealth of research on health information avoidance, there is little that directly focuses on information avoidance in weight and obesity. The most targeted study to date found that weight information avoidance predicts poorer compliance with self-monitoring of weight, food intake, and physical activity (Schumacher, Martinelli, Convertino, Forman, and Burtyn 2019). There is even less research about self-belief threat in this context. One study examined calorie information avoidance through the mechanism of strategic self-ignorance, which allows people to indulge in pleasurable activities that adversely impact their future selves (Thunström, Nordström, Shogren, Ehmke, and van't Veld 2016) Another study found that the desire to protect intuitive preferences that arise from beliefs and expectations may play a role in calorie information avoidance (Woolley and Risen 2018).

This mechanism has been also studied in the context of information that is conceptually related to weight and body image. Eil and Rao (2011) conducted an experiment in which participants had their beauty and IQ rated by others, then received a hint about the results. Participants upwardly adjusted their self-beliefs if they received a positive hint, but they did not make a corresponding downward adjustment to their self-beliefs if they received a negative hint. In a subsequent decision to obtain or avoid seeing their full rating, those who received a negative hint were more likely to avoid the information. Geier and Rozin (2008) found that college-aged females felt more discomfort at the prospect of being weighed when they believed that they were overweight, when they saw weight as an unflattering personal characteristic, and when they believed that their peers would underestimate their weight and thus find their actual weight “disappointing”. These findings suggest that information avoidance may be a strategic way to maintain positive self-evaluations and mitigate negative self-evaluations.

Finally, weight misperception may be related to the inclination to maintain positive self-beliefs, and thus related to information avoidance. A significant proportion of overweight and obese individuals misperceive their weight status to be “about right,” pointing to an increasing societal normalization of excess body weight (Burke, Heiland, and Nadler 2012). Individuals with a greater degree of weight misperception are also less likely to make weight loss attempts, and tend to engage in less-healthy diet and exercise habits (Duncan et al. 2011). Similarly, a significant proportion of overweight and obese individuals do not perceive their weight to be a health risk, or worry about weight-related health risks (Gregory et al. 2008). As greater perceived health risk is known to be associated with greater information seeking (especially when it is not accompanied by excessive worry or anxiety), the opposite may be true for information avoidance in this context.

RESEARCH QUESTIONS

The goal of the present study was to further our understanding of information avoidance, with a specific application in the domain of weight. Based on new and established methods of information avoidance measurement, and previous findings in the literature with respect to health information avoidance, weight information avoidance, and obesity, two overarching questions guided the research:

1. Can real-world information decisions be predicted using measures of trait information avoidance?

2. Do constructs related to self-belief threat play a role in the decision to obtain or avoid weight information?

The thought process used to address these questions is outlined below. The “Methods” section goes into further detail in describing the study design and relevant measures.

The Predictive Ability of Trait Information Avoidance Measures

To address the first question, the basic design of the study was modeled on previous information avoidance experiments (Dwyer et al. 2015, Ho et al. 2020). Participants would complete a survey containing the given measures of trait information avoidance, then engage with an opportunity to avoid or obtain information.

Selecting an appropriate type of information was critical for the success of the present study. The information had to present objective benefits to participants, but it also needed to conceivably pose psychological threats that would lead certain people to avoid it. Body fat percentage (BFP) information, in the form of results obtained from an online BFP calculator, was used to this end. For many people, BFP is a less-frequently encountered measure of body weight status than body weight alone. Research also suggests that BFP is a more accurate determinant of metabolic risk than body mass index (BMI) (De Lorenzo et al. 2013). Furthermore, BFP can be estimated using a few body circumference measurements. In summary, the rationale for selecting this type of weight information lied in its novelty, utility, and ease of access. Related to the second research question, BFP information also had the potential to introduce self-belief threats.

To best assess the predictive ability of trait information avoidance, the present study compared the Ho et al. Information Preferences Scale to the Howell and Shepperd Information Avoidance Scale. It was hypothesized that the two scales would predict the BFP information decision in opposite directions; higher IPS scores would predict a greater propensity to obtain, while higher IAS scores would predict a greater propensity to avoid. Other than this, the two scales differed in their degree of specificity for the context in which they measured trait information avoidance. The IAS items in this study were completed using the phrase "my weight status," which was closer conceptually to the BFP information decision (though not an exact match). Conversely, the IPS was designed to be general in scope. It averages scores across three domain-related subscales (IPS_{Health}, $IPS_{Finance}$, and $IPS_{Personal}$), and includes two general items to assess high-level information preferences. Similarly, the IPS_{Health} subscale could be seen as having a moderate level of specificity for trait information avoidance in the context of BFP information.

Finally, an important consideration in assessing the robustness of the predictions was avoiding framing effects that could arise from answering questions about information avoidance and making a subsequent information decision, or vice versa. A time-delay study design, separating the information avoidance measures from the BFP information decision by one week, was chosen in order to mitigate these effects. Demonstrating predictive ability in this way would also support the theory that information preferences, both domain-specific and general, are a largely stable trait.

The Role of Self-Belief Threat in Weight Information Avoidance

As previously mentioned, body fat percentage information was chosen for this study as it had the potential to both demonstrate utility to participants and involve self-belief threats that increased its disutility. A related consideration, especially given that the study would be administered online, was ensuring that the threats were salient enough so that some participants would be inclined to avoid the information. The BFP information was specifically chosen and framed to reflect three types of self-beliefs. First, self-beliefs about attractiveness may be related to body fat percentage (Koyuncu et al. 2010). The phrase "body fat percentage" may likewise be associated with the societal perception that "fat" is unappealing. Second, BFP information may support or threaten self-beliefs about physical fitness and identity with fitness culture (Olivardia et al. 2004). Finally, BFP information can provide insights about health.

A number of measures related to these self-belief threats were included in this study. The Multidimensional Body-Self Relations Questionnaire (MBSRQ), for example, directly assesses body image in relation to appearance, fitness, and health. It also differentiates between evaluation of these constructs (which could relate more closely to self-beliefs) and orientation towards these constructs (which could relate more closely to information preferences). Self-efficacy was also of interest, due to its theorized potential for lessening susceptibility to information-related threats. Finally, the idea of weight misperception was explored from a two-sided approach. Participants who perceived their weight status as lower than their actual weight status could potentially feel threatened that BFP information would disconfirm this belief, with the converse being the case among those who perceived their weight status as higher.

METHODS

Participant Recruitment

1000 participants were recruited through the online platform Prolific for the survey phase of the study, titled "Self-Attitudes & Behaviors Study." This sample was randomly selected from Prolific's panel to be representative of the United States (cross-stratified on age, sex, and ethnicity, according to the Simplified US Census).

After one week, participants who had completed the survey phase were re-contacted to complete the decision phase, titled “Health and Wellness Study.” The decision phase made no explicit reference to the survey phase. To reduce study dropout, a reminder was sent out a week after the initial invitation. Participants were paid $1.30 upon completion of the survey phase and $0.55 upon completion of the decision phase.

Procedure

Survey phase

After providing informed consent, participants completed a demographic questionnaire that included their self-reported height and weight. Subsequently, they completed a survey that included five measures pertaining to information avoidance and weight-related self-beliefs: the Information Preferences Scale (IPS; Ho, Hagmann, and Loewenstein 2020), the Information Avoidance Scale (IAS; Howell and Shepperd 2016), a modified version of the Multidimensional Body-Self Relations Questionnaire (MBSRQ; Cash 2018), the Generalized Self-Efficacy Scale (GSE; Schweizer and Jerusalem 1995), and the Social Physique Anxiety Scale (SPAS; Hart, Leary, and Rejeski 1989). These measures are discussed in further detail below. Measures were presented to participants in a random order.

Decision phase

To obscure the true purpose of the decision phase, participants were told upfront that they would answer a questionnaire about health and wellness-related behaviors, and then interact with an online tool. After providing informed consent, participants completed a demographic questionnaire that once again included self-reported height and weight. Next, participants read a blurb about body fat percentage measurement techniques and answered related distractor questions. They subsequently learned that they would have the opportunity to interact with an online body fat percentage (BFP) calculator. This calculator was designed to provide an estimate of BFP according to a formula used in the Navy Physical Readiness Program Body Composition Assessment (2016).

Critically, participants were told that they could choose to either learn their BFP results from the calculator (i.e. obtain the information), or interact with the calculator without seeing their results (i.e. avoid the information). This was framed so that the focus of the task was the act of interacting with the calculator, and participants were told that their decision did not affect their successful completion of the study. After making their decision, participants were shown the corresponding version of the BFP calculator that either included or omitted the results. As the Navy formula relies on body circumference measurements that need to be taken with a measuring tape, participants were told that they could enter their best guesses for the measurements, and that the results were not to be taken as a reliable assessment of their BFP. Due to the likely inaccuracy of the body circumference values that participants entered into the calculator, these values were not recorded for study purposes. Finally, participants were asked about their experience of using the calculator.

Measures

Trait information avoidance

The Ho, Hagmann, and Loewenstein Information Preferences Scale (IPS; 2020) was used to measure information preference as a general psychological trait. As previously discussed, the IPS contains thirteen items, describing hypothetical scenarios that involve opportunities to learn information about health, personal finance, or personal characteristics. For each scenario, participants indicated the degree to which they would want to know the information. Responses were on a 1-4 Likert scale (1 = “Definitely don’t want to know,” 2 = “Probably don’t want to know,” 3 = “Probably want to know,” 4 = Definitely want to know”). Information avoidance for each scenario was classified as the proportion of participants who reported that they definitely or probably did not want to know the given information. The total IPS score was calculated as the mean of all item scores. The health subscale score, IPS_{Health}, was calculated as the mean of the three health item scores. Higher IPS scores indicated a greater propensity to obtain information.

The Howell and Shepperd Information Avoidance Scale (IAS; 2016) was used to measure information avoidance in the specific domain of weight information. The IAS contains eight items in the form of statements like “I would rather not know _____” or “even if it will upset me, I want to know _____.” The blanks were filled in with the phrase “my weight status,” defined for participants as a concept that takes into account their height and body weight, and that can be classified using terms such as “underweight,” “normal weight,” and “overweight.” Responses to the IAS were on a 1-7 Likert scale, and the total IAS score was calculated as the mean of all item scores. Higher IAS scores indicated a greater propensity to avoid information.

Weight-related self-beliefs

The Cash Multidimensional Body-Self Relations Questionnaire (MBSRQ; 2018) was used to measure various aspects of body image, a construct defined as attitudinal dispositions towards one’s physical self. The MSBRQ contains 69 items related to ten factor subscales; only 60 items related to nine factor subscales were used for this study. They were: Appearance Evaluation (AE; feelings of physical attractiveness or unattractiveness), Appearance Orientation

(AO; investment in one's appearance), Fitness Evaluation (FE; feelings of being physically fit or unfit), Fitness Orientation (FO; investment in being physically fit), Health Evaluation (HE; feelings of physical health), Health Orientation (HO; investment in a healthy lifestyle), Illness Orientation (IO; reactivity to becoming ill), and Overweight Preoccupation (OP; fat anxiety and weight vigilance). These subscales therefore isolate three different dimensions of weight-related self-beliefs, namely appearance, fitness, and health. Self-Classified Weight (SCW; how participants perceive themselves and believe others perceive them, from very underweight to very overweight) was also measured. Responses to each statement were on a 1-5 Likert scale. Scores for each subscale were calculated as the mean response to subscale items.

A measure of weight perception was also included in the study. Self-reported height and weight was collected in addition to standard demographic information in both phases of the study. Participants' BMI was computed and classified (according to National Institutes of Health guidelines, 1998) as a proxy for their actual weight status. To mitigate the limitations of self-report data, participants were excluded from the final analysis if their BMI differed by more than 20% between the two phases. Participants' actual weight status was compared to their response on the MBSRQ Self-Classified Weight subscale. To simplify the comparison, SCW responses were recoded as "Underweight," "Normal weight," and "Overweight/Obese." Weight perception was classified as "Lower" if participants rated their SCW as lower than their actual weight status, "Match" if their SCW matched their actual weight status, and "Higher" if participants rated their SCW as higher than their actual weight status.

The Schwarzer and Jerusalem Generalized Self-Efficacy Scale (GSE; 1995) was used to measure participants' self-efficacy, defined as the degree of confidence in one's ability to perform novel tasks, cope with adversity, and exert control over life events. Though self-efficacy is not explicitly tied to weight-related self-beliefs, previous studies have found that low self-efficacy is associated with health information avoidance (Case et al. 2005). Additionally, the GSE was used by Ho et al. during the development of the IPS. Responses to the ten scale items were on a 1-4 Likert scale, and total GSE score was calculated as the mean response to the items.

Finally, the Hart, Leary, and Rejeski Social Physique Anxiety Scale (SPAS; 1989) was used as a proxy for susceptibility to weight-related self-belief threat. The scale measures the degree to which people are concerned that others may negatively judge their physique. Moreover, people with high SPAS scores report greater anxiety during actual evaluations of their physique (Hart, Leary, and Rejeski 1989). Therefore, although the SPAS may better represent social, rather than internalized, psychological threats, the constructs could conceivably overlap. Responses to the twelve scale items were on a 1-5 Likert scale, and total SPAS score was calculated as the mean response to the items.

Information decision

The outcome measure of weight information avoidance captured whether participants chose to obtain or avoid the BFP information in the decision phase of the study. To more accurately measure active information avoidance, participants had to click on a radio button corresponding to their decision before they could view the calculator. There was no default option selected. This measure was coded as a binary outcome variable, Decision (0 = Obtain information, 1 = Avoid information).

RESULTS

Sample

Of the 1000 participants who were initially recruited for the study, 893 completed both the survey phase and the decision phase. There were no significant differences in demographic variables (including BMI) between participants who completed both phases and those who dropped out after the survey phase. 57 participants were excluded from the analysis (41 who failed attention checks, 10 with a BMI difference > 20%, and 6 with an age difference > 1 year). This resulted in a final sample of 836 participants, 412 male, aged 18-78 (*M* = 45.1, *SD* = 15.7).

Descriptive Statistics

Table 1. Means, standard deviations, and ranges for all continuous study variables

	Mean	SD	Range
Age	45.12	15.69	18-78
BMI	27.80	7.54	13.63-81.58
IPS	2.94	0.52	1-4
IPS_{Health}	3.06	0.79	1-4
HS	2.64	1.33	1-7
AE	3.07	0.94	1-5
AO	3.15	0.78	1-5
FE	3.24	0.98	1-5
FO	3.02	0.96	1-5
HE	3.56	0.75	1-5
HO	3.38	0.72	1-5
IO	3.44	0.74	1-5
OP	2.62	0.98	1-5
GSE	3.11	0.49	1-4
SPAS	3.01	0.90	1-5

Table 2. Proportions for all categorical study variables

	Male	Female	Other	Perceive_H	Perceive_M	Perceive_L	Avoid
n	412	411	13	66	653	117	110
%	49.28	49.16	1.56	7.89	78.11	14.00	13.16

Data analysis was performed in R 4.0.0. First, descriptive statistics were calculated to describe the sample. Table 1 shows means, standard deviations, and ranges for all numerical variables, and Table 2 shows proportions for all categorical variables. Overall, 110 participants (13.2%) chose to avoid the BFP information. This avoidance rate was considerably lower than rates seen in other studies. For example, Ho et al. (2020) tested a variety of information types during the development of the IPS, and reported avoidance rates between 37.4% and 84.1%.

Figure 1. Density distribution plots for Information Preferences Scale and Information Avoidance Scale scores

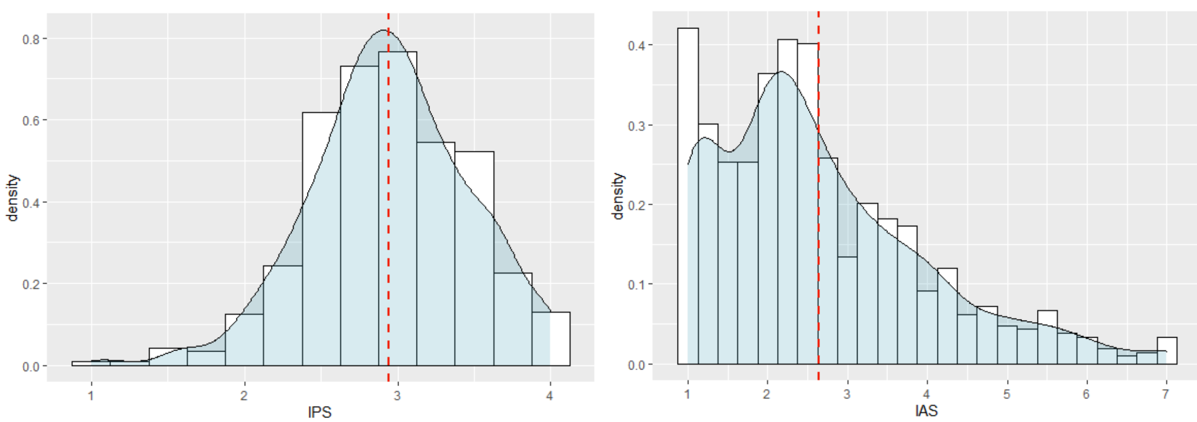

Figure 1 shows density distribution plots for IPS and IAS. Both distributions were skewed to the side of the scales corresponding to a greater degree of information avoidance. IPS scores were closer to being normally distributed than IAS scores. A two-sample t-test for means showed that the mean IPS score was not significantly different (p = 0.98) from the values reported by Ho et al. in a 2019 working paper of the principal IPS study.

Table 3. Pearson correlation matrix

	Age	Female	BMI	P_M	IPS	IPS_H	HS	AE	AO	FE	FO	HE	HO	IO	OP	GSE	SPAS	Avoid
Age	--																	
Female	.01	--																
BMI	.10**	.00	--															
P_M	.02	.12**	.24**	--														
IPS	-.08*	-.12**	-.05	.02	--													
IPS_H	-.07	-.07	-.04	.01	.70**	--												
HS	-.11**	.13**	.06	.03	-.33**	-.28**	--											
AE	-.11**	-.12**	-.43**	-.16**	.08*	.02	-.11**	--										
AO	-.20**	.20**	-.17**	-.07*	.11**	.03	-.09**	.22**	--									
FE	-.01	-.26**	-.23**	-.12**	.06	-.02	-.19**	.52**	.19**	--								
FO	-.07*	-.16**	-.30**	-.20**	.07*	.00	-.19**	.51**	.28**	.63**	--							
HE	.00	-.07	-.31**	-.12**	.05	.05	-.14**	.45**	.09**	.24**	.42**	--						
HO	.17**	.04	-.25**	-.18**	.08*	.02	-.26**	.47**	.30**	.50**	.68**	.36**	--					
IO	.00	.00	-.06	-.12**	.12**	.08*	-.19**	.25**	.35**	.21**	.27**	.01	.45**	--				
OP	-.06	.18**	.22**	.11**	.07	.04	-.12**	-.30**	.31**	-.08*	.03	-.18**	.09*	.12**	--			
GSE	.13**	-.05	.00	-.02	.10**	.07	-.18**	.32**	.24**	.44**	.35**	.37**	.41**	.21**	.00	--		
SPAS	-.12**	.27**	.30**	-.04	-.04	-.02	.13**	-.73**	.13**	-.44**	-.37**	-.39**	-.32**	-.08*	.49**	-.28**	--	
Avoid	-.10**	.04	.05	.07*	-.11**	-.15**	.25**	-.07	-.07	-.07*	-.11**	-.04	-.13**	-.03	-.03	-.11**	.06	--

$*p \leq 0.05$, $**p \leq 0.01$, $***p \leq 0.001$

Pearson correlations, shown in Table 3, were calculated to describe relationships among study variables. IPS scores were highly correlated with IPS_{Health} scores ($r = 0.70$, $p < 0.001$). IPS scores were negatively correlated with IAS scores ($r = -0.33$, $p < 0.001$), reflecting the expected inverse relationship between inclinations to obtain and avoid information, as measured by the two scales. Similarly, IPS and IPS_{Health} scores were negatively correlated with the avoidance decision ($r = -0.11$, $p = 0.002$; $r = -0.15$, $p < 0.001$), and IAS scores were positively correlated ($r = -0.25$, $p < 0.001$).

Point-biserial correlation coefficients were calculated to describe the relationship between being female and all other study variables. Being female was mildly but significantly correlated with some measures of self-beliefs that could play a role in weight-related information avoidance, such as negative fitness evaluation ($r = -0.26$, $p < 0.001$), overweight preoccupation ($r = 0.18$, $p < 0.001$) and social physique anxiety ($r = 0.27$, $p < 0.001$). Being female was also correlated with greater trait information avoidance, as measured by both scales (IPS $r = -0.12$, $p = 0.001$; IAS $r = 0.13$, $p < 0.001$). However, chi-square analysis showed no significant relationship between gender and the avoidance decision itself ($\chi^2 = 1.36$, df = 1, n = 823 [“Other” excluded], $p = 0.24$). There was also no significant relationship between weight perception and the avoidance decision ($\chi^2 = 5.59$, df = 2, n = 836, $p = 0.06$), though the number of observations classified as “Lower” or “Higher” among those who avoided the information was small (respectively, n = 13 and n = 3).

Logistic Regression Models

The two measures of trait information avoidance (i.e. the Information Preferences Scale and the Information Avoidance Scale) were assessed in their ability to predict the BFP information decision through a series of logistic regression models. The effects of the other study variables were also explored. The dependent variable in all models was the binary outcome variable Decision (0 = Obtain information, 1= Avoid information). Given the previously-discussed associations between being female, more negative weight-related self-beliefs, and trait information avoidance, Male was the baseline against which the variable Female was dummy coded. Due to the small number of observations for the gender category Other, these observations (n = 13) were excluded for all models containing Female as a predictor variable. The variable Perception was also dummy coded so that $\text{Perception}_{\text{Match}}$ was the baseline. The predictor variables, which were originally on different scales, were standardized so that their effect sizes could be directly compared.

Odds ratios (in terms of *SD*) and 95% confidence intervals were computed using the R package epiDisplay. The significance of the odds ratio was computed using the Wald chi-square test. Model fit was computed using McFadden's pseudo R-squared, ρ^2. This statistic uses the ratio of the log likelihoods of the fitted and null models to determine the extent to which predictive ability improves with the fitted model (McFadden 1974). Its significance was computed using a chi-square test.

Table 4. Logistic regression using isolated measures of trait information avoidance

	β_1	OR (*SD*)	95% CI	ρ^2
IPS	-0.62^{**}	0.54^{**}	[0.36, 0.80]	0.014^{**}
$\text{IPS}_{\text{Health}}$	-0.81^{***}	0.44^{***}	[0.30, 0.65]	0.026^{***}
IAS	1.27^{***}	3.56^{***}	[2.46, 5.14]	0.070^{***}

$^*p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$
n = 836

Table 4 shows results for the following logistic regression models, which consider each measure of trait information avoidance (IPS, IPS_{Health}, or IAS) in isolation:

$$\ln\left(\frac{P_{Avoid}}{1 - P_{Avoid}}\right) = \beta_0 + \beta_1 AvoidanceMeasure + \epsilon$$

All three measures, taken alone, were able to significantly predict the BFP information decision. A one-*SD* increase in IPS score decreased the odds of avoidance by 46% ($p = 0.002$). Although the IPS subscales were not intended to be used individually as predictors of information avoidance, isolating the Health score improved model fit and increased the effect size; a one-*SD* increase in IPS_{Health} score decreased the odds of avoidance by 56% ($p < 0.001$). Using IAS as the predictor resulted in the largest effect size (with a one-SD increase in IAS score increasing the odds of avoidance by 256%, $p < 0.001$) and best model fit overall ($\rho^2 = 0.070$, $p < 0.001$). Still, model fit was generally poor, even considering that ρ^2 suggests good fit at lower values (i.e. 0.2-0.4) than equivalent values of R-squared in ordinary least squares regression (McFadden 1974). Including all of the other study variables in each of the three above models retained significant effects for IPS (*OR* = 0.55, 95% CI [0.36, 0.84], $p = 0.006$), IPS_{Health} (*OR* = 0.41, 95% CI [0.27, 0.61], $p < 0.001$), and IAS (*OR* = 3.20, 95% CI [2.14, 4.78], $p < 0.001$).

Table 5. Logistic regression using all study variables

	β	OR (*SD*)	95% CI
Age	-0.51$^{\bullet}$	0.60$^{\bullet}$	[0.36, 1.01]
Female	0.17	1.18	[0.71, 1,97]
BMI	-0.02	0.98	[0.59, 1.64]
IPS	0.54	1.72	[0.89, 3.31]
$\text{IPS}_{\text{Health}}$	-0.92**	0.40**	[0.21, 0.74]
IAS	1.18***	3.27***	[2.09, 5.10]
AE	-0.21	0.81	[0.35, 1.86]
AO	-0.56$^{\bullet}$	0.57$^{\bullet}$	[0.32, 1.00]
FE	0.42	1.52	[0.81, 2.87]
FO	-0.40	0.67	[0.33, 1.38]
HE	0.58*	1.78*	[1.01, 3.14]
HO	-0.18	0.84	[0.42, 1.68]
IO	0.55*	1.74*	[1.03, 2.93]
OP	0.03	1.03	[0.58, 1.83]
GSE	-0.50$^{\bullet}$	0.61$^{\bullet}$	[0.36, 1.02]
SPAS	0.09	1.09	[0.49, 2.43]
$\text{Perception}_{\text{Lower}}$	0.18	0.83	[0.41, 1.69]
$\text{Perception}_{\text{Higher}}$	-1.31*	0.27*	[0.08, 0.96]
$\rho^2 = 0.126^{***}$			

$^{\bullet}p \leq 0.1$, $^{*}p \leq 0.05$, $^{**}p \leq 0.01$, $^{***}p \leq 0.001$
n = 823 (Gender = Other excluded due to small number of observations)

Table 5 shows the results of the following model, which controls for all three measures of trait information avoidance:

$$\ln\left(\frac{P_{Avoid}}{1 - P_{Avoid}}\right) = \beta_0 + \beta_1 Age + \beta_2 Female + \beta_3 BMI + \beta_4 IPS + \beta_5 IPS_{Health} + \beta_6 IAS$$
$$+ \beta_7 AE + \beta_8 AO + \beta_9 FE + \beta_{10} FO + \beta_{11} HE + \beta_{12} HO + \beta_{13} IO + \beta_{14} OP$$
$$+ \beta_{15} GSE + \beta_{16} SPAS + \beta_{17} Perception_{Lower} + \beta_{18} Perception_{Higher} + \epsilon$$

The significant effect for IPS did not persist in this model ($p = 0.106$). However, the main effect for $\text{IPS}_{\text{Health}}$ persisted, with a one-*SD* increase in score decreasing the odds of avoidance by

60% (p = 0.003). Although IPS and IPS_{Health} were highly correlated (r = 0.70), removing IPS_{Health} from the model did not result in a statistically significant effect for IPS (p = 0.641). Conversely, removing IPS from the model retained the significant effect of IPS_{Health} (OR = 0.56, 95% CI = [0.36, 0.88], p = 0.011). Likewise, the main effect for IAS persisted after controlling for all other variables, with a one-*SD* increase in score increasing the odds of avoidance by 227%. ρ^2 for this final model was 0.126, indicating moderate fit when all study variables were included.

Figure 2. Predicted probability of avoiding body fat percentage information compared to the actual information decision

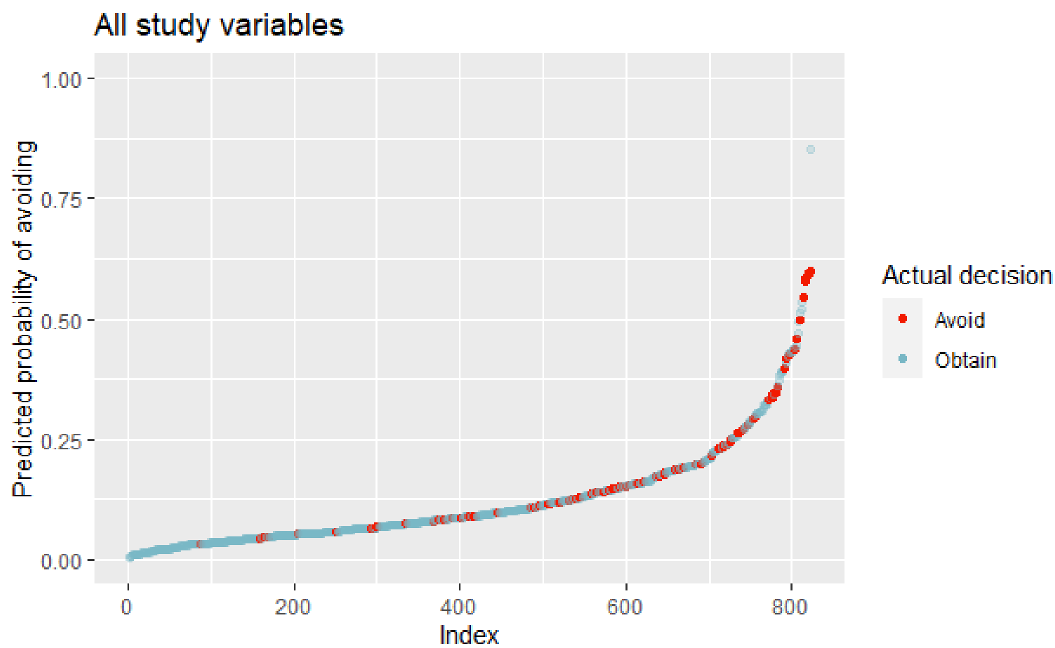

Figure 2 plots the predicted probability of avoiding the BFP information, as indicated by the fitted values from the above model, for each observation. Observations were ranked along the x-axis in increasing order of predicted probability, and color-coded according to the actual value of the variable Decision. The model generally predicted a low probability of avoidance, in agreement with the observed avoidance rate of 13.2%.

Lasso Regularization Models

The logistic regression model presented in Table 4 showed moderate predictive ability, with notably significant effects for IPS_{Health} and IAS. Most of the other study variables were not significant in this model, possibly due to the variables representing closely-related constructs. However, some variables (e.g. Age, Appearance Orientation, Health Evaluation, Illness Orientation, Generalized Self-Efficacy, and Perception, as well as gender effects) prompted investigation using a simpler model.

To this end, Lasso (L1) regularization was used to perform variable selection while optimizing predictive accuracy and interpretability. Simpler methods, such as stepwise selection, were unsatisfactory for this application due to their reliance on arbitrary cutoffs for statistics such as p-values or AIC values. The Ridge (L2) method was less useful in this case, since most of the parameters in the model were not large. The Elastic Net method was similarly not necessary because the sample was large and study variables were modestly correlated. In contrast, Lasso regularization is indicated when a standard logistic regression model contains a large number of non-significant parameters (Tibshirani 1996). This technique uses a tuning parameter λ, with a specified cutoff, to shrink the coefficients of certain variables to zero. Lasso regularization was performed using the R package glmnet. λ was chosen to be the value that minimized the cross-validation prediction error rate, as determined by the function cv.glmnet().

Table 6. Confusion matrix for the baseline assumption of random chance in obtaining or avoiding body fat percentage information

	$\text{Obtain}_{\text{Actual}}$	$\text{Avoid}_{\text{Actual}}$	Total %
$\text{Obtain}_{\text{Predicted}}$	43.5[1]	6.5[2]	50
$\text{Avoid}_{\text{Predicted}}$	43.5[3]	6.5[4]	50
Total %	87	13	100
Accuracy	**50%**		

1. True negative; 2. False positive; 3. False negative; 4. True positive

Three lasso regularization models were evaluated separately, using either IPS, $\text{IPS}_{\text{Health}}$, or IAS and all other study variables. Predictive accuracy was assessed in comparison to a baseline of random chance (i.e. a 50/50 chance of obtaining or avoiding the BFP information). The threshold value *t* was set at 0.5; the model predicted "Obtain" if the computed probability of avoiding was lower than *t*, and classified as "Avoid" if the probability was greater than *t*. Classification was performed using the package caret. An example 50/50 baseline confusion matrix using the observed avoidance rate is shown in Table 5. The model's predictive accuracy was computed according to the equation below, and its significance level was defined as *P(Accuracy > No Information Rate)*:

$$Accuracy = \left(\frac{True\ positive + True\ negative}{Total}\right) \times 100\%$$

To model this, a subset of the original sample was created, containing all participants who chose to avoid the information (n = 104, with Gender = Other removed due to the small number of observations). A random sample of the participants who chose to obtain the information (n = 104) was added, resulting in a total subset of n = 208. This was randomly split into a training set (75% for building the predictive model) and a test set (25% for evaluating the model). The process of randomly subsetting the data and splitting the subset into training and test sets was replicated 1000 times. This was based on an approach used by Hastie, Tibshirani, and Wainwright (2015) to obtain a bootstrap distribution of the coefficients of each parameter in the model. The bootstrap significance level of each parameter was determined based on the proportion of replicates in which its coefficient was equal to zero. The overall bootstrap accuracy of each model, and its significance, was likewise determined in this way.

Table 7. Bootstrapped coefficients for all study variables and associated significance levels

	IPS		IPS_{Health}		IAS	
	β	$P(0)$	β	$P(0)$	β	$P(0)$
Age	-0.090	0.506	-0.125	0.350	-0.081	0.466
Female	0.057	0.787	0.072	0.713	0.018	0.851
BMI	0.012	0.833	0.013	0.778	0.008	0.842
Avoidance Measure[1]	**-0.087**	**0.469**	**-0.251**	**0.137**	**0.470*****	**0.001**
AE	-0.008	0.906	-0.012	0.875	-0.005	0.901
AO	-0.025	0.773	-0.034	0.704	-0.034	0.704
FE	0.007	0.931	0.006	0.911	0.022	0.882
FO	-0.060	0.621	-0.080	0.512	-0.062	0.591
HE	0.021	0.880	0.032	0.826	0.033	0.822
HO	-0.061	0.585	-0.077	0.493	-0.030	0.728
IO	0.012	0.890	0.023	0.840	0.031	0.818
OP	-0.016	0.845	-0.016	0.817	-0.005	0.875
GSE	-0.053	0.613	-0.061	0.523	-0.054	0.585
SPAS	0.017	0.844	0.020	0.807	0.005	0.909
$Perception_{Lower}$	0.013	0.886	0.013	0.840	0.003	0.870
$Perception_{Higher}$	-0.350	0.512	-0.427	0.386	-0.397	0.418
Accuracy	**50.2%**		**52.4%**		**62.5%**	
95% CI	[0.36, 0.64]		[0.40, 0.68]		[0.48, 0.75]	
P(Acc > NIR)	0.688		0.548		0.265	

[1] "Avoidance Measure" refers to either IPS, IPS_{Health}, or IAS

*$p \leq 0.05$, ** $p \leq 0.01$, *** $p \leq 0.001$

n = 52 (Test sample size, based on a total sample of 208 and a training/test split of 75/25)

Figure 3a. Distribution of bootstrapped coefficient values for the Information Preferences Scale

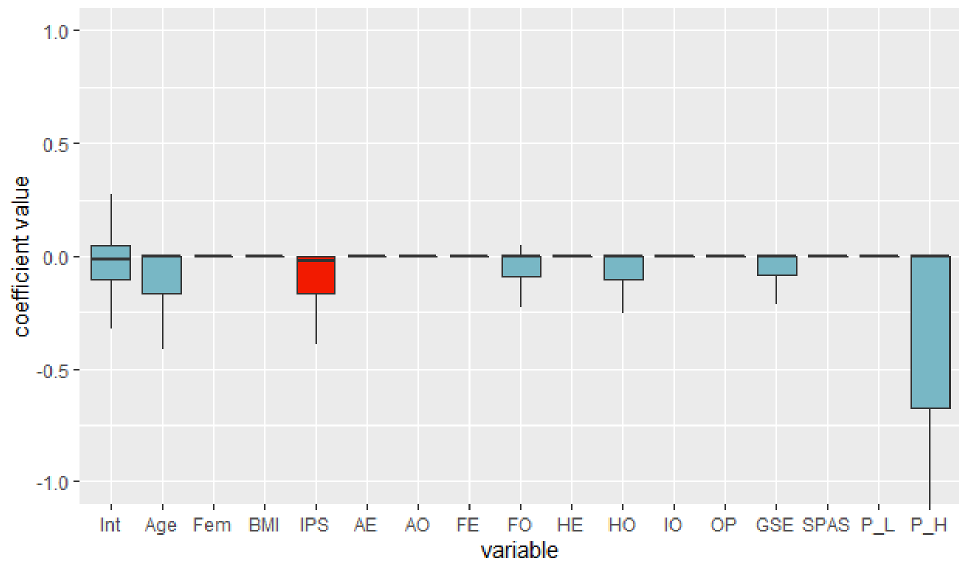

Figure 3b. Distribution of bootstrapped coefficient values for the Information Preferences Health subscale

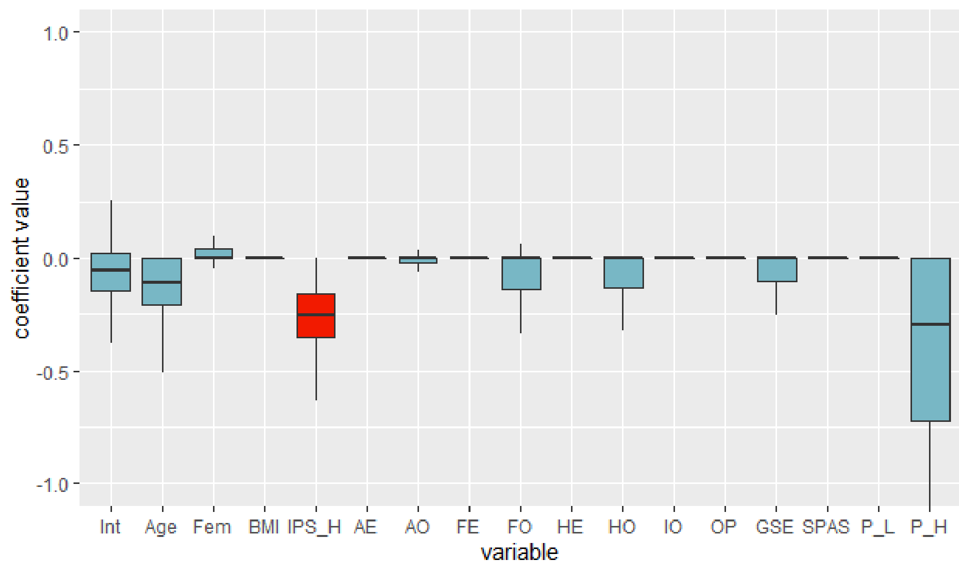

Figure 3c. Distribution of bootstrapped coefficient values for the Information Avoidance Scale

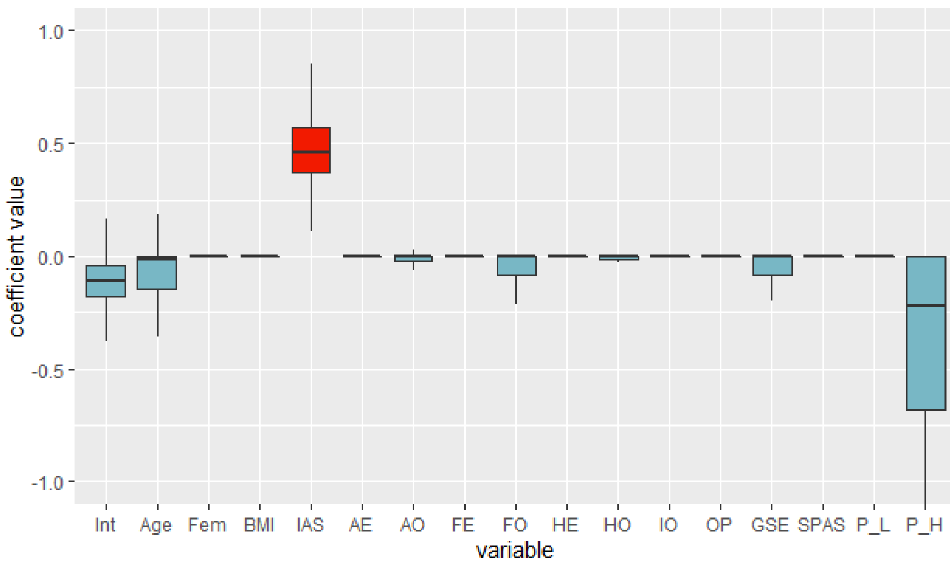

Table 7 summarizes the results of the three models, and Figures 3a-3c display the corresponding boxplots showing the bootstrap distribution of the coefficients. In the IPS model, the mean coefficient of IPS was -0.087 (OR = 0.92), indicating an 8.3% decrease in the odds of avoiding the BFP information for every one-*SD* increase in score. However, neither IPS nor any of the other variables met the criterion for statistical significance (i.e. having a coefficient equal to zero in fewer than 5% of replicates). Using the confusion matrix shown in Table 5, the mean accuracy of the model was found to be 50.2% (95% CI = [0.36, 0.64], $p = 0.688$), no better than the baseline of random chance.

In the model using the isolated $\text{IPS}_{\text{Health}}$ subscale, the mean coefficient of $\text{IPS}_{\text{Health}}$ was -0.251 (OR = 0.78), indicating a 22.2% decrease in the odds of avoiding the information for every one-*SD* increase in score. Although the $\text{IPS}_{\text{Health}}$ coefficient was only equal to zero in 13.7% of replicates, a marked improvement over the first model (46.9%), it likewise did not meet the criterion for statistical significance. The mean accuracy of the model was 54.2% (95% CI = [0.40, 0.68], p = 0.548).

In the IAS model, the mean coefficient of IAS was 0.470 (OR = 1.60), indicating a 59.9% increase in the odds of avoiding the information for every one-*SD* increase in IAS score. This was the only significant coefficient in the model, being equal to zero in 0.1% of repetitions. Though the mean accuracy of the IAS model was notably higher at 62.5%, it was still not a statistically significant improvement over random chance (95% CI = [0.48, 0.75], p = 0.265).

No other variables met the criterion for significance in these models. Some of the previously-mentioned variables of interest (i.e. Age, Fitness Orientation, Health Orientation, and Generalized Self-Efficacy) were selected in a non-negligible proportion of repetitions, though their average effect sizes were negligible. FO and GSE were especially notable; they were respectively selected in 40.9% and 41.5% of repetitions, even with the statistically significant predictor IAS being selected in 99.9% of repetitions. Although $\text{Perception}_{\text{Higher}}$ had a strong effect size overall, it was not significant. This was likely due to the small number of participants with Perception classified as Higher who chose to avoid the information (n=3), resulting in a large variance depending on the randomly selected subset of participants who chose to obtain the information. However, excluding Perception from the models did not result in any statistically significant differences in variable selection or model accuracy.

DISCUSSION

The Predictive Ability of Trait Information Avoidance Measures

One main research question addressed in this study was whether real-world information decisions could be predicted using measures of trait information avoidance. Both the Information Preferences Scale (Ho et al. 2020) and the Information Avoidance Scale (Howell and Shepperd 2016) showed promising results in this respect, though to varying degrees. Isolating participants' IPS, IPS Health subscale, or IAS scores significantly predicted their decision to obtain or avoid the body fat percentage information. The observed direction of the effect also agreed with the hypothesized direction, with scale scores that indicated a greater propensity to avoid information corresponding to increased odds of avoidance.

This predictive ability was demonstrated despite a one-week time lag between the survey phase and the decision phase of the study. While conducting the literature review, it was noted that many other studies did not separate their information decision tasks from survey instruments related to information avoidance or its mechanisms. This raises questions about any framing effects that could be at play, as well as the ecological validity of the findings. Conversely, one of the validation studies that Ho et al. performed found that the IPS was able to predict information decisions after a two-week time lag. This element of study design should be implemented whenever possible in the future, especially in any predictive contexts.

Significant effects remained for the IPS Health subscale and the IAS even after controlling for the large number of other study variables. Moreover, significant effects persisted for the IAS in a more rigorous Lasso regularization. Interestingly, the degree to which these measures were specific for the BFP information corresponded to the magnitude of their effect sizes (and levels of significance) across all models. The IAS items explicitly referred to knowing or not knowing one's "weight status," while none of the IPS scenarios described an opportunity to learn weight information. The IPS Health subscale items were related to life expectancy, Alzheimer's disease, and long-term health effects of stress. One item from the IPS Personal subscale referred to "attractiveness," but it did not qualify this further. This supports the intuition that trait information avoidance in a given domain is more predictive of information decisions in the same domain. However, the results of this study are also encouraging for the theory that information avoidance can be viewed and measured as a general trait.

Though greater degrees of information avoidance, as measured by the IPS and IAS, significantly increased the odds of actually avoiding the BFP information, model fit was generally poor to moderate. Moreover, the bootstrapped Lasso regularization showed that none of the three measures were significantly more accurate than random chance in predicting the information decision. The model's predictive accuracy was compared to the baseline assumption of random chance (i.e. a 50/50 chance of avoiding). An alternative approach would have been to compare its predictive accuracy to the baseline assumption that all participants would obtain the information. This would better correspond to the observed avoidance rate of 13.2% in the study, and allow for the expansion of the training/test set to the entire sample. However, a preliminary analysis showed that the model simply predicted all observations to obtain the information, reflecting its poor overall fit. Bootstrapping the model in this way nevertheless showed that IAS was a significant predictor through a more robust approach to variable selection than stepwise regression, which many other studies use. This type of machine learning model would be useful to implement in future research on predicting information decisions. Furthermore, robust predictive analytics methods will be critical to developing data-driven applications of information avoidance theory in the real world.

In summary, the IAS was shown to outperform the IPS in its ability to predict the particular information decision used in this study. This contradicted the results presented by Ho et al., which showed that the IPS outperformed the IPS across multiple domains, both in-sample and out-of-sample. A more robust approach for comparing the two in the present study would have been to limit the number of additional measures administered in the survey phase, in order to reduce respondent fatigue. As previously mentioned, the overall rate of avoidance in this study (13.2%) was very low relative to avoidance rates in studies using both the IAS (Dwyer et al. 2016 reported a rate of 34.2%) and the IPS (Ho et al. 2020 reported rates between 37.4% and 84.1%). This suggests that other forms of weight information involving more salient psychological threats should be explored in future research.

The Role of Self-Belief Threat in Weight Information Avoidance

The results of this study do not offer much concrete insight into the mechanisms that were at play in participants' decisions to either obtain or avoid the body fat percentage information. Similarly, the role of self-belief threat was not clearly defined.

In the theoretical framework surrounding the BFP information decision, three relevant self-beliefs were thought to be attractiveness-related, fitness-related, and health-related beliefs. One interesting finding was that the significant effects of the IPS Health subscale and the IAS persisted in a model controlling for Appearance Orientation, Fitness Orientation, Health Orientation, and Illness Orientation. "Orientation," as defined by the MBSRQ, refers to the degree of personal investment in these aspects of body image (Cash 2018). Intuitively, people with higher orientation would find the utility of body fat percentage information to be relatively high, and people who were not invested in their appearance, fitness, or health would find it to be relatively low. Subjected to the same level of information-derived psychological threat, those with greater orientation should be less inclined to avoid it. Though these predictors were not consistently significant, they stood out to varying degrees from the other self-belief measures in the all-variable and Lasso models. However, the persistently significant effects for the information avoidance measures suggests that trait information preferences (even in a highly-specific domain such as "weight status") are a separate construct from personal investment in aspects of oneself that are related to the domain.

The general approach used in this study was to cast a wide net of possible self-belief threat mechanisms, reflecting various insights from the still-limited weight information avoidance literature. This was decided on in the hope of finding a promising result that could be further explored in future studies. Additionally, using previously-validated measures of constructs related to self-belief threat would mitigate the challenges of developing robust ad-hoc measures. However, this approach had two main disadvantages. First, it increased the possibility that respondent fatigue would negatively affect data quality (especially in the case of the Multidimensional Body-Self Relations Questionnaire, which was 60 items long). Second, using existing instruments increased the potential for capturing something other than the desired construct. Further studies on weight information avoidance should consider exploring mechanisms concept-by-concept, and carefully selecting or developing relevant measures.

CONCLUSION

This study was one of the first to use the Ho, Hagmann, and Loewenstein Information Preferences Scale in any context. Its findings in terms of predicting real-world decision-making are encouraging for the further exploration of trait information avoidance. Overall, more research is still needed in order to conclusively cross-validate the IPS, especially that which solely focuses on its predictive ability. Still, in comparing the Information Avoidance Scale to the Information Preferences Scale, the present study highlights their respective strengths. The IAS offers a more targeted way to predict decisions regarding specific types of information, while the IPS is well-suited for predicting a broad variety of decisions using information preference as a general trait. Both instruments show promise in their potential applications to information avoidance research and the field of behavioral economics at large. This study also highlights the need for further research into weight information avoidance, as the mechanisms behind this phenomenon are likely multifaceted and individualized. The ultimate goal remains the ability to turn empirical findings into interventions that will help people make healthier, better decisions.

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