Measuring Information Preferences

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Abstract

Advances in medical testing and widespread access to the internet have made it easier than ever to obtain information. Yet, when it comes to some of the most important decisions in life, people often choose to remain ignorant for a variety of psychological and economic reasons. We design and validate an information preferences scale to measure an individual’s desire to obtain or avoid information that may be unpleasant, but could improve future decisions. The scale measures information preferences in three domains that are psychologically and materially consequential: consumer finance, personal characteristics, and health. In three studies incorporating responses from over 2,400 individuals, we present tests of the scale’s reliability and validity. We show that the scale predicts a real decision to obtain (or avoid) information in each of the domains, as well as decisions from out-of-sample, unrelated domains. Across settings, many respondents prefer to remain in a state of active ignorance even when information is freely available, and that information preferences are a stable trait but that an individual’s preference for information can differ across domains.

Measuring Information Preferences

## Introduction

We live in an unprecedented age of information. Advances in data aggregation have made it easier for both hiring managers and prospective employees to learn about the prevailing wages in their industry; crowd-sourced reviews on online shopping platforms reveal consumer (dis)satisfaction about virtually any consumer good or service, and social media ‘likes’ and shares provide simple feedback on the impact that our messages have on others. Much of this information is available at little or no (financial) cost and can be consequential for the decisions individuals make. Conventional economic models, dating back to George Stigler’s seminal paper on information as a scarce resource (Stigler 1961), assume that decision-makers will be eager to obtain information and will make full use of it. At worst, information that is not useful can simply be ignored.

Contrary to this perspective, a substantial body of experimental evidence from the laboratory as well as the field finds that people are often unwilling to learn information that could be painful. Sicherman et al. (2016), for example, show that investors are less likely to log on to their stock portfolios on days when the market is down - that is, when they expect to observe losses in their own investments. Much like people who would rather not see their losses in financial markets, they may also not wish to learn that some of their immutable characteristics compare unfavorably. Eil and Rao (2011) find, in a laboratory experiment, that many participants who learned that they were rated as less attractive than some other participants in the experiment were willing to pay money to not learn their exact rank. Perhaps most consequentially, people are also afraid of learning information related to their health. Oster et al. (2013) observe that only 7%

of individuals at high risk for Huntington's disease elect to find out whether they have the condition, despite the availability of a genetic test that is generally paid for by health insurance plans, and the patent usefulness of the information. Ganguly and Tasoff (2016) find that participants in a laboratory experiment are willing to forgo part of their earnings in order to not learn the outcome of a test for a sexually transmitted disease and that such avoidance is greater when the disease is more severe. Across contexts, people appear to deliberately and actively avoid information, even when it could be instrumentally useful and lead people to make different decisions (and, perhaps, especially in these cases; Woolley and Risen 2018).

What could explain such avoidance? Recent models of belief-based utility propose that people derive value not merely from their material consumption, but also from their beliefs about themselves and the world and their expectations about the future (Falk and Zimmermann 2014, Koszegi and Rabin 2006, Loewenstein 2006). That is, information itself can have hedonic costs and benefits that are traded off against the decision utility of the information. When decision-makers believe that the information could be unfavorable, they may decide to not obtain it in an effort to protect the value they derive from their (potentially false) belief, even if that may undermine the quality of subsequent decisions. For example, learning about the salary of your peers does not merely provide value because it informs other decisions (e.g., whether to leave your current position), but learning that one is under or overcompensated may provide (dis)utility regardless of whether the information changes one's decisions. The mechanism of anticipated regret (Zeelenberg 1999), for example, whereby we imagine a better outcome had an alternative been chosen, may cause people to avoid information about outcomes one would have experienced had one made a different one.

Failure to obtain information can have implications for society at large. In an organizational context, managers at firms may (deliberately) fail to learn about ethical transgressions of their employees (Bazerman and Sezer 2016), with costly consequences for society as well as, often, the firm itself. In the case of climate change, active avoidance of scientific consensus may contribute to policymakers' failure to take actions to deal with the problem (Ho et al. 2017, Marshall 2014). Voters may not consider information which challenges their ideological views, potentially causing insufficient and biased updating that may contribute to political polarization (Druckman et al. 2013). Communicable diseases such as HIV may fail to get diagnosed and proliferate as a result of avoidance of diagnoses (Caplin and Eliaz 2003, Sullivan et al. 2004).

Of course, not all individuals avoid potentially unpleasant information in all situations; some people actively seek information in one or more of the three domains we examine - e.g., on their personal investment performance or their health. This suggests that information preferences may be an important source of individual differences, similar (and, we expect, related) to time and risk preferences. Unlike for those two important economic characteristics, however, there is no commonly used measure to assess preferences for information. Indeed, despite the many serious consequences that avoiding information may have for society or the individual, we know little about who these avoiders are, and hence cannot identify them in empirical research or develop potential interventions that target them. Although economics and psychology both offer potential explanations for information avoidance (Golman et al. 2017, Sweeny et al. 2010), to date there has been no empirical work clarifying information preference as a psychological construct. Existing studies primarily test one-time, context-specific decisions and, with one exception that we discuss below (Howell and Shepperd 2016), there is no direct method of eliciting such individual preferences across a variety of situations. This leaves unanswered questions about the generality of information avoidance across domains, its prevalence, and its consequences.

In this paper, we report on the development and testing of a scale to measure information preferences. Our scale asks respondents to imagine themselves in a series of hypothetical scenarios in which they can choose to obtain (or not obtain) information. The scenarios cover three domains that span many high-stakes decisions, and for which there exists empirical evidence of avoidance: finance, e.g., learning about the performance of alternative investments that one could have pursued; personal characteristics, e.g., how attractive others believe one to be; and health, e.g., obtaining an estimate of one's life expectancy. We rely on scenarios to make salient the potential hedonic cost of obtaining the information. This is a different approach from scales measuring other constructs that rely on abstract questions (e.g., "When it comes to my finances, ignorance is bliss"). In the studies below, we show that a scale that includes such scenarios can better predict consequential information acquisition decisions than that of abstract questions.

We first outline the development of the Information Preferences Scale (IPS) building on insights from four pilot studies. Then, in Study 1, we identify the latent factors underlying information preferences and show prevalence of information avoidance across a variety of scenarios and domains. We also compare the discriminant and convergent validity of information preferences with established measures of related theoretical constructs. We predict that information preferences will differ across domains. For example, individuals not wanting to learn potentially negative news about their portfolio's performance may not be averse to learning about what others think of their personality. In Study 2, we confirm the latent factor structure of information preference on a new sample using a confirmatory structural equation model, and we verify test-retest reliability of the scale via two scale administrations four weeks apart. Using the theoretical constructs most related to information preferences from the prior study, we refine the conceptual (dis)concordance of information preferences by further comparing the IPS with additional established measures.

A large-scale third study provides a comprehensive test of predictive validity by investigating the extent to which the scale predicts real-world decisions to acquire information not only in the domains represented in the scale, but also for decisions in out-of-sample domains. To minimize demand effects, we uncouple the administration of the scale and the decision to obtain consequential information with a two-week lag. The study also provides an additional test of convergent validity by comparing our measurement to an alternative scale designed to measure information avoidance using abstract questions, rather than specific scenarios (Howell and Shepperd 2016). We show that our scale predicts not just self-reported intentions, but actual behaviors related to information acquisition beyond existing scales. We conclude with recommendations for applications of the scale.

## Scale Development

Given the difficulty of capturing the diverse situations in which a person might seek or avoids information, our scale development process focuses on three domains in which information avoidance has been empirically demonstrated and which plausibly provide information that people may be motivated to avoid: health, consumer finance, and personal characteristics. These are topics for which information of uncertain valence may induce anxiety and discomfort but for which attaining more accurate beliefs can yield considerable benefits.

Early health interventions can extend life expectancy, learning about financial mistakes can improve future financial well-being, and accurate information about how one is perceived by others can improve self-presentation and social interactions. The three domains allow us to cover a broad range of information acquisition decisions and to explore whether avoidance in one domain (e.g., finance) is also predictive of avoidance in another domain (e.g., personal characteristics). In the third and final study, we also develop and validate a subscale tailored for organizational behaviors.

We take a different approach to the common practice in the construction of psychological scales by designing each scale item to contain a specific hypothetical scenario, rather than asking broad attitudinal questions about the merit of acquiring information abstractly. Self-reported attitudes may not correspond to consequential behavior (Ajzen and Fishbein 1977), and we worry this is particularly an issue in the case of information, when people may not want to think of themselves as avoiders, but also can conjure justifications for why they would avoid information in specific instances. unless the attitude is related to the behavior. For each of our items, the information could inform future decisions, though perhaps at a risk of a negative surprise and/or immediate displeasure. Learning an outcome can increase the quality of later decisions, but at the possible expense of obtaining negative information that has a negative impact on mood or sense of well-being.

The scenarios are written to represent situations that people in developed countries may typically encounter and may already have experience with, e.g., whether to look at the performance of an investment opportunity they did not pursue. This increases content validity - i.e., the extent to which the scale is representative of a general population's experiences. To make the framing more natural and to minimize asking leading questions that might exaggerate information avoidance, all items ask about the desire to obtain the information (rather than avoid it).

In our first pilot study, we categorized people according to a four-fold classification of information preferences by giving participants in each scenario the choice of whether to either completely avoid an item of information, avoid the information only if a) they expect a negative outcome (e.g., to not look at credit score if they suspect it is low), b) avoid the information only if they expect a positive outcome (e.g., that they are viewed as more attractive than they thought), or c) seek information regardless of their expectations. Some items also tapped into the temporal aspect of avoidance: the choice to delay, but not entirely avoid consumption of information, e.g., by setting aside an envelope with a bill to be opened at a later date. Items such as the bill delay item, which attempted to differentiate between mental avoidance and physical avoidance, yielded inconsistent factor results and generally low factor loadings. A general information preference question described the tendency for people to avoid information when it could be painful or seek it even when it may be painful, and asked participants to rate themselves along this continuum.

Respondents were generally less interested in information when they expected negative outcomes, confirming similar experimental evidence (Eil and Rao 2011, Ganguly and Tasoff 2016, Oster et al. 2013). We retained pilot items if they exhibited a biserial correlation of greater than 0.25 for at least one part of the question with both the general information preference question and the total sum-score. Items examining delay in information-seeking did not meet this criterion and were excluded, along with three items that described situations less commonly encountered outside the United States that could have restricted international usage of the scale.

In the second iteration, participants evaluated separately whether they would obtain or avoid the information in two circumstances: when the expected outcome was positive and when it was negative. Again, participants typically reported more avoidance with a negative expected outcome. As a higher proportion of participants avoided information when it was expected to be negative, we rewrote and tested new general information items which measured the inclination to remain ignorant in a situation when someone else possessed negative information.

The penultimate pilot study tested a revised set of items such that no outcome (positive or negative) was explicitly stated, but the possibility of either a positive or negative outcome was implicit. The new items, in line with previously generated successful items, sought to capture universal experiences and situations (e.g., whether to check that your recommendation to a friend was well-received). The four-fold classification was initially distilled into a binary decision: the decision to acquire or avoid information. However, a final pilot study that used a four-point ordinal response scale yielded higher internal consistency (measured by Cronbach's $\alpha$) than when participants were presented only with a dichotomous choice; hence, the final resulting scale incorporates the ordinal responses.

In all the scenario-based questions, the information is depicted in a way so that information is of uncertain valence, i.e. it could be favorable or unfavorable. Prevalence of information avoidance is defined by the proportion of respondents who reported that they definitely or probably did not want to know a piece of information. The final scale contains 13 items (5 personal characteristic items, 3 health items, 3 finance items, and 2 general items; Table 1 for the scale items and the proportion of people willing to avoid the information in each scenario).

## Study 1

Study 1 explores the latent factor structure underlying the measure of information preference devised in earlier pilot studies. Additionally, we examine the relationship between the Information Preferences Scale (henceforth IPS) and other conceptually-related measures. Experiments frequently measure participants' time and risk preferences and we expected those measures to correlate with the desire for information. Because the psychological cost (e.g., anxiety, disappointment) occurs immediately and the benefits (e.g., realization of better financial decisions) occur in the future, those who discount the future more should also be less likely to desire information (Falk and Zimmermann 2014). Similarly, because the valence of the information is uncertain, individuals face the prospect of either learning favorable news or unfavorable news. We hypothesize that individuals who are more tolerant of risk would be more interested in obtaining information, and less likely to avoid it.

### Method

**Subjects** We recruited 400 participants (52.89% male with a mean age $M = 34.92, SD = 9.99$ via Amazon Mechanical Turk. Of those, 18 participants failed the attention check and 2 did not complete the survey. We analyze data from the remaining 380 participants.

**Procedure** Participants completed the 13-item scale generated from the pilot studies. To ensure consistency in response format across items, the response scale for all items was on a 1-4 Likert scale, from 1 = "Definitely don't want to know" to 4 = "Definitely want to know" (see Table 1 for the experimental material). To assess the relationship between information preference and other established constructs hypothesized to be related to our measurement, participants also completed measures for risk aversion (Gneezy and Potters 1997), time preferences (Kirby et al. 1999), receptiveness to opposing views (Minson et al. 2019), preference for coherence (Antonovsky 1993), need for cognition (Cacioppo et al. 1984), preference for consistency (Cialdini et al. 1995), as well as several general personality traits (BFI; John and Srivastava 1999). We presented the measures and scales (including our own) in random ordering to prevent order effects. Items in each measure were appropriately reverse-coded and, with the exception of the time discounting task, averaged to produce a mean score. The time discounting measure was calculated by identifying the point of indifference between two valuations and using the procedure in Kirby et al. (1999).

**Results**

The Cronbach's $\alpha$ of the IPS is 0.86, demonstrating adequate internal consistency. The respective coefficients for the domain and general subscales are $\alpha_{\text{Finance}}$ = 0.61, $\alpha_{\text{Personal}}$ = 0.76, $\alpha_{\text{Health}}$ = 0.79, and $\alpha_{\text{General}}$ = 0.79 (see Table 2 for internal consistency estimates across all studies). In all scenarios, we observe a considerable degree of avoidance, suggesting that information avoidance is highly prevalent. On average across all participants and items, 32.27% of responses indicated a definite or probable preference for not obtaining the information. The fraction of avoidant responses across items ranged from 20.52% to 51.05% (proportion of avoiders across all studies in Table 1). To produce an information preference score, items were averaged; mean IPS scores were $M = 2.91, SD = 0.6$. The distribution of scores for all studies are in Figure 1.

To determine whether demographic variables influence information preferences, we regress gender, education, political affiliation, income, and age on the scale scores. No coefficient was significant at the $\alpha$ = 0.05 level; nor is the resulting model containing all predictors, $R^2 =$

.05, $F(25{,}354) = 0.73$, $p = .824$. This suggests that information preferences do not differ across any broadly defined demographic group.

**Exploratory factor model** To examine the latent factor structure of information preference, we perform exploratory factor modeling on the scale in a two-step procedure. First, to determine the number of latent factors, we apply Kaiser (1960)'s rule, which retained 4 latent factors from the scale's 13 items. We hypothesize that information preference consists of three domain factors as well as general information preference factor. Then, we fit an exploratory factor analysis (EFA) on the 11 domain items using an oblimin factor rotation, which allows for correlations across latent factors. A three-factor model provides the best model fit. Consistent with the notion that information preferences can differ by domain, the items have high loadings on their intended domains (e.g., all health items cluster together to form an individual factor). The two general information preference items exhibited moderate correlations with items from all the three domains, (average inter-item correlation for G1 = 0.36 and G2 = 0.33). To incorporate the additional two general information preference items, we fit an exploratory structural equation model (Asparouhov and Muthén 2009) on all 13 items into a general factor while simultaneously accommodating the three-factor structure uncovered in the domain items. The exploratory factor loadings are presented in Table 4. We will verify this model in a confirmatory analysis in Study 2.

**Divergent validity** To examine the divergent validity of the 13-item scale, we compare the correlations between established measures, the IPS, and the domain-specific items (Table 5).

***Preference for cognitive activities***

To examine if information preferences are related to a propensity for satisfying other types of knowledge gaps, we examined the correlation between our scale and the Need for Cognition scale (NFC; Cacioppo et al. 1984). The correlation between the IPS and the NFC was positive, $r(378) = 0.21$, $p < 0.001$, indicating that those with a high need for cognition also have a tendency to desire information. The Receptiveness to Opposing Views scale (Minson et al. 2019) assesses the tendency to listen to opinions that are contrary to one's own, closely-held beliefs. As one might expect, participants who preferred information in general were also more likely to be receptive to hearing viewpoints that differed from their own, $r(378) = 0.23$, $p < 0.001$.

Need for Closure (Webster and Kruglanski 1994) measures a preference for order, structure, and predictability, over ambiguity (Kruglanski 2013). We hypothesize that those exhibiting a greater need for closure would also be more willing to disregard evidence that either does not correspond with already formulated opinions or induces re-evaluation. We observe a low but significant negative correlation between Need for Closure and the IPS, $r(378) = -0.12$, $p = 0.016$, suggesting that those who prefer order and structure are more likely to avoid potentially unpleasant and psychologically discomfiting information. The Preference for Consistency-Brief Scale (PfC-B; Cialdini et al. 1995) was not correlated with the IPS, $r(378) = -0.07$, $p = 0.2$, perhaps because the PfC-B scale measures both an individual preference for consistency and also a self-reported perception of how others see one in this regard, whereas the IPS measures only the individual trait.

***Risk, time, and information preferences*** Information in our scenarios can be both positive (e.g., living longer than one has expected) or negative (being viewed less attractively as expected). This suggests a role for risk preferences: acquiring information may be viewed like a gamble with a positive or negative outcome. Conversely, risk preferences may in part be information preferences, as taking a risk always exposes one to the possibility of a negative news shock (Koszegi and Rabin 2006) Consistent with this account, a willingness to take risk in a hypothetical task (Gneezy and Potters 1997) is positively related to the desire to obtain information, $r(378) = 0.12$, $p = 0.017$, similar to results from Ganguly and Tasoff (2016).

Information, even when it is unpleasant in the moment, promises to improve decision-making in the future. It may thus be that those who discount the future more are also more willing to avoid information that may be unpleasant in the moment. Consistent with this view, we observe a negative relationship between willingness to obtain information and individual discount rate, $r(378) = -0.16$, $p = 0.001$.

***General personality traits*** We look at the relationship between information preferences and the Big Five Personality Inventory (BFI; John and Srivastava 1999). The desire for information was uncorrelated with agreeableness $r(378) = 0.04$, $p = 0.434$, but positively correlated with extraversion $r(378) = 0.11$, $p = 0.037$, conscientiousness $r(378) = 0.14$, $p = 0.007$, and openness to new experiences $r(378) = 0.22$, $p < 0.001$. Extraversion, characterized by high sociability and expressiveness, may induce those exhibiting high levels of this trait to also seek information more. High conscientiousness, or a tendency towards perseverance, may safeguard against an intuitive impulse to delay or avoid unwanted information. People who score high on the openness to new experiences factor, which relates to a tendency towards intellectual pursuits, also score high on curiosity (John and Srivastava 1999), and may incur a cost from *not* having information that they know is available, irrespective of its valence.

Conversely, information preference is negatively correlated with neuroticism, the tendency to more readily experience unpleasant emotions, $r(378) = -0.17$, $p < 0.001$. Higher levels of neuroticism may increase the hedonic cost of obtaining unfavorable information and hence make one less likely to take a chance in obtaining it. As there is a moderate link between neuroticism and pessimism (Segerstrom et al. 2011), similar reasoning may also apply to those who are more pessimistic about the outcome of the information.

**Discussion**

Study 1 examines the factor structure of the IPS and its relationship to a broad range of other measured constructs. In a purely exploratory model, the domain items all load onto their respective latent factors (e.g., health items all mapped onto the same factor), providing a clear multi-dimensional factorial structure of information preference. This result implies that information preferences are sensitive to the context in which the information is embedded, providing support for our second hypothesis that information preferences are sensitive to domain. Yet, we also sought to capture a more general and contextless aspect of information preference with our two general items, and the exploratory factor model fitted suggests that the latent factor structure of information preference can accommodate both individual personality differences and context-dependent dimensions (Mischel and Shoda 1995). To the best of our knowledge, this is the first empirical evidence comparing within-subjects' differential propensities towards information; previous studies (e.g., Sullivan et al. 2004, Glaeser and Sunstein 2013) have focused instead on specific, one-time situations where usually only a single decision is involved.

We see sizable proportions of avoidance across the wide variety of situations depicted in the IPS. To the extent that self-reporting behavior introduces bias (e.g. because participants want to project a favorable view of themselves), and to the extent that information-seeking is viewed as normative, we are, if anything, underestimating the extent of avoidance. The discriminant validity of information preferences' psychological uniqueness is affirmed by its lack of correspondence with potentially related constructs such as measures of need for consistency, closure, cognition, risk attitudes, receptiveness to opposing views, time discounting, and general personality traits. The scale appears to measure a distinct construct, with none of the correlations between the scale and potentially related measurements exceeding an absolute value of 0.3. Additionally, information preferences are not correlated with standard demographic characteristics such as gender, income, education, age, or political affiliation. These findings suggest the mechanisms underlying the latent construct of information preference are unique and cannot be explained solely by existing measurements. To further confirm and replicate these results, we administer the IPS to another sample at two time points in the next study. This allows for test-retest reliability as well as providing additional, empirically motivated tests of convergent and discriminant validity.

## Study 2: Test-retest reliability

Study 2 confirms the proposed exploratory factor model from Study 1 with a new and larger sample. By eliciting the scale responses from the same respondents at two points in time, we also assess test-retest reliability. We further test, beyond the measures administered in Study 1, the discriminant validity of the IPS by comparing it with additional constructs that have potential theoretical overlap. This allows a further clarification of the correspondence between information preferences and other established personality traits. We selected measures that bore the most theoretical similarity to the constructs most highly correlated with information preference in Study 1: curiosity, self-efficacy, and different learning styles. For example, a moderate correlation between information preference and openness to new experiences in Study 1 suggests that information preference may also be linked to curiosity, which is typified by search for information that may not be particularly useful (Loewenstein 1994). Recently, receptiveness to opposing views has also been linked to curiosity (Kahan et al. 2017), further lending support to a potential relationship between preferences for information and curiosity.

## Method

### Subjects

We recruited 601 participants (48.59% male with a mean age $M = 36.11, SD = 12.12$ on Amazon Mechanical Turk to complete the scale at two time points approximately four weeks apart. To avoid biasing our results, we report results for the 500 participants who completed both rounds of data collection. Those who failed to respond to the follow-up survey do not differ on any demographic measure from those who did complete the follow-up.

### Procedure

To examine the stability of the psychological trait over time, participants completed the assessment twice, with a four-week lag between the two administrations. For the first administration of the IPS only, we included additional psychological measures: the Curiosity and Exploration Inventory (CEI-II; Kashdan et al. 2009) the General Self-Efficacy Scale (GSE; Schwarzer and Jerusalem 1995), and Learning Styles (Cassidy 2004).

## Results

The mean IPS score is $M = 2.92, SD = 0.52$. We observe high internal consistency in both the first (measured by average inter-item correlations; Cronbach's $\alpha$ = 0.81) and second ($\alpha$ = 0.83) administration of the IPS. Test-retest reliability, measured by the correlation of respondents' average scores across both time points, was $r(498) = 0.64$, $p < 0.001$, indicating that the IPS reliably measures the construct over time. The test-retest reliability for the subscales are similar for finance, $r(498) = 0.56$, $p < 0.001$, health, $r(498) = 0.67$, $p < 0.001$, personal, $r(498) = 0.63$, $p < 0.001$, and general, $r(498) = 0.58$, $p < 0.001$.

The respective coefficients for the domain and general subscales for the initial administration is $\alpha_{\text{Finance}} = 0.52$, $\alpha_{\text{Personal}} = 0.72$, $\alpha_{\text{Health}} = 0.75$, and $\alpha_{\text{General}} = 0.70$), similar to that of Study 1. The subscale coefficients do not change appreciably for the retest, $\alpha_{\text{Finance}} = 0.54$, $\alpha_{\text{Personal}} = 0.76$, $\alpha_{\text{Health}} = 0.72$, and $\alpha_{\text{General}} = 0.72$.

**Confirmatory factor analysis (CFA)** We fit a confirmatory structural equation model on the responses for the first administration of the scale. Due to the ordinal (non-continuous) response type, the IPS is non-normally distributed, Mardia Skewness = 1,188.56, $p < 0.001$, Mardia Kurtosis = 17.99 , $p < 0.001$ (Mardia 1970). In such a situation, Flora and Curran (2004) recommend using the diagonal weighted least squares estimation procedure to estimate the confirmatory latent model.

Confirming the exploratory factor model in Study 1, the resulting latent factor structure (Figure 2) contains four correlated factors: the three domains and a general information preference factor. The general factor loads onto the latent domains as well as the two general information preference observed items (Table 4). The root mean square error approximation (RMSEA), a model fit index (Steiger and Lind 1980), is RMSEA = 0.03, 90% confidence interval, [0.02, 0.04], and falls within guidelines of good model fit (< 0.08; (Hooper et al. 2008)). This is corroborated by other fit statistics, such as the Tucker-Lewis Index = 0.98 (Tucker and Lewis 1973), and Comparative Fit Index (CFI) = 0.99, above recommended cutoffs of 0.90 and 0.95, respectively (Hu and Bentler 1999). The latent factor correlations are in Table 3.

***Curiosity, self-efficacy, and learning style***

We further assess the theoretical correspondence between information preferences and other personality traits. Curiosity was positively related to information preferences, ($r(584)$ = 0.22, $p < 0.001$). Because conscientiousness exhibited a positive relationship with information preference, we hypothesized that a related construct, self-efficacy, might also influence the perceptions of information usefulness, such that efficacious individuals would feel more confident in their ability to make better decisions in face of potentially negative information and thus be more likely to obtain such information. We see a positive relationship between information-seeking preferences and general self-efficacy, $r(584)$ = 0.21, $p < 0.001$.

**Discussion**

Study 2 demonstrates the psychometric stability of the IPS over time. In addition, using a latent model approach, our confirmatory factor model provides further evidence that IPS reliably and validly measures both domain-specific preferences for information as well as information preferences as a general psychological trait: individuals may have different information-seeking preferences for health, finance and personal characteristics, but may also have a general tendency towards information preference (or avoidance). We further clarify the unique construct of information preference as compared to other psychological constructs most closely aligned with those possessing highest convergent validity in Study 1. The correlations, while statistically significant, remain moderate (Study 1 range: [-0.17, 0.23]; Study 2 range: [0.21, 0.31]), further lending evidence that the desire to seek or avoid information can be reliably measured by the IPS, and that information preference is not simply an amalgamation or derivation of other existing constructs.

## Study 3: Predicting information choices

Studies 1 and 2 showed that the scale was reliable, exhibited a stable factorial structure over time, and possessed adequate discriminant and internal validity. Having illustrated the psychometric robustness of the scale, we next explore the external, predictive validity of the scale with a preregistered design. This study design, hypotheses, and analyses were pre-registered on AsPredicted (#22904).

There were five primary goals in this study.[1] First, we investigate whether the IPS could predict consequential information acquisition across a wide variety of domains, both across domains represented in the IPS and domains not represented in the IPS. For out-of-sample domains, we chose domains where information avoidance may be costly for individuals and society: information about the gender wage gap (occupational), the consequences of climate change (environmental), and information that may negatively reflect upon one's political group (political). Individuals' decisions to avoid information in these domains can have consequences such as a failure to deal with societal problems and political polarization. We test whether the full 13-item IPS can predict decisions across different domains, both specifically and in the aggregate. We also test whether domain subscales are especially good at predicting domain-related decisions.

Second, we compare the performance of our scale in measuring information seeking and avoiding behaviors to an alternative assessment measuring information avoidance, the "HS"

[1] The first, second, and fourth hypotheses were pre-registered.

(Howell and Shepperd 2016), that uses abstract questions such as “I would rather not know how others perceive me,” instead of concrete scenarios, as the IPS does.

Third, given the widespread organizational implications of information avoidance, such as whistleblowing or a failure to notice unethical behavior (e.g., Gino and Bazerman 2009, Sezer and Bazerman 2016), we develop a set of items unique to managerial contexts, and test this subscale for psychometric properties and predictive validity.

Fourth, we examine the relationship between information preference and political affiliation. For the political decision, we hypothesized that the IPS will be predictive for conservatives when the information may be unpleasant for Republicans, and that we will see similar predictive validity for liberals when the information may be unpleasant for Democrats. To benchmark the IPS’s performance when it comes to predicting openness to receiving political information, we compared the predictive validity of the IPS to that of Minson et al. (2019)’s Receptiveness to Opposing Views scale.

Finally, we harness the statistical power of the large sample size present in this study to investigate whether the latent factor structure of the IPS is identical across studies, or whether the IPS exhibits measurement invariance.

## Methods

We recruited 2000 participants for a task labeled “study on decision-making” on Amazon Mechanical Turk, restricting the sample to those who had not previously completed our scale, and invited those who participated for a second wave two weeks later. The second wave made no reference to the first study. Following Study 2, and our pre-registered plan, we limit our analyses to those who completed both stages and passed an attention check. Participants were randomly assigned to one of four conditions in a 2 x 2 design that counterbalanced whether a single behavioral measure (an opportunity to gain access to information) was asked either during the first or second round of data collection, and whether the participant had the opportunity to acquire information related to politics in the first or second wave, with one of the five other domains presented in the other wave. One main survey (which was administered either in the first or the second round of data collection) included the 13-item IPS, three sets of items related to potential mechanisms underlying information preference, the Howell and Shepperd (2016) scale, and Minson et al. (2019)'s Receptiveness to Opposing Views Scale. The survey additionally included one consequential information acquisition decision and an attention check.

The other survey included only the option to be forwarded to a website to obtain information that might be valuable~~,~~ but that people might be motivated to avoid. We had people make this consequential information seeking/avoidance decision at a point in time separated from taking the measures by a two-week interval to avoid demand effects, and to ensure that information avoidance, as measured by the IPS, is a trait that is stable over time. If participants chose to obtain the information, they were forwarded to the relevant website upon completion of the study.

The format of HS is open-form (example item: "I would rather not know ______"). These sentence stems allow the test-maker to complete the sentence as they wished. In line with the phrases used in the Howell and Shepperd (2016) study, the sentences were completed using the phrases "my health", "my finances", and "how others perceive me" for the three domains. To mask the true purpose of our study (to ascertain whether our scale predicts behavior), the survey was interspersed with three sets of distractor items written in a similar format as the IPS (e.g., participants were asked if they "probably will act immediately" or "probably will share [information]").

Participants were randomly assigned to obtain information from an established website that provided information about one of six domains. The first five were: (1) occupational information (a website that compared average salaries in over 400 occupations), (2) consumer finances (a website to estimate their retirement income), (3) environment (consequences of climate change on biodiversity and weather in your zip code), (4) health (a website that informs people whether they are at risk of burnout), or (5) interpersonal (an algorithm that scored trustworthiness and other personality traits from the participant's picture). All participants saw one of those five items in one of the two waves. The sixth domain was in the domain of politics; participants were randomly assigned to making a decision about an issue aversive to Republicans or to Democrats. For the issue aversive to Republicans, participants were asked whether they wanted to know about the number of false and misleading claims that President Donald J. Trump has made. If participants wanted to know, we forwarded them to a tracker maintained by the Washington Post immediately after the close of the survey. For the issue aversive to Democrats, participants were asked whether they wanted to know about the fundraising efforts of Democratic presidential candidates (who had announced their candidacy by May 2019); specifically, for each candidate, what proportion of fundraising came from small donations, rather than larger, often corporate, donors. This was taken from a CNN article. For both pieces of information, participants were not told what the news source was.

By the time they had completed both rounds of data collection, therefore, participants had completed the IPS, the HS alternative, the Receptiveness to Opposing Views scale, three sets of distractor items, and made two consequential decisions, one of them being a political decision. In the survey containing the scales, the order of the scales was randomized, except for the IPS, which was fixed to be first. For the second wave, we contacted all participants from the first wave (except for the approximately 10% of participants who were assigned to complete the set of scales in the first wave and failed the attention check, as pre-registered). Participants then completed either the survey of scales or made a second decision. Participants who completed the decision about whether to be forwarded to an informational website only were paid 20 cents; those who completed the longer scale were paid $1.50. After one week, we sent out a reminder and increased the payment to 50 cents and $2.00, respectively.

**Subjects**

Out of 2000 participants who had previously not taken our survey, 1488 participants completed two surveys two weeks apart on Amazon Mechanical Turk. Of these participants, we removed 58 for violating conditions in our pre-registered report (including 38 participants who failed the attention check, 6 whose self-reported gender changed, and 17 whose age changed by more than one year between the two administrations; 3 of these participants violated more than one of these conditions). This resulted in a total sample size of 1430 participants (50.07% male with a mean age $M = 39.01, SD = 12.86$). Table 6 shows the breakdown of participants by domain category and round of data collection.

**Results**

We first wanted to determine whether there was an order spillover effect such that completing the IPS first would influence subsequent decisions to acquire information, or vice versa. Using the IPS scores and the survey order as predictions in a logistic regression model yielded a non-significant interaction of order, $OR$ = 1.11, 95% CI [0.72, 1.71], $z$ = 0.46, $p =$

0.646. That is, it does not appear that taking the IPS primed participants to be more consistent with their decision - unless the effect of taking the scale persisted for at least two weeks, which seems unlikely. In line with our pre-registration report, we thus analyzed both decisions from all participants.

We used the mean score of all item responses to create a total IPS score and also computed scores for each domain.[2] The mean IPS score is $M = 2.93, SD = 0.49$, which is very similar to the mean scores from the prior studies (see Figure 1 for distribution of scores). We rescale the range of the HS and the ROV so all scores are bounded between [1, 4] and use the mean score, rather than the sum score, so that the effect size of the different scales can be directly compared.

Overall, the IPS is able to predict information acquisition across all conditions, in a mixed effects logistic regression with a random effect for participants, $OR$ = 1.83, 95% CI [1.48, 2.28], $z$ = 5.46, $p < 0.001$. It also predicts the odds of an individual acquiring information two weeks after completing the IPS scale, $OR$ = 1.84, 95% CI [1.28, 2.71], $z$ = 3.2, $p = 0.001$. Looking at participants who made a decision first and then took the IPS two weeks later confirms this positive link between IPS scores and the decision to acquire information, $OR$ = 2.04, 95% CI [1.41, 2.70], $z$ = 3.75, $p < 0.001$.

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[2] In our pre-registration report, we specified using the mean of the domain scores instead. We report these results, which do not differ qualitatively, in the appendix, but suggest future studies use the simple mean reported in the main text and as is commonly used for other scales.

The total IPS and the HS scale were moderately and negatively correlated, $r(1424) = -0.54$, $p < 0.001$, indicating an opposite theoretical correspondence between the desire to obtain information and the desire to avoid it, as expected. However, looking at all six domains simultaneously, the HS did not predict information seeking or avoiding behaviors, $OR = 0.94$, 95% CI [0.79, 1.12], $z = -0.69$, $p = 0.492$, and we find similar results for the Receptiveness to Opposing Views scale, $OR = 0.94$, 95% CI [0.8, 1.12], $z = -0.68$, $p = 0.499$.

Even when controlling for HS and Receptiveness to Opposing Views scores, the main effect for IPS scores persists, $OR = 2.2$, 95% CI [1.7, 2.86], $z = 5.97$, $p < 0.001$. Each additional point in IPS scores increases the log odds of obtaining information by 2.20. However, an additional point in HS scores does not lead to a decrease in the log odds of obtaining information, as one would expect, given that the HS scale measures information avoidance. Instead, such a change in HS scores in a model including the IPS and the ROV produces a non-significant change, $OR = 0.94$, 95% CI [0.79, 1.12], $z = -0.69$, $p = 0.492$, suggesting that HS scores provide no incremental value in predicting information avoidance or acquisition. The variance inflation factors for all three predictors do not exceed 2, suggesting that multicollinearity is not the issue.

A statistical comparison of the two scales further illustrates that the IPS can significantly explain variations in information-seeking and avoidant behaviors beyond what the alternative scale can provide. We applied dominance analysis (Azen and Budescu 2003, Azen and Traxel 2009) to an ordinary least squares regression specification containing both scales. This approach uses changes in model fit statistics (i.e., $R^2$ in ordinary least squares regression) to determine predictor importance. In a dominance analysis with this full model of predictors, the contribution in variance explained by the IPS scores is larger than that of the HS scores by a magnitude of more than 5, providing support that the IPS has unique predictive value.

**Occupation subscale** We also tested the feasibility of an occupational subscale (see Table 7 for items and prevalence rates). Using the existing IPS items as a model, we generated five scenarios in which respondents could seek out or avoid information related to their work. On those items, we observed avoidance rates ranging between 14.82% and 41.40% (see Table 7). We cross-validated our findings by randomly dividing half of our sample (N = 715) and performing exploratory modeling, and then using the remaining half of participants for our confirmatory analyses.

In the exploratory phase, the five-item subscale exhibited good internal consistency, $\alpha$ = 0.59, similar to that of the IPS. All the items loaded onto a one-factor EFA solution, with good model fit, RMSEA = 0.03, 90% CI = [0, 0.06]. A one-factor CFA (Table 7) showed similarly good model fit: RMSEA = 0, 90% CI = [0, 0.02]; TLI = 1.02, and CFI = 1. Additionally, the subscale exhibited strong correlation with the total scale, $r(1428) = 0.57$, $p < 0.001$. Having ascertained the psychometric validity of this occupational subscale, we later test its behavioral and predictive validity.

**Predictive validity of the IPS across subdomains**

Having shown that the full 13-item IPS is able to broadly predict information acquisition across domains, we further tested the ability of the IPS scores to predict decisions in different domains. With the exception of the finance domain, the IPS is able to predict domain-related decisions well (see Table 8 and Figure 3).

Notably, the IPS predicts decisions in domains that are not represented in the scale. For the occupational domain, the IPS significantly predicted whether individuals would want information about the gender pay gap in their occupation, $OR$ = 2.56, 95% CI [1.42, 5.09], $z$ = $2.95$, $p = 0.003$, meaning that each one-point increase in the IPS score by approximately 10%. IPS scores also increased the log-odds of obtaining information about biodiversity and weather impacts (the environmental domain) by $OR$ = 1.69, 95% CI [1.02, 2.94], $z$ = 1.98, $p = 0.048$.

In the domains represented in the IPS, the scale scores was able to predict the propensity to obtain information about individual's risk of burnout (health domain), $OR$ = 2.78, 95% CI [1.49, 5.82], $z$ = $3.01$, $p = 0.003$. The IPS significantly predicted the likelihood that someone would want to know about whether an algorithm would infer personality traits based on an uploaded picture, $OR$ = 2.04, 95% CI [1.07, 3.01], $z$ = $2.14$, $p = 0.032$. The IPS also predicted political information acquisition for both whether participants wanted to fact-check President Trump, $OR$ = 1.48, 95% CI [1.04, 2.15], $z$ = $2.13$, $p = 0.033$, or know about the breakdown of donors for Democratic presidental nominees, $OR$ = 1.78, 95% CI [1.25, 2.58], $z$ = 3.2, $p =$ $0.001$. We examine the breakdown of information preference predictiveness by political affiliation in a later section.

**Predictive validity of IPS domain subscales** We can also test whether domain subscales in the IPS can predict a) general information acquisition and b) domain-related decisions. Figure 3 shows the predicted probability of obtaining information for each domain by IPS score. We conducted a series of regressions, presented in Table 8, using the IPS and the HS subscales on the decision to acquire information for all decisions, as well as each specific domain. The IPS subscales encompassed the occupational, finance, health, personal, and general domains; the HS subscales included the finance, health, and personal domains. For the purposes of interpretability, we use a linear probability model for all subsequent analyses, though the statistical results are unchanged if a mixed effects logistic regression is used.

When examining the subscale correlations between the HS and the IPS, we find relatively large negative correlations; for example, the health subscales have similar correlational magnitude but in the opposite direction, $r(1428) = -0.56$, $p < 0.001$, suggesting divergent validity. A complete subscale-by-subscale comparison of the convergent and divergent validity of both scales is in Table 5.

The prevalence of information acquisition differed across domains (see Table 6). Yet, IPS subscales (in addition to the full IPS) were also able to broadly predict decisions to acquire information, regardless of domain. whereas the HS was unable to predict information avoidance or acquisition (see last column of Table 8).

The linear probability models for both scales are presented in Table 8. The IPS subscores had mixed and differential predictive validity across domains. For example, the finance subscale scores were able to predict the occupational decision of looking at information about the gender pay gap in one's profession, $b = 0.15$, 95% CI [0.07, 0.23], $t(290) = 3.64$, $p < .001$, but was not able to predict the finance decision to look at a retirement savings calculator. The health subscale scores were able to predict the decision to find out about burnout, but also environmental impacts on local biodiversity.

The new occupational subscale was also able to predict general information acquisition across both time points, $b = 0.09$, 95% CI [0.06, 0.12], $t(2858) = 5.91$, $p < .001$, as well as for the specific occupational decision, $b = 0.15$, 95% CI [0.05, 0.25], $t(290) = 3.05$, $p = .002$, indicating that each point increase in the occupational subscore increases the percentage of information-seeking by 15.37%.

**Political information** For those who changed their political affiliation between the two waves (212 participants, or 14.83% of the sample), we retained the political affiliation at the time point that they made their political decision, as preregistered. Of those participants, (179 changed their response by only one gradation (e.g., from “very liberal” to “slightly liberal”).

We hypothesized that political affiliation would predict information avoidance if the information might be aversive to the individual’s political affiliation. All participants were randomly assigned to want to know about either the Republican-aversive or Democrat-aversive piece of information. We conduct a median split on political orientation. In a mixed effects logistic model across both political decisions, we find a main effect of IPS scores, $OR$ = 1.76, 95% CI [1.01, 3.15], $z$ = 1.98, $p = 0.048$, and a non-significant interaction, $OR$ = 0.78, 95% CI [0.36, 1.65], $z$ = $-0.65$, $p = 0.513$. As we had not hypothesized an interaction, subsequent models examine main effects only.

Figure 4 shows a main effect of IPS by political affiliation and political information. For those identifying as liberals, we see a main effect of IPS score about information regarding the fundraising sources of Democratic presidential candidates, $OR$ = 1.62, 95% CI [0.99, 2.75], $z$ = 1.88, $p = 0.06$, and fact-checking President Donald Trump, $OR$ = 1.76, 95% CI [1.01, 3.32], $z$ = 1.98, $p = 0.048$. The benchmark predictor, the Receptiveness to Openness Views scale (Minson et al. 2019) does not predict information acquisition decisions for either liberals, $OR$ = 0.94, 95% CI [0.65, 1.36], $z$ = $-0.32$, $p = 0.746$, or conservatives, $OR$ = 1.34, 95% CI [0.84, 2.25], $z$ = 1.23, $p = 0.219$.

Table 9 presents an additional series of regression specifications designed to test the robustness of the IPS against various controls in predicting political decisions. We find that the IPS is predictive for information seeking as a sole predictor (Model 1), when controlling political affiliation (Model 2), additionally for Receptiveness to Opposing Views and HS scale (Model 3), and the when randomization order of the study is accounted for (Model 4). This provides additional evidence that the IPS is able to predict information acquisition, particularly in out-of-sample domains.

**Measurement invariance** Finally, we capitalized on the large sample size gathered in this study to conduct a measurement invariance analysis, which tests whether the same construct is being measured across multiple groups. Specifically, we wanted to determine whether the latent factor model proposed in Study 1 and confirmed in Study 2 would also be replicated in this study. As an additional analysis, we tested for the equality of factor loadings across the three studies, a test of metric invariance (Kline 2011). More stringent assumptions of latent factor equality are rarely satisfied in practice (Marsh et al. 2018, Vandenberg and Lance 2000), even with established and widely used scales (e.g., Rasmussen et al. 2015) and were not tested.

To test for measurement invariance across participants in three studies, we fitted the same CFA model across the three groups and compared the relative decrease in model fit statistics when a) the latent factor model was the same as in Figure 2 and b) the factor loadings for each item were constrained to be equal. We fit a factor model that imposes the same latent factor structure across all three studies. The two fit statistics (CFI = 0.93; RMSEA = 0.058) were similar to that of prior studies, which fall within suggested guidelines of good model fit. We then further fit a second factor model to be constrained such that the factor loadings were assumed to be equal. If the total change in the CFI and RMSEA both differ by an amount greater than 0.01 (Cheung and Rensvold 2002, Rutkowski and Svetina 2014), then it is likely that the factor loadings across the three studies are not equal. In the second factor model, the fit statistics are virtually unchanged (CFI = 0.93, $\Delta$ = 0; RMSEA = 0.057, $\Delta$ = -0.01), suggesting that the latent factor structure of the IPS is stable and generalizable to a large sample.

**Discussion**

Study 3 finds that the IPS is able to predict consequential decision to obtain (or avoid) information across multiple domains. When we compare our scale with a related elicitation relying on abstract questions on information avoidance (Howell and Shepperd 2016), we find that the two scales are moderately and negatively correlated. However, only the IPS is able to predict a variety of real-world behaviors related to information acquisition. Information preferences scores also predicted participants' decisions about whether to obtain political information, when the information was aversive to the individual's particular political affiliation.

The domain-related subscales on their own were often able to predict the specific domain-related decision; moreover, the domain-specific subscales were also able to predict information preferences in general. The IPS achieves both psychometric and ecological validity in its ability to use both the domain-specific items, as well as the entire scale, to predict behaviors related to preference for information across a wide variety of domains, with the sole exception of the finance subscale. While these results suggest that it may not be necessary to present all scenarios in some instances, administering the whole scale imposes low costs and can provide additional insights.

We were also able to develop an information preference subscale applicable to a managerial setting, and to validate a one-factor model of the items in an independent sample. Similar to the other domain-specific subscales, this occupational subscale predicts an occupational decision to acquire information, even with a substantial time lag.

This study also was able to establish the ability of the IPS to predict information avoidance for topics not covered in the scale (i.e., occupational, political and environmental information). Some of the subscales themselves were able to predict related out-of-domain decisions (e.g., a one-point shift in a finance subscale yielded a 14.82% increase in obtaining information about salary ranges).

Finally, a measurement invariance analysis of the latent factor structure in all three studies supported the stability of the proposed factor structure and the equality of factor loadings for the individual items, suggesting the IPS has a stable and multidimensional factor structure.

In concert, these results suggest that information preferences may be a robust individual difference. Our scale provides the first demonstration of an easily implementable scale that bridges the often wide chasm between measurement of psychological constructs and prediction of relevant behaviors.

## General Discussion

Making good decisions is often contingent on obtaining information, even when that information is uncertain and has the potential to produce unhappiness. Substantial empirical evidence suggests that people are often ready to make worse decisions in the service of avoiding potentially painful information. We propose that this tendency to avoid information is a trait that is separate from those measured previously, and developed a scale to measure it. The scale asks respondents to imagine how they would respond to a variety of hypothetical decisions involving information acquisition/avoidance. The predictive validity of the IPS appears to be largely driven by its domain items, and although it incorporates domain-specific subscales, it appears to be sufficiently universal to capture preferences for information in a broad range of domains.

In three studies incorporating responses from over 2400 participants, we test the validity and reliability of the Information Preferences Scale, with a particular focus on its capacity as a behaviorally predictive tool. The IPS differs from scales that have been used to measure many other individual difference constructs in three important ways. First, it uses realistic and actionable scenarios as a foundation for defining the construct of information preference. In contrast with measures that ask people abstract questions about their personal characteristics, the IPS is oriented towards behavioral outcomes. Second, IPS items tap into a wide range of situations that are both psychologically and economically consequential in the domains of health, finance, and personal attributes. Third, the IPS was behaviorally validated using a series of contextualized decisions to acquire information across domains, and shows promise in predicting information acquisition behavior in domains not included in the scale itself.

The IPS was designed specifically to measure information acquisition in situations in which the information one might obtain is of uncertain emotional valence. We acknowledge here that the scenario-based approach to measuring a psychological construct may limit generalizability, as some of the vignettes represented are quite specific. Further lines of inquiry with different populations and, possibly, different scenarios, may reveal fruitful insights. However, our results show that the tendency to avoid information varies substantially across individuals, but not along any of the standard demographics we assessed (e.g., gender, age, and education). Reassuringly, we find in our final study that our scale is able to predict information acquisition and avoidance, even when participants made the decision after the passage of a considerable length of time.

Individual differences in information preference may have especially important implications for disseminating information and raising awareness. Governments (and private actors) currently apply informational campaigns broadly, based on the assumption that individuals generally prefer to receive the information and would actively seek it out if given the choice. However, the impact of information campaigns may differ, across domains and people, based on people's tendency to avoid information. Specifically, the expectation of a hedonic cost might motivate some people to avoid information in a way that undermines information provision policies. For example, financial education literacy interventions, have been found to have small impacts on behavior (e.g., Fernandes et al. 2014), perhaps in part because many people are anxious about their finances and avoid information - e.g., about the adequacy of their savings for retirement - that they fear might make them uncomfortable. Similarly, the presence of calorie labels does not always help consumers make healthier choices (Elbel et al. 2009), undoubtedly in part because people who are overweight, or who are going to eat unhealthy foods regardless of their nutritional content, might find the information aversive.

Sunstein (2019) notes that in some cases, the hedonic cost of obtaining information may result in a net reduction in overall welfare. That is, calorie labels might nudge consumers toward a healthier option, but may drastically decrease enjoyment of the meal. Information disclosure may be especially effective for the subset of consumers who are not predisposed to avoid potentially unpleasant information. For those who are disposed to avoid information, other tactics will need to be explored, including ways of encouraging people to attend to information they might otherwise be motivated to avoid.

Given the societal welfare implications of avoidance, people's preferences for information ought to be accounted for when designing interventions to help reduce an unwanted behavior (e.g., smoking cessation) or increase uptake of actions with positive outcome (e.g., more annual physicals). Studies in health behavioral phenotyping have begun to personalize care based on behavioral trends and prior responses to health interventions (Jethwani et al. 2010). Automated algorithms in the form of robo-advisors now guide the information that is delivered to consumers based on balance and prior investing experience (e.g., Betterment and Wealthfront). Personalized interventions are considered promising in drug development (Ginsburg and McCarthy 2001, Schork 2015, Swan 2009); similarly, personalized messaging campaigns may make informational campaigns more effective. Knowing who is likely to engage with certain kinds of information could improve the effectiveness of informational campaigns and avoid exposing people to information they would be better off not obtaining (in terms of their belief utility) and are unlikely to act on. Information seekers and avoiders may benefit from different messaging, much like extremely risk-averse investors may desire different products than do those who are more tolerant of volatility. An important caveat is that targeted interventions, such as informational campaigns, that condition on IPS scores ought to be designed with caution so that ethical considerations (e.g., intrusions on privacy, but also individuals' rights to make informed decisions) are fully accounted for. Such pursuits ought to reflect a careful balance of both normative and subjective welfare when it comes to the costs and benefits of acquiring information (Loewenstein and O'Donoghue 2006, Sunstein 2019). This work is the first empirical articulation of how interested parties might quantify such subjective preferences, and estimate subsequent costs of such individual differences.

With the recent emergence of information avoidance as a central topic in economics and other disciplines, measuring information preferences in laboratory and field experiments may become as important as measuring risk and time preferences. Already, areas of inquiry in political science and psychology are reckoning with the consequences of misinformation campaigns, and the growing hyperpolarization of public discourse (Tucker et al. 2018). As Sunstein (2017) writes, online consumption of selectively curated news can easily form informational cascades of distorted, grossly amplified, and often false knowledge. A better understanding of information preferences and avoidance may be pivotal to combating such threats to democracy and other arenas that deeply influence public life.

**Tables**

Table 1

*IPS items and proportion of avoiders*

| Items | Study 1 | Study 2 | Study 3 |
|---|---|---|---|
| As part of a semi-annual medical checkup, your doctor asks you a series of questions. The answers to these questions can be used to estimate your life expectancy (the age you are predicted to live to). Do you want to know how long you can expect to live? | 43.68 | 36.60 | 21.26 |
| You provide some genetic material to a testing service to learn more about your ancestors. You are then told that the same test can, at no additional cost, tell you whether you have an elevated risk of developing Alzheimer's. Do you want to know whether you have a high risk of developing Alzheimer's? | 21.32 | 19.80 | 20.14 |
| At your annual checkup, you are given the option to see the results of a diagnostic test which can identify, among other things, the extent to which your body has suffered long-term effects from stress. Do you want to know how much lasting damage your body has suffered from stress? | 25.52 | 23.20 | 38.18 |
| Ten years ago, you had the opportunity to invest in two retirement funds: Fund A and Fund B. For the past 10 years, you have invested all your retirement savings in Fund A. Do you want to know the balance you would have, if you had invested in Fund B instead? | 51.05 | 45.80 | 37.83 |
| You decide to go to the theater for your birthday and give your close friend (or partner) your credit card so they can purchase tickets for the two of you, which they do. You aren't sure, but suspect that the tickets may have been expensive. Do you want to know how much the tickets cost? | 20.52 | 17.60 | 17.14 |
| You bought an electronic appliance at a store at what seemed like a reasonable, though not particularly low, price. A month has passed, and the item is no longer returnable. You see the same appliance displayed in another store with a sign announcing 'SALE.' Do you want to know the price you could have bought it for? | 37.37 | 37.40 | 44.33 |
| You gave a close friend one of your favorite books for her birthday. Visiting her apartment a couple of months later, you notice the book on her shelf. She never said anything about it; do you want to know if she liked the book? | 23.68 | 22.40 | 26.15 |
| Someone has described you as quirky, which could be interpreted in a positive or negative sense. Do you want to know which interpretation he intended? | 31.31 | 31.60 | 35.73 |

| | | | |
|---|---|---|---|
| You gave a toast at your best friend's wedding. Your best friend says you did a good job, but you aren't sure if he or she meant it. Later, you overhear people discussing the toasts. Do you want to know what people really thought of your toast? | 39.21 | 35.60 | 40.42 |
| As part of a fund-raising event, you agree to post a picture of yourself and have people guess your age (the closer they get, the more they win). At the end of the event, you have the option to see people's guesses. Do you want to learn how old people guessed that you are? | 24.21 | 25.00 | 23.35 |
| You have just participated in a psychological study in which all the participants rate one-anothers' attractiveness. The experimenter gives you an option to see the results for how people rated you. Do you want to know how attractive other people think you are? | 39.21 | 33.40 | 39.79 |
| Some people seek out information even when it might be painful. Others avoid getting information that they suspect might be painful, even if it could be useful. How would you describe yourself? | 28.69 | 25.40 | 24.47 |
| If people know bad things about my life that I don't know, I would prefer not to be told (R) | 33.69 | 32.20 | 37.48 |

*Note*. R = reverse-coded; Percentage of participants rating that they either definitely or probably did not want to know.

Table 2

*Cronbach's alpha for IPS subscales*

| Study | Finance | Personal | Health | General | Occup | IPS |
|---|---|---|---|---|---|---|
| 1 | 0.61 | 0.76 | 0.79 | 0.79 | | 0.86 |
| 2 | 0.52 | 0.72 | 0.75 | 0.70 | | 0.80 |
| 3 | 0.49 | 0.69 | 0.72 | 0.63 | 0.59 | 0.77 |

Table 3

*Latent factor correlations (Study 2)*

| | Finance | Personal | Health | General |
|---|---|---|---|---|
| Finance | | | | |
| Personal | 0.48 | | | |
| Health | 0.39 | 0.54 | | |
| General | 0.44 | 0.53 | 0.76 | |

Table 4

*Standardized factor loadings for the EFA (Study 1) and CFA (Study 2 and 3)*

| Factor | Item | Study 1 EFA | Study 2 CFA | Study 3 CFA |
|---|---|---|---|---|
| Health | H1 | 0.64 | 0.71 | 0.65 |
| | H2 | 0.83 | 0.72 | 0.68 |
| | H3 | 0.74 | 0.69 | 0.70 |
| Finance | F1 | 0.63 | 0.64 | 0.66 |
| | F2 | 0.32 | 0.27 | 0.31 |
| | F3 | 0.72 | 0.70 | 0.61 |
| Interpersonal | I1 | 0.25 | 0.40 | 0.39 |
| | I2 | 0.53 | 0.59 | 0.60 |
| | I3 | 0.52 | 0.56 | 0.62 |
| | I4 | 0.63 | 0.66 | 0.53 |
| | I5 | 0.84 | 0.68 | 0.66 |
| General | G1 | 0.81 | 0.81 | 0.83 |
| | G2 | 0.81 | 0.67 | 0.55 |

*Note.* All CFA loadings significant at alpha = 0.05;
EFA = Exploratory Factor Analysis; CFA = Confirmatory Factor Analysis.

Table 5

*Divergent validity correlations*

| Study | Scale | α | Finance | Health | Personal | Total |
|---|---|---|---|---|---|---|
| Study 1 | Need for Consistency | 0.92 | 0.03 | -0.06 | -0.03 | -0.07 |
| | Need for Closure | 0.90 | 0.04 | -0.07 | 0.04 | -0.12 * |
| | Receptiveness to Opposing Views | 0.91 | -0.02 | 0.13 ** | 0.09 . | 0.23 *** |
| | Need for Cognition | 0.93 | 0.09 . | 0.12 * | 0.15 *** | 0.21 *** |
| | General Risk | - | 0.07 | 0.05 | 0.13 ** | 0.12 * |
| | Time Discounting | 0.81 | -0.08 | -0.07 | -0.12 * | -0.16 *** |
| | BFI: Extraversion | 0.90 | 0.11 * | 0.00 | 0.13 ** | 0.11 * |
| | BFI: Agreeableness | 0.83 | -0.04 | 0.02 | 0.07 | 0.04 |
| | BFI: Conscientiousness | 0.88 | 0.13 ** | 0.03 | 0.04 | 0.14 ** |
| | BFI: Neuroticism | 0.92 | -0.08 . | -0.03 | -0.03 | -0.17 *** |
| | BFI: Openness | 0.88 | 0.10 * | 0.18 *** | 0.18 *** | 0.22 *** |
| Study 2 | Curiosity | 0.90 | 0.03 | 0.13 *** | 0.13 *** | 0.22 *** |
| | Self-Efficacy | 0.92 | 0.08 * | 0.14 *** | 0.18 *** | 0.21 *** |
| | Learning Styles | 0.83 | 0.11 ** | 0.23 *** | 0.25 *** | 0.31 *** |
| Study 3 | Receptiveness to Opposing Views | 0.90 | 0.03 | 0.05 * | 0.08 *** | 0.11 *** |
| | HS: Health | 0.94 | -0.12 *** | -0.56 *** | -0.22 *** | -0.41 *** |
| | HS: Finance | v.91 | -0.11 *** | -0.19 *** | -0.10 *** | -0.20 *** |
| | HS: Interpersonal | 0.94 | -0.24 *** | -0.31 *** | -0.56 *** | -0.54 *** |
| | HS: Total | 0.92 | -0.22 *** | -0.49 *** | -0.42 *** | -0.54 *** |

*Note*. . $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6

*Study 3 avoidance rates across domain*

| Wave | | Occupational | Finance | Environmental | Health | Personal | Politics (D) | Politics (R) |
|---|---|---|---|---|---|---|---|---|
| 1 | Percent Avoid | 70.29 | 77.18 | 65.00 | 73.88 | 87.05 | 65.24 | 71.07 |
| | N | 138 | 149 | 140 | 134.00 | 139 | 374 | 356 |
| 2 | Percent Avoid | 48.70 | 56.94 | 37.41 | 50.35 | 70.83 | 44.38 | 55.52 |
| | N | 154 | 144 | 147 | 141 | 144 | 347 | 353 |

Table 7

*Factor loadings for Occupational subscale*

| Item | Item Text | EFA | CFA | Avoid |
|---|---|---|---|---|
| O1 | Employees commonly encourage workers to complete health risk assessments that gauge their health characteristics and risk. These are usually used to estimate workplace-wide risks the company may face. If you had the opportunity, would you like to get your individual risk assessment? | 0.51 | 0.50 | 19.02 |
| O2 | Most people spend some time at work on activities they are not proud of (e.g., browsing social media). Suppose you could compose a list of these activities and have your computer track how much time you spend oing them. The information would not be shared with your employer. Would you like to know what fraction of each hour at work you spend on these activities? | 0.43 | 0.49 | 41.82 |
| O3 | As part of a unit-wide evaluation, you and your coworkers are asked how easy it is to get along with each other and what your strengths and weaknesses are. Would you like to know how your co-workers rated you? | 0.54 | 0.50 | 21.26 |
| O4 | The rise of artificial intelligence is likely to lead to job losses in a wide range of occupations, affecting workers in industries from long-distance trucking to health care. Would you like to know whether your job is at risk due to automation in the next 10 years? | 0.54 | 0.46 | 15.10 |
| O5 | One option in your employer's retirement plan allows you to compare your investment return to that of your coworkers. Would you like to know how your investment return compares to the average and highest investment returns earned by employees at your firm? | 0.35 | 0.42 | 36.65 |

*Note.* All CFA loadings significant at alpha = 0.05; Avoid is the percentage of participants who either 'definitely' or 'probably didn't want to know'.

Table 8

*Regression coefficients for subscales on information acquisition decisions (Study 3)*

| | | Occupational | Finance | Environmental | Health | Personal | Politics (D) | Politics (R) | All Decisions |
|---|---|---|---|---|---|---|---|---|---|
| IPS | All | 0.22 ** | 0.00 | 0.13 * | 0.23 ** | 0.11 * | 0.14 ** | 0.09 * | 0.12 *** |
| | Occupational | 0.15 ** | 0.00 | 0.08 . | 0.14 * | 0.09 * | 0.11 *** | 0.09 ** | 0.09 *** |
| | Finance | 0.15 *** | 0.04 | 0.06 | 0.07 . | 0.04 | 0.04 | 0.02 | 0.05 *** |
| | Health | -0.01 | -0.02 | 0.08 * | 0.11 ** | 0.02 | 0.06 * | 0.02 | 0.03 ** |
| | Interpersonal | 0.09 * | -0.02 | 0.04 | 0.10 * | 0.06 | 0.06 * | 0.04 | 0.05 *** |
| | General | -0.04 | 0.03 | 0.02 | 0.06 | 0.00 | 0.06 * | 0.01 | 0.02 . |
| HS | All | 0.05 | 0.06 | 0.01 | -0.02 | -0.03 | -0.07 * | -0.01 | -0.01 |
| | Finance | -0.03 | 0.01 | -0.02 | 0.03 | -0.01 | 0.00 | 0.01 | 0.00 |
| | Health | 0.04 * | 0.02 | -0.01 | -0.03 | -0.01 | -0.02 | 0.00 | 0.00 |
| | Interpersonal | -0.01 | -0.01 | 0.00 | -0.04 . | -0.02 | -0.02 | 0.00 | -0.01 . |

*Note*. D = aversive to Democrat information; R = aversive to Republican information; . $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 9

*Mixed effects logistic regression on decision to acquire information in political decisions (Study 3)*

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| (Intercept) | $-1.781^{***}$ | $-1.504^{***}$ | $-1.434^{*}$ | $-1.884^{**}$ | $-1.205^{*}$ |
| | (0.387) | (0.394) | (0.705) | (0.723) | (0.531) |
| Information Preference Scale | $0.479^{***}$ | $0.500^{***}$ | $0.536^{***}$ | $0.666^{***}$ | $0.398^{*}$ |
| | (0.129) | (0.132) | (0.155) | (0.159) | (0.180) |
| Conservative | | $-0.731^{***}$ | $-0.726^{***}$ | $-0.733^{***}$ | -1.363 |
| | | (0.115) | (0.111) | (0.113) | (0.780) |
| Receptiveness to Opposing Views | | | -0.101 | -0.055 | |
| | | | (0.104) | (0.107) | |
| HS Scale | | | 0.037 | 0.214 | |
| | | | (0.123) | (0.128) | |
| Scale First | | | | -0.074 | |
| | | | | (0.113) | |
| First Decision | | | | $-0.804^{***}$ | |
| | | | | (0.115) | |
| IPS x Conservative | | | | | 0.214 |
| | | | | | (0.261) |
| Log Likelihood | -959.518 | -937.240 | -934.256 | -908.894 | -936.904 |
| Num. obs. | 1430 | 1430 | 1426 | 1426 | 1430 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

# Figures

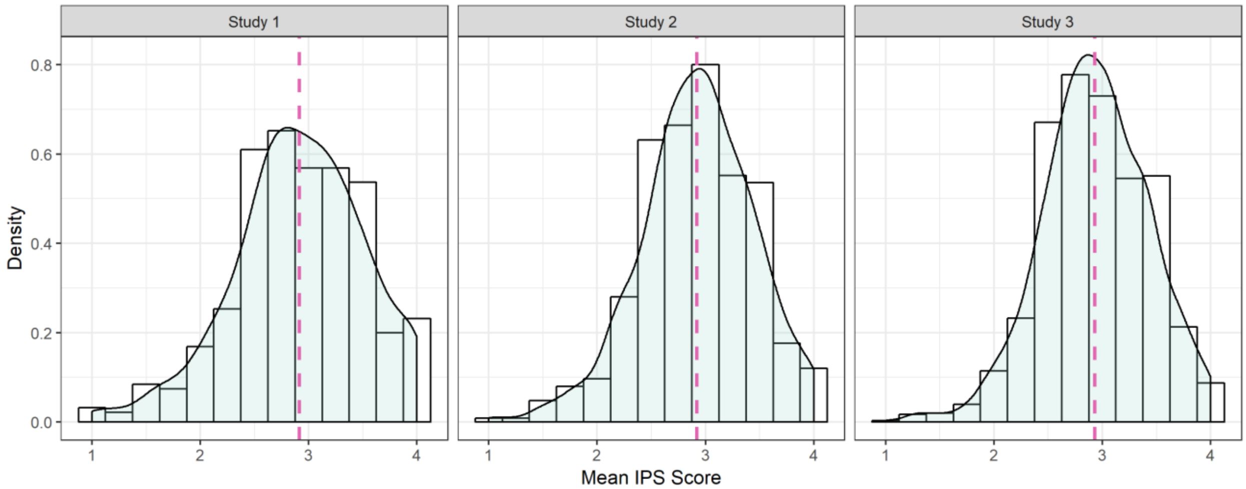
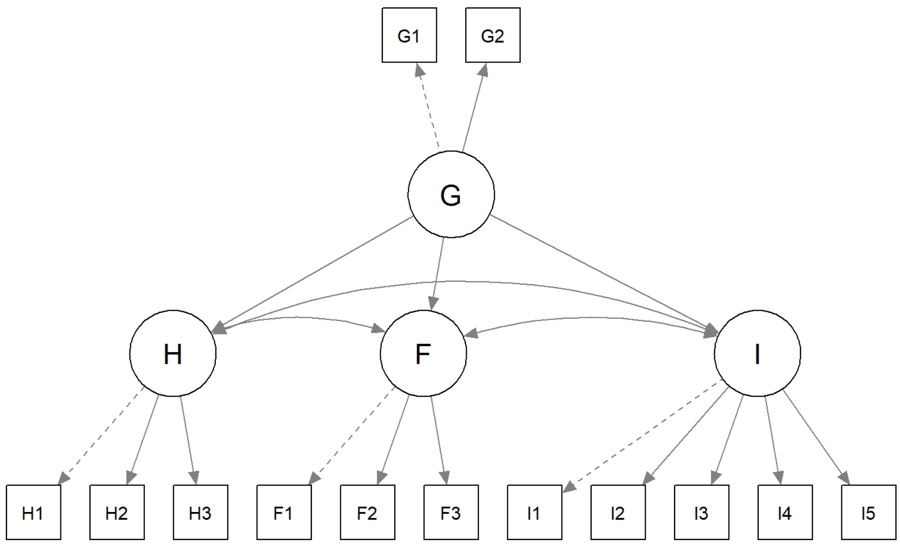



Figure 1 IPS score distribution density plots with median (Studies 1-3)




*Note*. Dotted lines represent the indicators (items) for which there is a fixed loading of 1.0 (necessary to identify the model; see Kline 2011 for details). Solid lines represent path coefficients (the factor loadings in Table 4). Curved lines between the latent factors represent factor correlations (Table 3).

Figure 2 Structural equation model diagram of IPS's latent factor structure (Study 2).

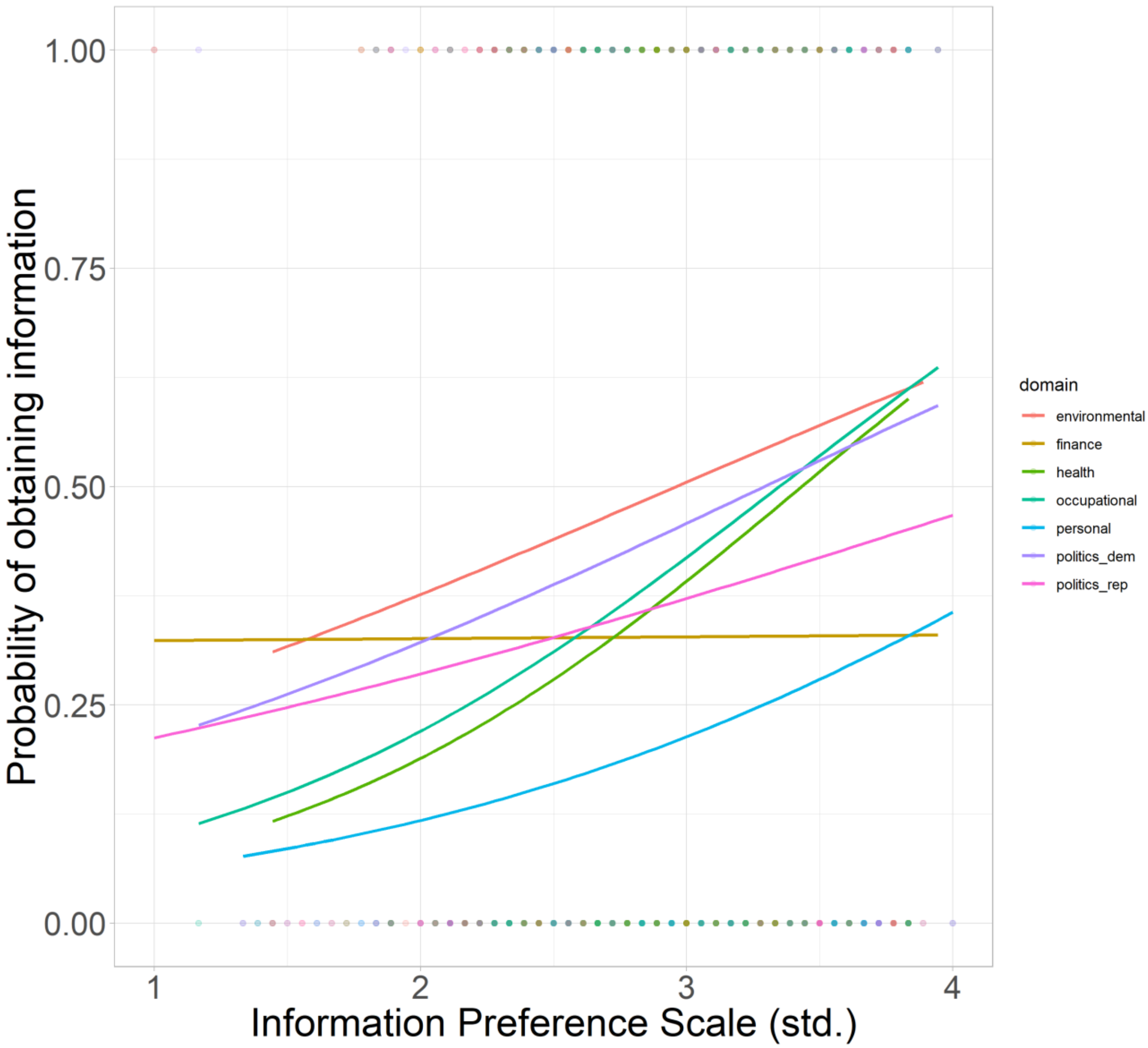



Figure 3 Predictive validity of IPS on decision to acquire or avoid information.

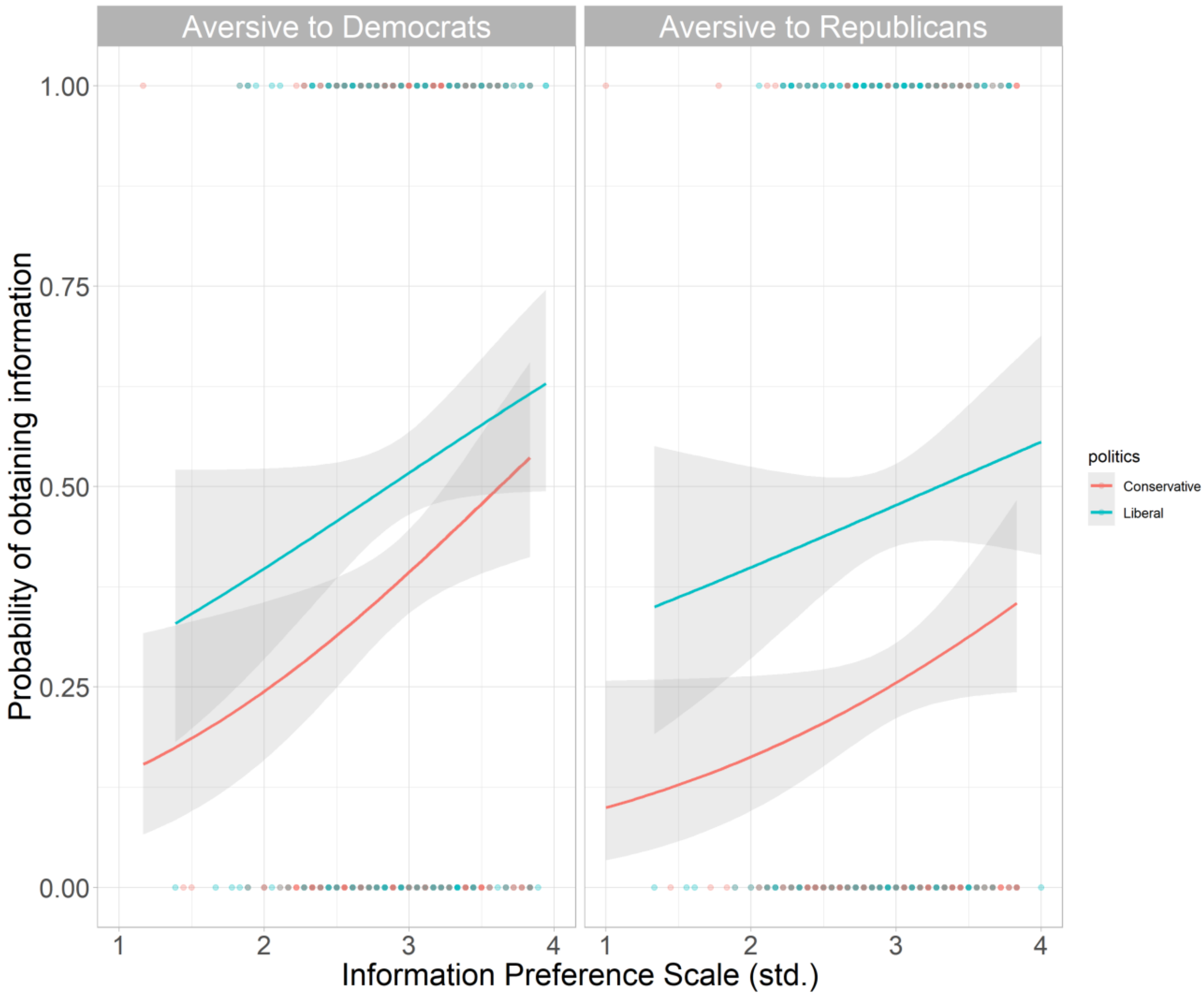



Figure 4 Predictive validity of IPS to predict political decisions using a logistic regression model

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# Appendix: Measuring Information Preferences

# Appendix

## Study 3

We report the same analyses in the main text using a domain-weighted version of the IPS, as pre-registered.

### Results

We first wanted to determine whether there was an order spillover effect such that completing the IPS first would influence subsequent decisions to acquire information, or vice versa. Using the IPS scores and the survey order as predictions in a logistic regression model yielded a non-significant interaction of order, $OR$ = 1.09, 95% CI [0.75, 1.59], $z = 0.46$, $p = 0.643$. That is, it does not appear that taking the IPS primed participants to be more consistent with their decision - unless the effect of taking the scale persisted for at least two weeks, which appears unlikely. In line with our pre-registration report, we thus analyzed both decisions from all participants.

We take the mean score of all domain responses and average the IPS finance, health, interpersonal, and general subscales to produce a IPS total score. We rescale the range of the HS and the ROV so all scores are bounded between [1, 4] and use the mean score, rather than the sum score, so that the effect size of the different scales can be directly compared. The total IPS and the HS scale were moderately and negatively correlated, $r$(1424) = -0.62, $p < 0.001$, indicating an opposite theoretical correspondence between the desire to obtain information and the desire to avoid it, as expected.

Overall, the IPS is able to predict the odds that an individual will choose to obtain information two weeks after completing the IPS scale, $OR$ = 1.44, 95% CI [1.05, 2], $z$ = 2.24, $p = 0.025$. Looking at participants who made a decision first and then took the IPS two weeks later confirms this positive link between IPS scores and the decision to acquire information, $OR$ = 1.55, 95% CI [1.13, 1.97], $z$ = 2.71, $p = 0.007$.

In a mixed effects logistic regression with a random effect for participants, we regressed the decision to acquire information on IPS scores across all domains, finding a significant effect, $OR$ = 1.49, 95% CI [1.24, 1.81], $z$ = 4.21, $p < 0.001$. The HS was not able to predict information seeking or avoiding behaviors, $OR$ = 0.94, 95% CI [0.79, 1.12], $z$ = $-0.69$, $p = 0.492$, and we find similar results for the Receptiveness to Opposing Views scale, $OR$ = 0.94, 95% CI [0.8, 1.12], $z$ = $-0.68$, $p = 0.499$.

With the exception of the finance, occupational, and interpersonal domain, the IPS is able to predict domain-related decisions as well.  Higher IPS scores also increased the log-odds of obtaining information about biodiversity and weather impacts (the environmental domain), $OR$ = 1.49, 95% CI [0.96, 2.41], $z$ = 1.73, $p = 0.083$. Similarly, the IPS was able to predict the propensity to obtain information about individual's risk of burnout (health domain), $OR$ = 2.18, 95% CI [1.3, 3.98], $z$ = 2.8, $p = 0.005$. The IPS predicted political information acquisition as well, but only for those who wanted the breakdown of donors for the Democratic nominees, $OR$ = 1.63, 95% CI [1.2, 2.23], $z$ = 3.14, $p = 0.002$.

When controlling for HS and ROV scores, the main effect for IPS scores persists, $OR$ = 1.77, 95% CI [1.4, 2.26], $z$ = 4.7, $p < 0.001$, suggesting that each additional point in IPS scores increases the log odds of obtaining information by 1.77. However, an additional point in HS scores does not lead to a decrease in the log odds of obtaining information, as one would expect, given that the HS scale measures information avoidance. Instead, such a change in HS scores produces an *increase in information seeking*, $OR$ = 0.94, 95% CI [0.79, 1.12], $z = -0.69$, $p = 0.492$, suggesting the HS scores are unstable predictors for information avoidance or acquisition. The variance inflation factors for all three predictors do not exceed 2, suggesting multicollinearity is not the issue.

A statistical comparison of the two scales further illustrates that the IPS can significantly explain variations in information-seeking and avoidant behaviors beyond what the alternative scale can provide. We apply dominance analysis (Azen and Budescu 2003, Azen and Traxel 2009) to an ordinary least squares regression specification containing both scales. This approach uses changes in model fit statistics (i.e., $R^2$ in ordinary least squares regression) to determine predictor importance. In a dominance analysis with this full model of predictors, the contribution in variance explained by the IPS scores is larger than that of the HS scores by a magnitude of more than 4, providing support that the IPS has unique predictive value.

**Political Information** For those who changed their political affiliation between the two waves (212 participants, or 14.83% of the sample), we retained the political affiliation at the time point that they made their political decision, as preregistered. Of those participants, (179 changed their response by only one gradation (e.g., from "very liberal" to "slightly liberal").

We hypothesized that political affiliation would predict information avoidance if the information might be aversive to the individual's political affiliation. All participants were randomly assigned to want to know about either the Republican-aversive or Democrat-aversive piece of information. We conduct a median split on political orientation. In a mixed effects logistic model across both political decisions, we do not find a main effect of IPS scores, $OR$ = 1.45, 95% CI [0.89, 2.4], $z$ = 1.47, $p = 0.142$, and a non-significant interaction, $OR$ = 0.77, 95% CI [0.4, 1.47], $z$ = $-0.8$, $p = 0.424$. As we had not hypothesized an interaction, subsequent models examine main effects only.

Figure A1 shows a main effect of IPS by political affiliation and political information. For those identifying as liberals, we see a main effect of IPS score when the information is aversive to Democrats, $OR$ = 1.5, 95% CI [0.99, 2.32], $z$ = 1.9, $p = 0.057$, but not for conservatives, $OR$ = 1.45, 95% CI [0.89, 2.5], $z$ = 1.47, $p = 0.142$. The benchmark measure, the Receptiveness to Openness Views scale (Minson et al. 2019) does not predict information acquisition decisions for either liberals, $OR$ = 0.94, 95% CI [0.65, 1.36], $z$ = $-0.32$, $p = 0.746$, or conservatives, $OR$ = 1.34, 95% CI [0.84, 2.25], $z$ = 1.23, $p = 0.219$.

An additional series of specifications we conducted about the robustness of the IPS against various controls in Table A3. This provides additional evidence that the IPS is able to predict information acquisition, particularly in out-of-sample domains.

## Appendix Tables

Table A1

*Study 1 exploratory factor loading model.*

| | Factor 1 (X) | Factor 2 (X) | Factor 3 (X) | Factor 1 (Y) |
|---|---|---|---|---|
| H1 | 0.01 | 0.64 | 0.03 | 0.52 |
| H2 | -0.07 | 0.83 | 0.02 | 0.49 |
| H3 | 0.10 | 0.74 | -0.04 | 0.54 |
| F1 | -0.04 | 0.04 | 0.63 | 0.36 |
| F2 | 0.11 | 0.08 | 0.32 | 0.25 |
| F3 | 0.05 | -0.02 | 0.72 | 0.42 |
| I1 | 0.19 | 0.15 | 0.16 | 0.25 |
| I2 | 0.53 | 0.05 | 0.12 | 0.44 |
| I3 | 0.52 | 0.06 | 0.15 | 0.50 |
| I4 | 0.63 | -0.02 | 0.10 | 0.38 |
| I5 | 0.84 | 0.00 | -0.08 | 0.57 |
| G1 | 0.34 | 0.37 | 0.07 | 0.81 |
| G2 | 0.23 | 0.32 | 0.18 | 0.81 |

*Note.* Exploratory SEM is a multivariate extension of exploratory factor analysis and looks at two sets of latent variables. In this case, the second set of latent variables is meant to only map onto the general items.

Table A2

*Study 3 exploratory factor loading model.*

| | Factor 1 (X) | Factor 2 (X) | Factor 3 (X) | Factor 1 (Y) |
|---|---|---|---|---|
| H1 | -0.05 | 0.74 | -0.04 | 0.44 |
| H2 | 0.08 | 0.60 | 0.03 | 0.42 |
| H3 | 0.02 | 0.66 | 0.04 | 0.47 |
| F1 | 0.14 | 0.05 | 0.46 | 0.21 |
| F2 | 0.12 | 0.05 | 0.14 | 0.20 |
| F3 | -0.02 | 0.00 | 0.92 | 0.15 |
| I1 | 0.35 | 0.02 | 0.05 | 0.22 |
| I2 | 0.62 | 0.00 | -0.01 | 0.30 |
| I3 | 0.63 | -0.04 | 0.04 | 0.36 |
| I4 | 0.56 | -0.01 | -0.01 | 0.26 |
| I5 | 0.62 | 0.07 | -0.04 | 0.39 |
| G1 | 0.28 | 0.40 | 0.03 | 0.67 |
| G2 | 0.19 | 0.29 | -0.02 | 0.67 |

*Note.* Exploratory SEM is a multivariate extension of exploratory factor analysis and looks at two sets of latent variables. In this case, the second set of latent variables only maps onto the general items.

Table A3

*Mixed effects logistic regression on decision to acquire information in political decisions (Study 3)*

| | **Model 1** | **Model 2** | **Model 3** | **Model 4** | **Model 5** |
|---|---|---|---|---|---|
| (Intercept) | $-1.391^{***}$ | $-1.055^{**}$ | -0.892 | -1.390 | -0.790 |
| | (0.336) | (0.341) | (0.708) | (0.726) | (0.452) |
| Information Preference Scale | $0.346^{**}$ | $0.345^{**}$ | $0.361^{*}$ | $0.491^{***}$ | 0.255 |
| | (0.111) | (0.113) | (0.143) | (0.147) | (0.151) |
| Conservative | | $-0.721^{***}$ | $-0.715^{***}$ | $-0.721^{***}$ | -1.305 |
| | | (0.115) | (0.111) | (0.113) | (0.675) |
| Receptiveness to Opposing Views | | | -0.095 | -0.048 | |
| | | | (0.104) | (0.106) | |
| HS Scale | | | 0.015 | 0.209 | |
| | | | (0.132) | (0.137) | |
| Scale First | | | | -0.067 | |
| | | | | (0.113) | |
| First Decision | | | | $-0.797^{***}$ | |
| | | | | (0.115) | |
| IPS x Conservative | | | | | 0.198 |
| | | | | | (0.225) |
| Log Likelihood | -961.702 | -939.943 | -937.104 | -912.169 | -939.558 |
| Num. obs. | 1430 | 1430 | 1426 | 1426 | 1430 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

## Appendix Figures

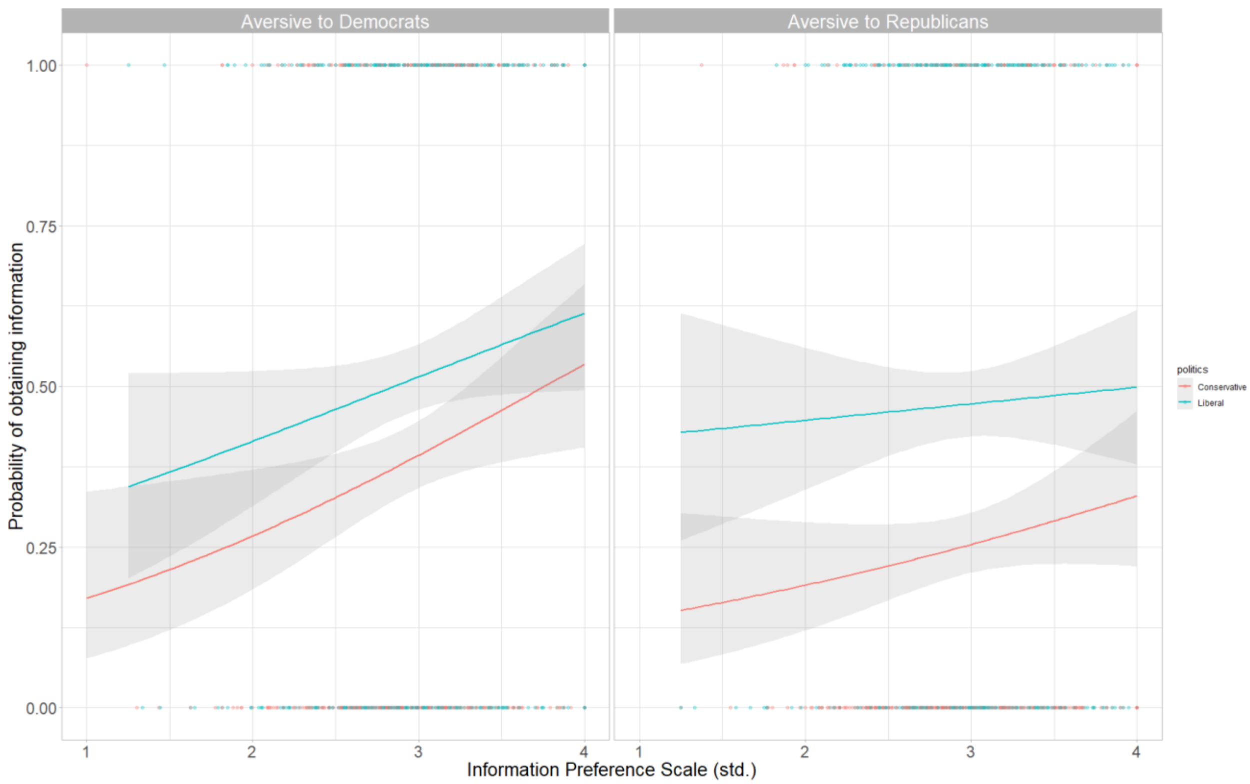


Figure A1 Predictive validity of IPS (using domain weighting) to predict political decisions using a logistic regression model