How personality psychology and cognitive neuroscience can enrich one another: Insights from information seeking to machine learning

Hayley Kristina Muirden Jach
Student ID: 357863
ORCID: 0000-0001-6808-8713

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Melbourne School of Psychological Sciences
The University of Melbourne

Abstract

Personality psychology investigates individual differences in emotion, behaviour, cognition, and motivation, whereas cognitive neuroscience investigates the neurobiological bases of these phenomena. This substantial content overlap suggests that these areas are well placed to integrate knowledge. Accordingly, I present results from two empirical research programs that demonstrate how combining theories and methods from personality psychology and cognitive neuroscience can provide a new perspective on outstanding research questions and spur novel research programs.

Part 1 (Studies 1-5) assessed how theory from personality psychology can address a current question in cognitive neuroscience: why people seek information that provides no extrinsic reward. One explanation is that uncertainty is aversive, and information reduces this uncertainty. This would suggest that the personality trait *uncertainty intolerance* would relate to information seeking. However, this conflicts with a theory from personality psychology whereby *openness/intellect* (describing tendencies toward imagination and intellect; thought to relate to greater *tolerance* for uncertainty) is grounded in increased information seeking. Because no explicit confirmatory study has assessed the putative negative relation between uncertainty intolerance and openness/intellect, Study 1 (N = 308) investigated—and confirmed—these relations. Next, Studies 2 (N = 151) and 3 (N = 301) assessed personality trait correlates of information seeking to gauge relative evidence for either conflicting theory. Openness/intellect did not predict information seeking; however, *joyous exploration* (a facet of curiosity positively related to openness/intellect) predicted information seeking across both studies, and uncertainty intolerance predicted information seeking in Study 3. These results informed a conceptual model featuring two motivations to seek information—either to *explore* (related to joyous exploration and openness/intellect) or to *feel safe* (related to uncertainty intolerance and neuroticism)—each differentially elicited depending on how the situation is perceived. To evaluate this model, Study 4 (N = 436) assessed personality and situation perception predictors of information seeking across four stimulus sets. Study 5 (N = 316) provided a partial replication and extension. Results provided consistent evidence for the exploration pathway, but more tentative evidence for the safety pathway. These findings suggest that an incorporation of person and situation factors can assist theory-development for information seeking.

Part 2 provided a complementary approach to interdisciplinary dialogue by investigating how methods from cognitive neuroscience could be applied to explore possible neural bases of personality. Specifically, the machine learning technique *multivariate pattern*

analysis was used to explore, then confirm, relations between personality and spectral power derived from electroencephalography. Study 6 (N = 174) found that agreeableness and neuroticism could be consistently decoded in particular frequencies across four testing conditions. Study 7 (N = 197) failed to replicate Study 6 in the full testing sample, but when subsequent analyses were stratified by country, agreeableness could be decoded in participants from Australia and neuroticism from participants from Germany. Caution is warranted for these latter findings given their unexpected nature and the smaller sample size of individual groups. The advantages of employing new methods are counterbalanced by a need to accept some measure of uncertainty in our inferences. However, open documentation of this complexity can spur new investigations to gain future insight into the neural bases of personality.

Together, these studies emphasise the challenges, but also substantial benefits, from combining knowledge and methods from personality psychology and cognitive neuroscience to constrain existing theory, form links between research domains, and propose new avenues for research.

Declaration

This is to certify that:

1. The thesis comprises only my original work towards the degree of Doctor of Philosophy, except where indicated in the Preface;
2. Due acknowledgment has been made in the text to all other material used; and
3. The thesis is fewer than 100,000 words, exclusive of tables, figures, footnotes, references, and appendices.

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Preface

The author of this thesis played a substantial role in all studies contained within. The empirical chapters forming this thesis (Chapters 2-6) have been published in scientific journals (Studies 1-3, Study 6) or are currently under review (Studies 4 and 5) or in preparation for submission (Study 7). In all studies, the author led study design, analysis, interpretation of results, manuscript drafting, and manuscript revision. In Studies 1-4 and 7 the author collected all data or was involved in data collection (Studies 5 and 6 used data primarily collected for a different project). No third-party editorial assistance was provided in preparation of the thesis. The publication details and indication of the author's contribution for empirical chapters are listed below.

Chapter 1: General Introduction

This chapter includes unpublished material not submitted for publication.

Chapter 2: To Fear or Fly to the Unknown: Tolerance for Ambiguity and Big Five Personality Traits (Study 1)

This chapter includes the following published manuscript: Jach, H. K., & Smillie, L. D. (2019). To fear or fly to the unknown: Tolerance for ambiguity and Big Five personality traits. *Journal of Research in Personality, 79,* 67-78.

The manuscript was written with Associate Professor Luke Smillie, the author's primary PhD supervisor. The author's contribution to this manuscript was 80%.

Chapter 3: Testing the Information-Seeking Theory of Openness/Intellect (Studies 2 and 3)

This chapter includes the following published manuscript: Jach, H. K**,** & Smillie, L. D. (2021). Testing the Information-Seeking Theory of Openness/Intellect. *European Journal of Personality,* 35(1), 103-119.

The manuscript was written with Associate Professor Luke Smillie. The author's contribution to this manuscript was 80%.

Chapter 4: Why Do People Seek Information? The Role of Personality Traits and Situation Perception (Studies 4 and 5)

This chapter includes the following manuscript: Jach, H. K, DeYoung, C., & Smillie, L. D. (Under Review) Why Do People Seek Information? The Role of Personality Traits and Situation Perception. The manuscript was written with Associate Professor Luke Smillie and collaborator, Professor Colin DeYoung. The author's contribution to this manuscript was 75%.

Chapter 5: Decoding Personality Trait Measures from Resting EEG: An Exploratory Report (Study 6)

This chapter includes the following manuscript: Jach, H. K, Feuerriegel, D., & Smillie, L. D. (2020). Predicting personality from resting state EEG using Multivariate Pattern Analysis: An exploratory report. *Cortex, 130*, 158-171.

The manuscript was written with Associate Professor Luke Smillie and collaborator, Dr. Daniel Feuerriegel. The author's contribution to this manuscript was 70%.

Chapter 6: Personality in the Power Spectrum: A Replication MVPA EEG Study (Study 7)

This chapter includes the following manuscript in preparation: Jach, H. K., Feuerriegel, D., Pickering, A., Bonfim, L., Duong, V. N., Robinson, E., Wacker, J., & Smillie, L.D. (In prep). Personality in the Power Spectrum: A Replication MVPA EEG Study.

The manuscript was written with Associate Professor Luke Smillie and collaborator, Dr. Daniel Feuerriegel. Data collection was provided by Luiza Bonfim, Vu Ngoc Duong, and Elizabeth Robinson. An additional dataset was provided by Jan Wacker. The author's contribution to this manuscript was 70%.

Chapter 7: General Discussion

This chapter includes unpublished material not submitted for publication.

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Thesis Presentation

The seven chapters of this thesis include a General Introduction (Chapter 1), General Discussion (Chapter 7) and five empirical chapters (Chapter 2-6). The studies that form Chapters 2, 3, and 5 (Studies 1-3 and 6) have been published in academic journals and are therefore presented in the format in which they appear in these journals. Due to this formatting, references for these published studies are included at the end of their respective chapter and do not appear in the final References list unless they are cited elsewhere in the thesis. As Studies 4, 5, and 7 are not yet published, these chapters are formatted similarly to the non-empirical chapters of the thesis. Accordingly, references for these chapters appear in the final References section alongside citations for non-empirical chapters. Finally, throughout all chapters, figures and tables are presented sequentially without noting individual chapters of the thesis (for example, Figure 1 in Chapter 3 is labelled *Figure 1*).

Chapter 1: General Introduction

1.1 Introductory Overview

Personality psychology is the study of how and why people differ from one another, and the impact that these differences have on our choices and life outcomes (John & Srivastava, 1999). Any relatively stable individual difference concerning emotion, behaviour, cognition, or motivation is considered relevant for personality. This wide-ranging focus encompasses almost the whole of psychological science, and reflects the inherently interdisciplinary nature of personality psychology as a hub for creative integration and a home for generalists (Little, 2010; Revelle et al., 2011).

Conversely, cognitive neuroscience is the study of how and why the brain makes the mind (Gazzaniga et al., 2009). This field's title speaks to its historical fusion of neuroscience and cognitive psychology that began in the 1970s (Gazzaniga et al., 2009). Moreover, the passing years have seen cognitive neuroscience become an even larger tent, encompassing affective science (Lane & Nadel, 2000), decision science (Shiv et al., 2005), and social science (Adolphs, 2003) in addition to its traditional focus on cognition, particularly attention, perception, learning, and language.

Taken together, cognitive neuroscience investigates the biological bases of emotion, behaviour, cognition, and motivation, just as personality psychology investigates individual differences in these factors. This close correspondence in research explananda suggests that theory and knowledge from cognitive neuroscience can be useful to attempt to understand mechanisms underlying individual differences (the *why* of personality). Indeed, for the past 50 years and more, personality psychology has drawn on cognitive neuroscience and related psychobiological perspectives to investigate neural correlates of personality and propose mechanistic explanations for reported personality scores (Allen & DeYoung, 2017; DeYoung, 2013; McNaughton & Smillie, 2018; Pickering & Pesola, 2014; Smillie, 2008; Zuckerman, 1991). Similarly, theory and knowledge from personality psychology can be useful to attempt to understand individual differences of cognitive neuroscience. Although cognitive neuroscience has rarely explicitly incorporated personality psychology for this purpose, an appreciation of inter-individual variability can be seen in a large body of research concerning differences in psychopathology, ageing, speed and accuracy of responses, and decision-making (Ly et al., 2017; McCandliss & Noble, 2003; Montague et al., 2012; Tam et al., 2015; White et al., 2016).

The studies presented in this thesis contribute to each of these research programs. The aim of the thesis is to investigate how personality psychology and cognitive neuroscience can

be combined to provide new perspectives on outstanding research questions and to discover effects that could spur novel research programs. This overarching aim is tackled with two distinct approaches forming two parts of the thesis. Part 1 (Studies 1-5) investigates how person and situation factors relate to information seeking, and Part 2 (Studies 6 and 7) uses emerging methods from cognitive neuroscience to explore, then attempt to confirm, relations between electrophysiological data and personality. The two parts thus demonstrate how theory from personality psychology can benefit cognitive neuroscience (Part 1), and how methods from cognitive neuroscience can benefit personality psychology (Part 2). By including very different methods, theories, and topics in each part, I highlight the rich diversity of ways in which these fields can be integrated to create new knowledge.

The remaining parts of this introduction explain fundamental concepts from personality psychology, in addition to fundamental concepts from the study of information seeking. A summary of chapters within each section of the thesis follows.

1.2 Personality Traits

Researchers can investigate personality in multiple ways. One can study participant's self-defining descriptions of their lives (*life narratives*; McAdams & Pals, 2006) or their context-dependent interpretations, strategies, or goals (*characteristic adaptations;* DeYoung, 2015). However, personality psychologists will most commonly study differences between people in terms of their *personality traits.*

Personality traits describe regularities in patterns of emotion, behaviour, cognition, and motivation (John et al., 2008). They were originally identified by assessing the co-occurrence of different words or phrases describing emotion, cognition, behaviour, or motivation, and finding groups where endorsement within a group was stronger than endorsement between groups (Fiske, 1949). For example, people who agree that they are assertive also tend to endorse words like enthusiastic and social. Those agreeing that they are polite also claim to be compassionate and prosocial. The unlucky who rate themselves as highly anxious also often claim to be depressed and volatile. The tidy folks tend to also agree to being industrious and persistent. And finally, people who rate themselves as imaginative are also more likely to call themselves artistic and curious. However, people who call themselves imaginative are not generally more likely than any other person to call themselves tidy, anxious, polite, or assertive.

Despite some initial disagreement on the number of dimensions necessary to parsimoniously describe these patterns of covariation in responses (Cattell, 1943; Eysenck, 1991), consensus grew, with factor-analytic methods grouping participant responses—regardless of the particular words chosen—into five somewhat independent dimensions or

domains (Digman & Inouye, 1986; Fiske, 1949; McCrae & Costa, 1985; Norman, 1963; Trapnell & Wiggins, 1990). This was called the *Big 5* or *Five Factor* model of personality (John & Srivastava, 1999). The Big 5 is a descriptive model of patterns of covariance. The five factors of this model are *openness/intellect* (describing variance in imagination, creativity, intellect, and aesthetic appreciation), *conscientiousness* (describing variance in work ethic, goal-directedness, and appreciation of order), *extraversion* (describing variance in sociability, enthusiasm, and assertiveness), *agreeableness* (describing variance in prosocial tendencies, compassion, and politeness), and *neuroticism* (describing variance in negative emotionality and anxious/depressive tendencies; see John et al., 2008, for a review).

Personality traits are hierarchically organised: some items within a Big 5 domain correlate more strongly with each other than with other items within the same domain, and these interrelations form mini traits called *facets.* Unlike the Big 5, which tends to emerge regardless of the particular scale used to measure it and thus can be considered a real statistical entity[1], the precise number of facets detected in a questionnaire will vary depending on the questionnaire chosen. For example, the Big Five Inventory 2 includes 3 facets per trait (e.g., for openness/intellect, *intellectual curiosity, aesthetic sensitivity,* and *creative imagination*; Soto & John, 2017), whereas the NEO Inventory includes 6 facets per trait (for openness/intellect, *fantasy, aesthetics, feelings, actions, ideas,* and *values*; Costa & McCrae, 1992). Recently, Schwaba and colleagues (Schwaba et al., 2020) constructed an "atlas" of all facets represented across 10 measures of the Big 5. This highly comprehensive study was able to map the relations between each facet and demonstrate how central or peripheral facets were to each broad trait. However, even this study does not exhaustively document all possible facets, and it is unlikely that we will conclusively know how many facets form each trait (indeed, Schwaba and colleagues observed that more than half of the facets were related to more than one trait, and hence, were likely *interstitial*; Hofstee et al., 1992).

Between broad traits and narrow facets, a third way of organising item intercorrelations was empirically derived. Using factor analysis, DeYoung and colleagues found that each Big 5 domain could be divided into two personality *aspects* that were correlated but clearly distinct, and each included multiple facets (DeYoung et al., 2007). For example, the aspects *intellect* (reflecting intellectual curiosity and quick thinking) and *openness* (reflecting aesthetic

[1] By "real", I mean that the Big 5 traits demonstrate a robustly detected pattern, not that the Big 5 necessarily have an independent life outside of this pattern (DeYoung & Krueger, 2020).

sensitivity, absorption, and fantasy) only intercorrelated at about r = .40, but together comprised the broad domain openness/intellect (DeYoung et al., 2007).

Further, although the Big 5 domains were originally thought to be orthogonal to one another (Costa & McCrae, 1992; Norman, 1963), more recent research observed intercorrelations between extraversion and openness/intellect on the one hand, and between conscientiousness, agreeableness, and neuroticism on the other (Digman, 1997). These meta-traits can be labelled *plasticity* and *stability,* respectively (DeYoung, 2006). Taken together, the Big 5 is a hierarchically-ordered structural model—a taxonomy that organizes the universe of traits. Figure 1 displays this trait hierarchy.

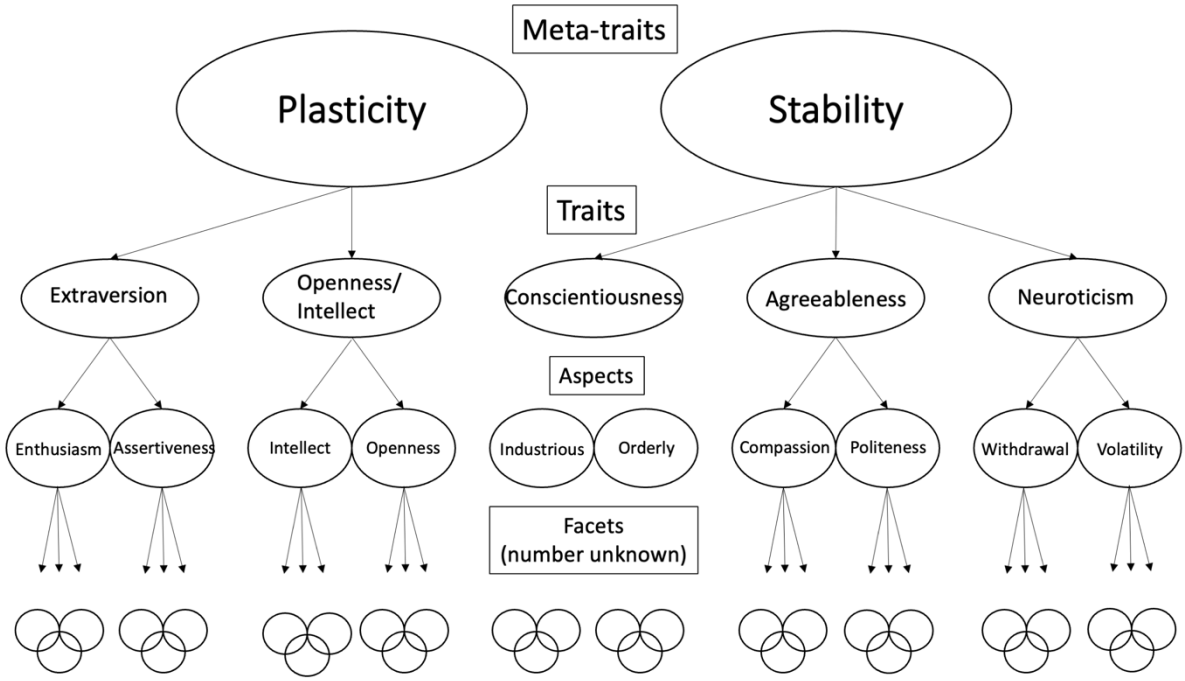

Figure 1. The Big 5 trait hierarchy. Adapted from DeYoung (2015).

The Big 5 is a remarkable statistical regularity. Despite substantial societal change throughout the last century, the structure of responses from participants in the 1940s resembles that from those of the 2010s (Fiske, 1949; Soto & John, 2017). Further, when participants are measured across time, their rank-order stability—that is, a person's relative score on a trait compared to others—stays somewhat unchanged (Roberts et al., 2006; Roberts & DelVecchio, 2000). Moreover, traits are heritable (Vukasović & Bratko, 2015), and the Big 5 have been observed across multiple cultures (McCrae et al., 2005; Rolland, 2002; Yamagata et al., 2006).

Yet the Big 5 does not just sit, happily accruing questions about its ontological status. Personality traits can predict future health and longevity, wellbeing, relationship satisfaction, addiction, career choice (Soto, 2019), psychopathology (Lamers et al., 2012), neurobiological indices (Allen & DeYoung, 2017), and everyday behaviours from the mundane to the surprising (for example, openness/intellect predicts lounging around the house without clothes on; Chapman & Goldberg, 2017). Thus, your responses on a survey can provide clues to your actions and your future.

Finally, many personality traits have been proposed that were not intended to fit within a broad personality structure such as the Big 5. These standalone measures were often developed through independent research histories focusing on a particular psychological construct of interest. Despite being developed outside the tradition of the Big 5, it is possible to locate these standalone scales within one Big 5 trait (to be considered a facet) or between multiple Big 5 traits (an interstitial facet; e.g., see Markon et al., 2005; Whiteside & Lynam, 2001), and some recent research suggests that this is likely to be the case for the majority of standalone scales (Bainbridge et al., Accepted).

For the purpose of this thesis, the three most important standalone constructs are *ambiguity tolerance, uncertainty intolerance,* and *curiosity.* Ambiguity tolerance and uncertainty intolerance both describe the degree to which attitudes to ambiguity/uncertainty are appealing and enticing versus frightening and unpleasant (Carleton et al., 2012; Furnham & Marks, 2013). These constructs were developed separately, with descriptions of ambiguity tolerance thought to reflect rigid thinking and premature closure versus an open acceptance of difference and love of complexity (Frenkel-Brunswik, 1949) and descriptions of uncertainty intolerance thought to reflect excessive worry and anxiety disorders versus a lack of worry or anxiety (Carleton et al., 2012; Freeston et al., 1994). When considering possible Big 5 correlates of these traits, intolerance of uncertainty has been frequently linked to neuroticism (Berenbaum et al., 2008; de Bruin et al., 2007; McEvoy & Mahoney, 2012), whereas ambiguity tolerance has been linked to openness/intellect (Caligiuri & Tarique, 2012; Lauriola et al., 2016). However, as described in more detail in Chapter 2, these constructs intercorrelate quite highly and can be considered somewhat interchangeable, with the main difference being that measures of uncertainty intolerance tend to include more negatively-valenced and high intensity emotion terms than ambiguity tolerance. The relations between ambiguity/uncertainty intolerance and openness/intellect and neuroticism are the focus of Study 1 of the thesis.

Meanwhile, curiosity has been studied by many researchers across numerous fields, including personality psychology, behavioural economics, and cognitive neuroscience

(Berlyne, 1954; Kashdan et al., 2004; Kidd & Hayden, 2015; Loewenstein, 1994). Though curiosity has been defined in different ways throughout its history as a subject of academic investigation, when considering curiosity as a personality trait, the most prevalent definition today is the *desire and interest to seek and explore what is new, complex, and/or uncertain* (Kashdan et al., 2018). Curiosity itself comprises lower-order facets, partially reflecting the different histories of use of this term in research. Similar to the Big 5 itself, there are debates around the precise number of facets necessary to describe this trait. However, two facets are consistent across multiple measures of curiosity (Kashdan et al., 2018; Litman, 2008). These are *joyous exploration* (also called curiosity as a feeling of interest or I-type) and *deprivation sensitivity* (also called curiosity as a feeling of deprivation or D-type). Joyous exploration is thought to reflect an attitude of delight, excitement, interest, or joy related to exploring what is new, complex, and/or uncertain; for example, a child eager to see what they will discover on their first day of school. Conversely, deprivation sensitivity is thought to reflect a hunger and desire to know the answer to something, and this feeling can be at least partially aversive; for example, a philosopher spending all night awake in bed trying to uncover the solution to a logic puzzle.

Curiosity has been proposed to be a core element of openness/intellect (Silvia & Christensen, 2020; Woo et al., 2014), and indeed, both joyous exploration and deprivation sensitivity correlate with this trait, although joyous exploration appears to be far more strongly associated, $r \sim .65$ (Kashdan et al., 2020), suggesting that joyous exploration could be considered a facet of openness/intellect. This idea is taken further in Chapter 3 (Studies 2 and 3) and forms one part of a conceptual model proposed in Chapter 4 (Studies 4 and 5).

1.3 Recent Advances in Personality Science: States, Situations, and Mechanistic Theories

During the past several decades there have been several important developments in personality science, including investigations of how personality traits link to momentary states, how states and traits may relate to perceptions of situations, and the mechanistic processes underlying the coherence of structural models (the *why* of personality). All elements are relevant for the upcoming chapters.

1.3.1 Psychological states. Because personality traits reflect tendencies of behaviour and experience, this suggests that a person scoring higher on a given trait will be more likely to demonstrate trait-relevant behaviour and feel trait-relevant emotions and motivations in any given moment. Momentary trait expressions or experiences are termed *psychological states,* and a personality trait score was proposed to reflect a summary of a distribution of psychological states over time (Fleeson, 2001; Fleeson & Jayawickreme, 2015). For example,

a person who scores very highly on extraversion will not necessarily be highly extraverted at every moment and in every situation. However, they will act in extraverted ways across more situations and/or time points than someone scoring lower on extraversion, and this summary of their momentary actions should somewhat approximate their trait level of extraversion. A substantial body of research finds close correspondence between reported personality traits and behavioural state manifestations (Fleeson & Gallagher, 2009), supporting the perspectives that trait scores approximate the properties of distributions of states (but see also Rauthmann et al., 2019).

1.3.2 Situation perceptions. Despite the impressive predictive power of personality traits, there is little doubt that momentary emotions, cognitions, behaviours, and motivations are also impacted by other factors. Indeed, the research on psychological states described above demonstrates strong variability in behaviour over time and situations, indicating that momentary behaviour and experience have other influences even though personality traits are excellent at describing summary statistics (Fleeson, 2004). One important explanatory variable is the particular context or *situation* in which one finds oneself. Although proponents of *situationism* sought to establish the situation as the dominant force in psychology during the lively person-situation debate of the 1970s (Mischel, 1968), they subsequently gave way to person-situation *interactionism* (Ekehammar, 1974; Mischel, 1977), the long-held perspective that behaviour is a function of both the person and the situation (Furr & Funder, 2021; Lewin, 1936). More recent research within personality psychology has embraced this complexity and attempted to quantify how the person and situation interactively describe behaviour (e.g., Sherman et al., 2015). Initially, quantification of the objective elements of situations were thought to be most relevant for understanding behaviour (Saucier et al., 2007); these *situation cues* answer the basic *who, what, where,* and *when* questions that describe an environment (Pervin, 1978). However, situation cues proved challenging to measure comprehensively, given the limitless variety of possible cues, and the fact that individuals may perceive cues differently (Edwards & Templeton, 2005; Hogan, 2009). Indeed, as the situation is always filtered through an individual's perception and biases, it is arguably more important to focus on the *perceived* situation, rather than situation cues, to understand the influence of the situation on an individual's behaviour. This idea underpins the development of taxonomies of situation perceptions (Parrigon et al., 2017; Rauthmann et al., 2014; Ziegler et al., 2019; see Horstmann et al., 2018, for a review). Similar to personality taxonomies such as the Big 5, these models aim to describe the most important psychological characteristics of any situation. Dimensions within these models have been shown to incrementally predict psychologically important

outcomes above the variance accounted for by personality traits (Parrigon et al., 2017; Rauthmann et al., 2014; Ziegler et al., 2019).

Of the situation perception models, the most prominent is arguably the DIAMONDS framework (Rauthmann et al., 2014), which proposes eight factors that describe the main dimensions of a situation: Duty (*does a job need to be done?*), Intellect (*Does the situation require cognitive processing?*), Adversity (*Does the situation contain threats?*), Mating (*Are romantic or sexual opportunities present?*), pOsitivity (*Are there positive and enjoyable elements in the situation?*), Negativity (*Is the situation stressful or anxiety-inducing*), Deception (*Does the situation contain possible distrust, lying, or deception?*), and Sociality (*Is social interaction possible?*). Research using this taxonomy has also revealed that personality traits relate to the likelihood of construing a situation in a particular light. For example, neuroticism relates to perceiving a situation as higher in Negativity and lower in pOsitivity, and openness/intellect relates to perceiving a situation as higher in Intellect (Rauthmann et al., 2014, 2015).

1.3.3 Mechanistic theories of personality. Models of personality such as the Big 5 describe but do not explain personality; they are the explananda (the phenomena to be explained), not the explanans (the explanation). Once a phenomenon and its impacts have been established and well-documented, theories explaining the phenomenon are the next step along the path towards understanding. This drive is central to scientific endeavour, valued both for the possibility of unexpected innovations and benefits to society, but also as a basic human need (Goymann, 2019). In this vein, as researchers thread an ever-growing tapestry of knowledge that describes how personality is structured and what it predicts, some have also turned their attention to explaining these observations. These theories can be integrative and broad (Denissen & Penke, 2008; DeYoung, 2015; Fleeson & Jayawickreme, 2015; McAdams & Pals, 2006; Quirin et al., 2020; Revelle & Condon, 2015) or specific to select traits or facets (DeYoung, 2013; Rueter et al., 2018; Smillie, 2013). In general, theories are proposed at a conceptual level, although some attempts have been made at computationally instantiating theories (Pickering & Pesola, 2014; Read et al., 2010, 2017; Revelle & Condon, 2015). Absent specific computational models to precisely specify each element of a theory and particular linking functions, there is an increasing recognition of the need to ground theory in evidence from multiple methods, such as experimental and neural data (DeYoung & Krueger, 2020; Quirin et al., 2020) to avoid issues such as common method variance leading to background correlational noise that is erroneously picked up as signal (i.e., the “crud factor”; Meehl, 1990). Many theories of personality have incorporated knowledge from cognitive neuroscience into

theories or triangulated evidence from diverse neural methods (Allen & DeYoung, 2017; DeYoung, 2013; Rueter et al., 2018; Smillie, 2008, 2013). This practice lead to the emergence of the integrative subfield *personality neuroscience,* which aims to uncover how the brain forms personality (Allen & DeYoung, 2017).

One relevant example of a mechanistic theory drawing insight and evidence from cognitive neuroscience is the *information-seeking theory of openness/intellect* (DeYoung, 2013). This theory proposes that individuals higher in openness/intellect are more sensitive to the reward value of information, and hence are more likely to seek information. The theory incorporates knowledge of the neurotransmitter *dopamine* which has previously been linked to reward sensitivity and responses to reward (Bayer & Glimcher, 2005; Schultz, 1998, 2016) and also to extraversion (Smillie, 2013; Wacker & Smillie, 2015). Recently, dopamine has been found to relate not just to anticipation of rewards, but also anticipation of information that cannot be used to increase the likelihood of rewards (Bromberg-Martin & Hikosaka, 2009; Bromberg-Martin & Monosov, 2020). DeYoung (2013) proposed that this shared connection that dopamine has with rewards and information may explain why extraversion and openness/intellect share variance and form the meta-trait *plasticity.* This theory is considered further in the Introduction (Section 1.6) and also in Chapters 2-4 of the thesis.

1.4 Defining the Scope of *Cognitive Neuroscience*

As described, cognitive neuroscience is concerned with interrelations between the brain and the mind. From the first issue of the *Journal of Cognitive Neuroscience,* Editor-in-Chief Michael Gazzaniga emphasised that existing disciplines trying to understand how the mind works (e.g., philosophy, computer science, and cognitive science) can benefit from knowledge gained in neuroscience; and conversely, neuroscientists trying to uncover mechanisms that produce recorded brain outcomes can benefit from learning from the complex psychological factors related to mental processes that have been well documented by prior disciplines (Gazzaniga, 1989). In this way, principles of neural data can be used to constrain or "narrow the search space" on proposed theories of cognition (Churchland & Sejnowski, 1988, p. 744), and vice versa.

Because cognitive neuroscience has always been an integrative field with fuzzy discipline boundaries, specifying which studies are, or are not, examples of cognitive neuroscience can be challenging. For example, a study does not have to include an explicit neural measure in order to be considered within this field, because behavioural paradigms can be just as good as or better at understanding the relation between the brain and mind than neural indices (Niv, 2020). However, authors of studies that contain experimental data without neural

measures might prefer for their studies to be described as being located within cognitive psychology, mathematical psychology, affective science, decision science, behavioural economics, computer science, computational psychiatry, and so on. For the purposes of this thesis, I use the term *cognitive neuroscience* inclusively to describe any study that aims to understand the relation between the brain and the mind, no matter their methodological process to do so. Of course, this encompasses a huge variety of research and studies, and to provide a review of these is outside of the scope of the thesis (but see Gazzaniga et al., 2009, for an overview). Instead, I limit myself to a discussion of individual differences within cognitive neuroscience (Section 1.5), and to one example of a research topic—information seeking—that forms the foundation of Part 1 of the thesis (Section 1.6).

1.5 Individual Differences in Cognitive Neuroscience

There is an increasing interest in relating individual differences to or accounting for individual differences observed within studies in cognitive neuroscience (Kanai & Rees, 2011). For example, in addition to individual differences being noted across topics such as psychopathology, ageing, speed and accuracy of responses, and decision-making (Ly et al., 2017; McCandliss & Noble, 2003; Montague et al., 2012; Tam et al., 2015; White et al., 2016), there are also flourishing research topics concerned with understanding variability in particular neural markers, such as individual alpha frequency (Bazanova & Vernon, 2014; Cross et al., 2020; Gulbinaite et al., 2017; Klimesch, 1997, 1999). And as will be discussed extensively in Section 1.6, researchers frequently observe individual differences in the choice to seek information.

To provide somewhat objective evidence of the increased focus on individual differences over the past few decades, I tallied the number of times that the term "individual differences" was mentioned from 1997 to 2020 in two leading cognitive neuroscience journals: *Cortex* and *Journal of Cognitive Neuroscience.* Figure 2 displays a clear trend with increasing mentions of this term over time. Of course, this is a conservative example as individual differences may be discussed without using this exact term.

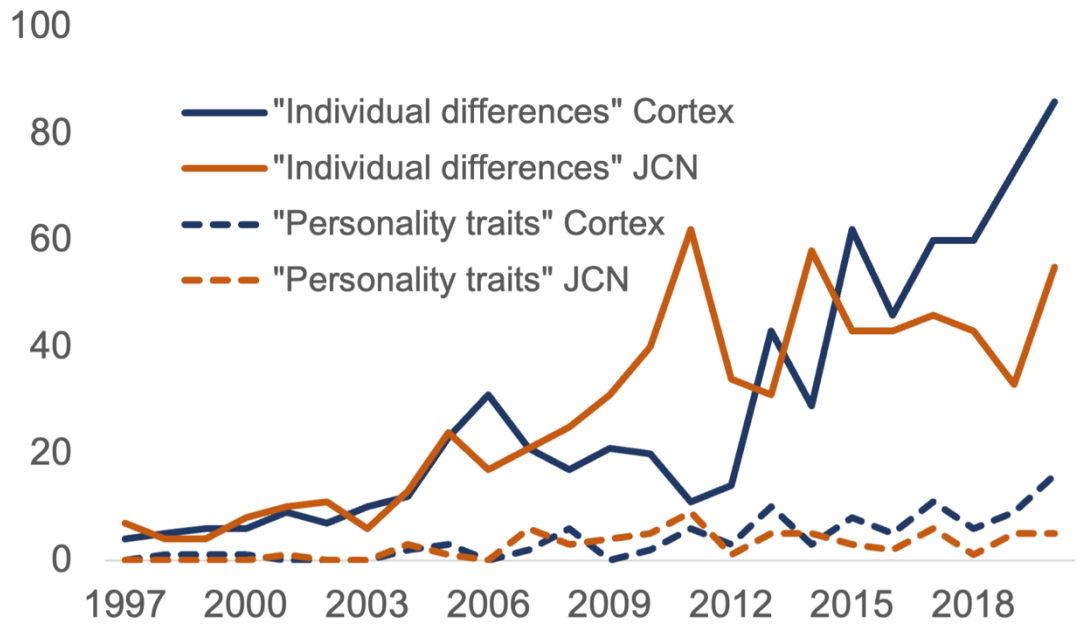

Figure 2. Mention of "individual differences" or "personality traits" in journal title, abstract, or keywords in two leading cognitive neuroscience journals from 1997 to 2020. JCN = Journal of Cognitive Neuroscience.

Given that individual differences are observed, it is possible that differences may be explained by differences in tendencies toward behaviour and experience—that is to say, personality traits. However, despite this apparent interest in documenting inter-individual variability, personality traits are rarely explicitly considered within this research. This can also be observed in Figure 2, which tracks the term "personality traits" over the same time frame in the same journals. Although there is a positive trend in mentioning personality traits, there are far fewer mentions than individual differences broadly.

What can account for this disparity? First, it is possible that researchers do not think that personality traits are relevant for the particular individual differences that they are observing. This may well be true for specific individual differences related to attention or perception (Kanai & Rees, 2011). However, even for these more basic cognitive processes, prior research does suggest relations to personality traits are present. For example, in a study of binocular rivalry, openness/intellect correlated with the tendency to experience a mixed percept, combining different images from the left and right eye into one's mental experience (Antinori et al., 2017). Individuals higher in openness/intellect also display reduced latent inhibition, a phenomenon where attention tends to decline toward repeated stimuli, resulting in "learned irrelevance" (Peterson et al., 2002).

Second, it is possible that researchers do not mention personality traits because their study samples are not large enough to detect or stably estimate correlations involving personality traits. Small samples have been acknowledged as an issue for cognitive neuroscience (Button et al., 2013), and studies measuring personality traits require higher samples than is typical for a study with neural indices. For example, a study requires 191 participants to have 80% power to detect a correlation of $r = .20$, which approximates a typical effect size in personality psychology (Gignac & Szodorai, 2016). A sample this size is prohibitive for studies using fMRI or EEG, which require extensive money and/or time to test each participant. However, this concern is less valid for purely experimental research, particularly studies that can be completed by participants in parallel.

Finally, it is possible that researchers have little knowledge of personality psychology beyond vague memories of introductory social and personality undergraduate classes, and hence do not think to consider personality traits, or if they do, think that they will be worthless additions. Given that cognitive neuroscience is an inherently interdisciplinary area that already requires a huge amount of content to learn, this perspective is understandable. However, with a basic primer to personality traits as given in Section 1.2, benefits may start to become apparent. Just as knowledge of neuroscience can be used to constrain theory development in cognition, knowledge of the structure of personality can be used to constrain theories drawn from cognitive neuroscience; particularly those theories that make reference to emotion, behaviour, cognition, or motivation. Further, developments in personality science such as an understanding of states and traits, perceptions of situations, and mechanistic theories of personality can be used to relate to observed findings and be proposed as explanations for unexpected results.

Below, I present one example of a topic where individual differences in behaviour are almost always observed, but personality traits are rarely explicitly considered: information seeking.

1.6 Part 1: Why Do We Seek Information?

Information can be defined as data that produce a shift from your prior to posterior belief (Lawrence, 1999). Similar to psychological theories that explain motivated action in terms of approaching rewards and avoiding punishments (Carver, 2006; McNaughton et al., 2016), economists initially assumed that people would seek information only if it increased the likelihood of rewards or reduced the likelihood of costs (Stigler, 1961; Hirschleifer & Riley, 1979). For example, a person may pay to meet a financial advisor if they believe that they will learn how to wisely invest their money, thus producing a net financial gain that exceeds the

cost of seeking information. This form of information seeking is inherently instrumental. However, these economic theories cannot account for many real-word instances of seeking information that provide no specific extrinsic rewards, called *non-instrumental information*. Why do some students want to know their exam results as early as possible, when this will not change their grade? When diagnosed with a disease that cannot be altered, why do some individuals try to learn more about it? Why do people study Latin or Ancient Greek, which is no longer spoken? Why do we care who the culprit was in a murder mystery novel?[2] The question of why people seek information is a current pressing issue within cognitive neuroscience and related disciplines (Bromberg-Martin & Monosov, 2020; Gottlieb et al., 2013; Kidd & Hayden, 2015) and is the central question for Part 1 (Studies 1-5) of the thesis.

Beyond anecdotal evidence from daily life, studies from cognitive neuroscience have convincingly demonstrated that both humans and non-human animals will frequently choose to seek non-instrumental information, and are sometimes also willing to pay a cost in time or money to obtain this (Bennett et al., 2016, 2020; Bromberg-Martin & Hikosaka, 2009; Charpentier et al., 2018; Eliaz & Schotter, 2010; Vasconcelos et al., 2015; Wang & Hayden, 2019). Although studies almost always demonstrate individual variability in terms of whether and how frequently people seek information, an explicit accommodation of how individual differences may relate to information seeking is mostly lacking (though see Bennett et al., 2020).

One prevalent explanation for non-instrumental information seeking within cognitive neuroscience is that it reflects a desire to reduce uncertainty (Bennett et al., 2016; Bromberg-Martin & Monosov, 2020; Caplin & Leahy, 2001; Crupi et al., 2018; Eliaz & Schotter, 2010; Schwartenbeck et al., 2019; Wu, 1999). This accords with the view that uncertainty is fundamentally aversive, and that we are motivated to reduce uncertainty in order to make our environment more predictable and manageable (e.g., Hirsh et al., 2012).

At this point, two notable relations to ideas and concepts from personality psychology arise. Firstly, a decision to seek information to reduce uncertainty is more likely to be made by people who find uncertainty aversive. As previously described (Section 1.2) a tendency to find uncertainty aversive can be described by the personality traits *uncertainty intolerance* or *ambiguity tolerance* (Carleton et al., 2007; McLain, 2009). If the uncertainty reduction theory

[2] Of course, any information that is sought must have value to the seeker. But the longstanding definition of "instrumental" information only refers to extrinsic, measurable rewards, such as money or food. This allows other possible value or rewards (e.g., psychological value) to be proposed as possible explanations for non-instrumental information seeking.

is correct, then it is likely that people who are less tolerant of uncertainty or ambiguity would be more likely to seek information.

Second, information seeking is thought to be a core mechanism underlying variance in the trait openness/intellect (DeYoung, 2013). However, the information-seeking theory of openness/intellect appears to conflict with the uncertainty-reduction theory stated above, because openness/intellect is typically considered to relate to greater tolerance for uncertainty. Indeed, the *enticing* nature of uncertainty is proposed to be what underpins information seeking: individuals higher in openness/intellect are enticed by the potential of gaining future information from the unknown (DeYoung, 2013). This contrasts with neuroticism, which has been thought to relate to greater aversion of uncertainty, whereby uncertainty is seen as containing possible threats (Carleton et al., 2012).

Can both the uncertainty-reduction explanation of information seeking and the information-seeking theory of openness/intellect be correct? How can both explanations be true: that people seek information because they fear the unknown, and that people seek information because they are curious about what is contained in the unknown? This question forms the impetus for all of the studies within Part 1 of the thesis.

1.6.1 Summary of Part 1 studies. The aforementioned patterns of Big 5 personality relations to ambiguity/uncertainty intolerance have not been conclusively established (see Chapter 2 for extensive documentation), nor has any study yet found that openness/intellect predicts seeking information (see Chapter 3 for extensive documentation). Thus, Study 1 was designed to confirm these putative links between Big 5 personality traits and ambiguity/uncertainty tolerance, and Studies 2 and 3 were designed to investigate whether openness/intellect relates to an increased likelihood of information seeking. In Study 1 I find that, as predicted, individuals higher in openness/intellect are more tolerant of ambiguity and uncertainty, and conversely, individuals higher in neuroticism are less tolerant of ambiguity and uncertainty. Meanwhile, the results of Studies 2 and 3 suggest that openness/intellect does not predict information seeking. However, both joyous exploration and uncertainty intolerance positively predict information seeking. Given that joyous exploration is strongly positively correlated with openness/intellect, and uncertainty intolerance is strongly negatively correlated with openness/intellect, this could suggest multiple divergent pathways for information seeking that combine to produce a net null effect for openness/intellect; and may indicate that the uncertainty-reduction theory of information seeking *and* the information-seeking theory of openness/intellect could be correct. The findings of these studies are subsequently combined with an understanding of hierarchical models of personality and person-by-situation

interactions, from which I derive an overarching conceptual model of information seeking that incorporates person and situation-specific factors. This model suggests multiple motivations to seek information: one driven by exploration (related to joyous exploration and openness/intellect) and one driven by safety (related to uncertainty intolerance and neuroticism). These patterns of relations are investigated in Studies 4 and 5. I find consistent evidence for the exploration pathway but more tentative evidence for the safety pathway. This research program demonstrates the potential to tackle research questions from cognitive neuroscience (i.e., information seeking) with knowledge and theory from personality psychology.

1.7 Part 2: Exploring the Neuroscience of Personality with Machine Learning

The second part of this thesis (Chapters 5 and 6) presents an alternate way of integrating personality psychology and cognitive neuroscience than in Part 1: rather than drawing on theory and concepts from personality psychology to address current research questions in cognitive neuroscience, methods from cognitive neuroscience are used to investigate possible biological bases of personality. Specifically, I introduce the machine learning method *multivariate pattern analysis* (MVPA) and employ it to explore whether we can predict personality traits from electroencephalographic (EEG) data recorded in participants at rest (Study 6) and whether we can confirm exploratory findings (Study 7). Note that although Study 6 was an exploratory study, one question we were particularly interested in was whether MVPA could decode openness/intellect, which would have provided a close substantive link to Part 1 of the thesis, where this trait's possible cognitive and motivational mechanisms were investigated. However, results of Study 6 reoriented the substantive focus of Part 2 away from openness/intellect. Nonetheless, the two thesis halves share the strong conceptual focus of combining cognitive neuroscience and personality psychology perspectives, demonstrating two different but complementary ways of how integration is possible.

As previously described, knowledge from cognitive neuroscience can be valuable to refer to for evidence supporting particular theories from personality psychology, or to employ when developing these theories (Section 1.3.3). Connections between each Big 5 personality trait and particular neural indices have been noted (Allen & DeYoung, 2017), suggesting that there are many possible effects observed in the literature that could be drawn on when developing such theories. However, the current existence of effects does not imply that there are no new effects of interest to be discovered. Rather, the vast complexity of the brain suggests that we may have only scratched the surface of possible links between the brain and personality traits. Further investigation could be highly valuable to add to current reviews of personality-

brain relations and assist in uncovering the biological basis of personality. This approach—whereby possible new effects are investigated with no prior expectations for what may be detected—is inherently exploratory, and such research is fundamental to generate new hypotheses that can be tested in confirmatory research studies, thus aiming to derive a solid research base of effects from which theories can be developed (McIntosh, 2017).

The majority of findings linking personality traits to neural measures have been observed with fMRI, or with EEG in the time domain (Allen & DeYoung, 2017). Relatively fewer have investigated EEG in the frequency domain. An EEG signal can be transformed from the time to the frequency domain with the aid of spectrum analysis such as the Fourier transform, which summarises the energy within different spectral frequencies across the course of the testing period. This data is thought to contain information representing both rhythmic oscillations (e.g., alpha waves, which oscillate ~8-12 Hz) and arrhythmic brain activity, and both components have been found to be relevant for individual differences (Başar et al., 1999; Dave et al., 2018; Knyazev, 2007; Ouyang et al., 2020; Ward, 2003). Such an analysis is particularly useful to summarise longer periods of testing that do not involve particular experimental paradigms where the time course of processing is important. For example, in *resting state* studies, participants sit quietly at rest while their neural data is acquired. Given that personality traits describe consistent patterns of behaviour and experience, it is possible that such patterns might be detected in the resting state. Further, studies of the relation between personality traits and the resting state fMRI have uncovered intriguing results, particularly related to openness/intellect and related traits such as creativity (Beaty et al., 2016, 2018). Thus, there may be value in assessing these correlates for EEG.

For Part 2 of the thesis, I used MVPA to investigate possible EEG correlates of personality. MVPA describes a cluster of related supervised machine learning approaches that can be used to predict neural indices or behaviour from multivariate data (in this case, the spectral power across many frequencies and EEG channels). MVPA is particularly appropriate for exploratory research because it can economically and systematically trawl a large feature space to find signals that might be related to the outcome of interest, and also includes important checks on inferring signal from noise, such as cross-validation. MVPA methods are rapidly growing in use in cognitive neuroscience (see introductions of Study 6 and Study 7 for reviews). Given the nascent state of uncovering EEG-derived measures of personality at rest, this makes the method a valuable addition to the personality neuroscience toolbox.

1.7.1 Summary of Part 2 Studies. In Study 6 (Chapter 5), I first explore whether any personality traits can be predicted by MVPA across two testing conditions (before and after

taking part in an unrelated experiment), and when participants are sitting at rest with their eyes open and also closed. I find that the personality traits *agreeableness* and *neuroticism* can be consistently decoded in similar frequencies across these four conditions, suggesting that there is information contained in the power spectrum that can distinguish individual self-reports of these traits.

For Study 7 (Chapter 6), I conduct a preliminary confirmatory replication of Study 6. Given COVID-19 restrictions on in-person data collection, I collaborated with a research team in Germany who had access to further existing resting-state data to reach a sample size that exceeded our prespecified minimum. Results did not straightforwardly replicate either trait in the combined sample, though intriguing results emerged when stratified by country, suggesting that an effect could be present for agreeableness in the Australian sample, and for neuroticism in the German sample. However, these results should be considered with a high degree of caution given that they were not predicted in advance and given that there is not an obvious explanation for divergent prediction across countries.

1.8 Discussion of Thesis (Chapter 7)

This final chapter provides an overview of results and an assessment of the strengths and challenges of an interdisciplinary approach. Concerning Part 1, I discuss how personality knowledge and theory provides a framework to understand results and refine particular psychological theories from cognitive neuroscience. For Part 2, I discuss the challenge of integrating novel methods into the study of personality, which often requires large samples to have confidence in the stability of estimates. Finally, I propose guidelines for future studies employing these methodologies.

1.9 Open Science Practices

This thesis makes every attempt to follow the principles of transparency, accountability, and rigour outlined as key features of credible research (Vazire, 2018; Vazire et al., 2020). Where possible, data and study materials are made freely available (Studies 1-6; Study 7 will be made open during peer review). I also clearly distinguish between exploratory research/non-pre-registered follow-ups (Studies 2, 5, and 6) and confirmatory research (Studies 1, 3, 5, and 7). Where confirmatory, I have pre-registered study hypotheses and analysis plans.

Part 1

Chapter 2:
To Fear or Fly to the Unknown:
Tolerance for Ambiguity and Big Five Personality Traits (Study 1)

2.1 Overview

Study 1 presents an investigation of whether putative Big 5 correlates of ambiguity tolerance and uncertainty intolerance hold in the context of a pre-registered confirmatory analysis. This first study is important to clarify the nomological network of these traits (Markon, 2009) for future chapters assessing personality trait correlates of information seeking. As previously described, the uncertainty-reduction theory suggests that uncertainty intolerance will predict seeking more information, whereas the information-seeking theory of openness/intellect suggests that openness/intellect will predict seeking more information. These predictions conflict because openness/intellect is thought to be strongly positively correlated with ambiguity and uncertainty tolerance (and hence if openness/intellect positively predicts information seeking, then uncertainty intolerance would predict *less* information seeking), compared to neuroticism, which is thought to relate to being less tolerant of ambiguity and uncertainty. Assessing the relations between ambiguity/uncertainty intolerance and each of openness/intellect and neuroticism can clarify whether to pursue an answer to these conflicting explanations. That is, if the pattern of suggested relations is not supported in a confirmatory study, then there may be no conflict to explain.

Study 1 results find that openness/intellect positively relates to ambiguity/uncertainty intolerance, whereas neuroticism negatively relates to ambiguity tolerance/uncertainty tolerance, as predicted and in concert with prior research. These findings are consistent with the perspective that individuals higher in openness/intellect tend to find the unknown enticing, whereas individuals higher in neuroticism tend to find the unknown threatening.

2.1.1 Note. In the following published manuscript, openness/intellect is called by the alternative label *openness to experience.* There are multiple labels for this personality trait, reflecting its status as the loosest and broadest of the Big 5 (Trapnell & Wiggins, 1990). Although these terms sometimes differ in their emphasis on certain facets, for the purposes of this thesis they can be considered to describe the same construct.

Additionally, several research questions are included in this study that are not a core focus of the current thesis: specifically, assessing the relations between extraversion and ambiguity tolerance; whether a behavioural measure of ambiguity tolerance has the same pattern of relations to Big 5 personality traits as ambiguity tolerance measured by a self-reported survey; and exploring a network analysis of how facets of ambiguity

tolerance/uncertainty tolerance relate to facets of extraversion, neuroticism, and openness/intellect.

2.2 Empirical Study 1

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Full Length Article

To fear or fly to the unknown: Tolerance for ambiguity and Big Five personality traits ☆

Hayley K. Jach *, Luke D. Smillie

The University of Melbourne, Australia

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ABSTRACT

The present study investigated whether ambiguity tolerance relates to personality traits that are theoretically grounded in fear (neuroticism) or attraction (openness to experience; extraversion) for the unknown. Our hypotheses were supported for self-report measures (and openness to experience predicted ambiguity tolerance controlling for intelligence), but behavioral choice measures of ambiguity tolerance demonstrated poor reliability and were unrelated to self-reported ambiguity tolerance and basic personality traits. An exploratory network analysis revealed that ambiguity tolerance was more strongly related to the intellectual curiosity (vs. aesthetic appreciation) facet of openness to experience, and the assertiveness (vs. energy or sociability) facet of extraversion. Our findings reinforce the fragmented literature in this area, and support predictions derived from psychological entropy theories of personality.

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1. Introduction

Ambiguity is a ubiquitous part of life. A researcher may spend her career searching for the cure for a rare disease, without knowing if the search will be in vain. A tourist may stare at an abstract painting on a gallery wall, uncertain if the vague shape is a bicycle or a product of his own imagination. A smile could indicate enjoyment or derision of your attempt at a joke.

The tendency to view ambiguous and uncertain situations as appealing versus threatening is known as *ambiguity tolerance* (Budner, 1962; Frenkel-Brunswik, 1949) or *uncertainty intolerance* (Freeston, Rhéaume, Letarte, Dugas, & Ladouceur, 1994). People who are more tolerant of ambiguity report being happier (Bardi, Guerra, Sharadeh, & Ramdeny, 2009), more motivated to learn (Tapanes, Smith, & White, 2009), more self-efficacious (Wolfradt, Oubaid, Straube, Bischoff, & Mischo, 1999), and more likely to engage in cross-cultural experiences (Caligiuri & Tarique, 2012). Conversely, people who are less tolerant of ambiguity and uncertainty tend to be more worried (Buhr & Dugas, 2006; Dugas, Gosselin, & Ladouceur, 2001), anxious and depressed (Bardi et al., 2009; Carleton et al., 2012), obsessive-compulsive (Tolin, Abramowitz, Brigidi, & Foa, 2003), and show greater stress-related physiological responses (Greco & Roger, 2001).

Despite extensive research linking ambiguity tolerance to such diverse outcomes, there has been far less research assessing where ambiguity tolerance is located within dominant models of the structure of personality traits such as the Big Five (John, Naumann, & Soto, 2008). Similarly, within the mainstream personality literature, ambiguity tolerance is a construct that is discussed surprisingly little. Perhaps owing to the lack of cross-talk between personality and ambiguity tolerance literatures, an interesting correspondence between mechanistic theories of personality and concepts of ambiguity has been overlooked. Specifically, *psychological entropy* theories of personality propose that some domains of the Big Five are partially underpinned by individual differences in responses to the unknown (Hirsh, Mar, & Peterson, 2012; DeYoung, 2013). Whereas *openness to experience* and *extraversion* have been attributed to individual differences in one's motivational drive to explore the unknown (DeYoung, 2013), *neuroticism* and its narrower sub-trait of *anxiety* have been attributed to individual differences in aversive responses to the unknown (Hirsh et al., 2012). As unknown situations are inherently ambiguous, it is

☆ Author contribution: Both authors designed the study. The first author collected and analyzed data and wrote the manuscript. The second author provided guidance on all stages of the research process and editing assistance on the manuscript.

* Corresponding author.
E-mail address: hayleyjach@gmail.com (H.K. Jach).

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possible to test the initial stages of psychological entropy theories by measuring the relation between ambiguity tolerance and the basic domains of personality. In the current study, we first expand the theoretical justification for this argument, and subsequently consolidate the sparse existing literature by conducting a pre-registered investigation of whether ambiguity tolerance relates robustly to openness to experience, extraversion, and neuroticism.

1.1. Personality and psychological entropy

At the heart of the theories by Hirsh et al. (2012) and DeYoung (2013) is the concept of entropy. Entropy is a measure of uncertainty and disorder within a system (Wiener, 1961), and has been used to describe the behavior of complex systems throughout diverse fields such as information theory, thermodynamics, and cybernetics. Mathematically, outcomes that are certain have an entropy of zero, and more probable outcomes will have lower entropy than less probable outcomes (Weaver, 1964; Shannon, 1948). For example, the entropy of a two-headed coin will be zero, as the outcome will always be heads.[1] And as the outcome of flipping a coin (a one-in-two chance) is more predictable than that of rolling a six-sided die (a one-in-six chance), the former has a lower entropy than the latter.

Extending this concept to preferences as well as events, Hirsh and colleagues define *psychological entropy* as the number of possible options available to an individual—either for their perception of the world, or for their behavior. When there are multiple potential interpretations or actions, and it is unclear which interpretation or action is best, psychological entropy will be high. Conversely, when there is a single clear path forward, or multiple paths but a clear choice, psychological entropy will be low. Consider the example of deciding whether to attend a party or stay at home. Psychological entropy will be higher when there are two parties to choose from, and higher still with three parties, so long as no alternative is clearly more appealing than the other.

The Cambridge online dictionary defines ambiguity as "the fact of something having more than one possible meaning and therefore possibly causing confusion". This description converges with Hirsh et al. (2012) definition of psychological entropy given above. It is difficult to imagine a situation where psychological entropy would increase without also increasing ambiguity; and likewise, for psychological entropy to decrease without there being a corresponding decrease in ambiguity. In the example of considering parties to attend, all other things being equal, the option of two parties is a more ambiguous a single party. Thus, in the current paper, psychological entropy and ambiguity will be treated as highly overlapping and, for the contexts discussed herein, equivalent.

Hirsh et al. (2012) contended that (1) increases in psychological entropy will lead to increased distress and anxiety, and thus (2) individuals desire to reduce their experience of entropy to a manageable level. However, given that individual differences in one's tolerance for ambiguity have been extensively documented in survey research (Budner, 1962; McLain, 2009), responses to increases in entropy might not uniformly involve stress and anxiety. This is central to DeYoung (2013) argument that entropy (and thus, we argue, ambiguity) can be simultaneously aversive and enticing: although it can signal a potential threat, it can also signal a potential reward. DeYoung (2013) contended that the rewarding nature of psychological entropy would be most relevant for the personality traits extraversion (i.e., the tendency to engage with the social and material world with energy, enthusiasm, and assertiveness; Wilt & Revelle, 2017) and openness to experience (i.e., the tendency to experience and appreciate depth, originality, and complexity in one's mental and experienced life; McCrae & Costa, 1997). Specifically, extraverts would be motivated by the potential for rewards in the unknown (Depue & Collins, 1999), whereas those higher in openness to experience would be motivated by the potential to gain future information from the unknown. DeYoung (2013) also argued that the shared motivation to explore the uncertain nature of the environment—to "increase the experience of uncertainty to an interesting level" (p. 8)—partially explained the shared variance between extraversion and openness to experience, which together form the higher-order *meta*-trait *plasticity*. As explorers must place themselves in a state of temporary ambiguity in order to gain their rewards—whether they be social, financial, informational, or purely aesthetic—this theory predicts that openness to experience and extraversion are related to higher ambiguity tolerance. In contrast, neuroticism—which describes the tendency to experience negative states such as anxiety, depression, and volatility—would be expected to relate to stronger aversive responses to ambiguity, as these individuals would be more likely to perceive threats in the unknown. Thus, the theory also predicts that neuroticism would be related to greater *intolerance* of ambiguity. If there is sufficient evidence linking ambiguity tolerance to these traits in the expected direction, then this is consistent with the hypothesis that extraversion and openness to experience share variance due to a tendency to explore of the unknown (DeYoung, 2013); and is also consistent with the view that neuroticism is grounded in aversive responses to uncertainty (Hirsh et al., 2012; DeYoung, 2013, 2014).

1.2. Empirical links between ambiguity tolerance and Big 5 personality traits

To our knowledge, no existing paper has focused solely on assessing how openness to experience, extraversion, and/or neuroticism relate to one's attitude toward ambiguity. However, there have been several studies where these relations were reported tangentially to the central research question. For example, Caligiuri and Tarique (2012) investigated predictors of leadership effectiveness, measuring personality traits and ambiguity tolerance as part of their test battery. They found that openness to experience and extraversion correlated positively with ambiguity tolerance (*r*s for both = .24) but did not observe a significant correlation between neuroticism and ambiguity tolerance.

Given the shared variance between extraversion and openness to experience, it is possible that extraversion would only predict ambiguity tolerance via its relation to openness to experience. However, Caligiuri and Tarique (2012) found that extraversion was a significant predictor of ambiguity tolerance after accounting for openness to experience. This would be promising for entropy theories of personality, but the study is limited by employing an early 4-item measure of ambiguity tolerance with poor internal consistency, making it possible that this incremental prediction (and the pattern of correlations) would not replicate.

In a more recent study, Lauriola, Foschi, Mosca, and Weller (2016) conducted a principal components analysis of seven ambiguity tolerance measures and assessed how each component correlated with a range of variables, including personality traits. They found that extraversion and openness to experience were weakly negatively related to distress or discomfort for ambiguous situations ($r = -.22$ and $r = -.16$, respectively), more strongly and positively related to need for complexity and novelty ($r = .20$ and $r = .35$, respectively), but only openness to experience was significantly (weakly) related to the third component, moral absolutism and rigid thinking ($r = -.12$). Conversely, neuroticism was only significantly related to the first component, discomfort for ambiguity ($r = .29$).

These two studies are the only ones we have found measuring ambiguity tolerance and extraversion or neuroticism, but neuroti-

[1] For sticklers considering the event of a coin balancing on its edge, please indulge in imagining the entropy of a two-headed coin to be slightly higher than zero.

cism has demonstrated strong correlations ($r \sim .50$) with *uncertainty intolerance* (Berenbaum, Bredemeier, & Thompson, 2008; de Bruin, Rassin, & Muris, 2007; Greco & Roger, 2001; McEvoy & Mahoney, 2012). Uncertainty intolerance and ambiguity tolerance are sometimes conceptualized as separate constructs. However, measures of uncertainty intolerance and ambiguity tolerance demonstrate close empirical and conceptual overlap, as evidenced by the very high correlations between measures when they are included in the same study (e.g., Lauriola et al., 2016).[2] Thus, the present study treats ambiguity tolerance and uncertainty intolerance as interchangeable constructs. Nevertheless, as the example items above demonstrate, the items included in intolerance of uncertainty scales tend to be more negatively valenced, and to employ more strongly emotional language. Thus, it is possible that the high association between neuroticism and uncertainty intolerance is driven by the negative item content, rather than to uncertainty or ambiguity per se. This would lead neuroticism to be a better predictor of uncertainty intolerance than ambiguity tolerance, even if uncertainty intolerance and ambiguity tolerance are conceptually measuring the same construct. This may provide an explanation for the non-significant relationship observed by Caligiuri and Tarique (2012), and the smaller effect sizes documented by Lauriola et al. (2016). The current study aims to assess the relative association between neuroticism and measures of ambiguity tolerance and uncertainty intolerance, and to assess whether neuroticism is a better predictor of uncertainty intolerance than openness to experience.

For openness to experience, one additional high-powered study measured how openness to experience and ambiguity tolerance related to wellbeing in the context of academic life transitions (Bardi et al., 2009), finding the correlation between openness and ambiguity tolerance to be stronger for first year university students ($r = .42$) than for final year students ($r = .25$). Though we have found no further studies that directly test these relations, some researchers have found associations between ambiguity tolerance and measures conceptually related to openness to experience. For example, Wolfradt et al. (1999) found that interpersonal ambiguity tolerance was associated with a drive to learn things and understand the world. Rajagopal and Hamouz (2009) observed that ambiguity tolerance correlated positively with openness to try food from many cultures and styles. Also of relevance is a study by Swami, Stieger, Pietschnig, and Voracek (2010), who found that ambiguity tolerance correlated positively with appreciation of surrealist art and films (which open people tend to be more interested in). Finally, openness to experience was also related to the tendency to experience mixed (i.e., more ambiguous) emotions (Barford & Smillie, 2016), and to provide mixed appraisals of art (Barford, Fayn, Silvia, & Smillie, 2018).

Importantly, openness to experience correlates with intelligence at $r \sim .30$ (DeYoung, Quilty, Peterson, & Gray, 2014). It is plausible that any observed relation between openness to experience and ambiguity tolerance could be driven primarily by intelligence. For instance, more intelligent individuals may think more comprehensively about their choices when options are ambiguous, and thus be less affected by any aversive properties in ambiguity. To our knowledge, no prior study has tested whether openness to experience relates to ambiguity tolerance after controlling for *g*. We evaluate this in the current study.

[2] One apparent distinction is that uncertainty intolerance includes a future-orientation absent in ambiguity tolerance (Gignac & Szodorai, 2013). However, this is not consistent across items in uncertainty intolerance scales. For example, the uncertainty intolerance scale used for the present study (Carleton et al., 2007) includes several items related to inhibitory anxiety in which no future orientation is specified, such as *when it's time to act, uncertainty paralyses me*. Indeed, there is a very similar item employed in a common measure of ambiguity tolerance, *I find it hard to make a choice when the outcome is uncertain* (Moutafi et al., 2003).

1.3. Measuring tolerance for ambiguity via self-report and behavior

Until recently, most measures of ambiguity tolerance had lower than acceptable psychometric properties (Furnham & Marks, 2013): for example, internal consistency for the most well-cited ambiguity tolerance scale was $\alpha = .49$ (Budner, 1962). Two recent scales of ambiguity tolerance have been developed with much improved psychometric properties: the Multiple Stimulus Types Ambiguity Tolerance Scale-II (MSTAT; McLain, 2009) and the Tolerance for Ambiguity measure (TfA; Herman, Stevens, Bird, Mendenhall, & Oddou, 2010). Each of these have reported internal consistencies of $\alpha > .70$. The MSTAT (version I) was included in Lauriola et al. (2016) and most items loaded heavily on the need for complexity/novelty component. Meanwhile, items comprising the TfA appear on face value to tap more diverse sub-domains of ambiguity tolerance. Indeed, Herman et al. (2010) found evidence of four dimensions: valuing diverse others, change versus stability, challenging perspectives, and unfamiliarity versus novelty. In the current study, we will use both the MSTAT and TfA along with a measure of uncertainty intolerance (Carleton, Norton, & Asmundson, 2007), thereby aiming to provide comprehensive coverage of this construct.

In parallel to the research on ambiguity tolerance as measured by self-report, *behavioral* measures of ambiguity tolerance have a long history of use in economics and decision theory (Ellsberg, 1961). In these fields, ambiguity tolerance is assessed using the *Ellsberg paradigm* as the preference for an ambiguous versus unambiguous gamble (for reviews, see Camerer & Weber, 1992; and Trautmann & Van De Kuilen, 2015). For example, a participant may be given a choice between two equally risky gambles: a 50/50 chance of winning $1, or an entirely unknown chance of winning $1. Both options are equivalent in terms of their subjective expected utility, and should be equally valued for that reason (Camerer & Weber, 1992). The options are also equivalent in terms of risk, and thus participants' choices should not be influenced by risk aversion (which has well-documented links to neuroticism; Nicholson, Soane, Fenton-O'Creevy, & Willman, 2005; Soane & Chmiel, 2005). Critically, however, the latter option (unknown chance of winning) is the more ambiguous of the two, suggesting that a preference against this option is indicative of intolerance of ambiguity.

In previous studies using such choice gambles, participants tend to be ambiguity averse (with the exact percentage varying by amount of reward or degree of ambiguity), but there is a substantial minority who choose more ambiguous options (Trautmann & Van De Kuilen, 2015). To our knowledge, no study has yet assessed how Big Five personality traits may relate to behavioral responses to ambiguity as measured by the Ellsberg paradigm. Thus, in the current study, we employ five variations of this paradigm to assess whether openness to experience, extraversion, and neuroticism predict behavioral ambiguity tolerance.

1.4. Exploring facets of personality and ambiguity tolerance

Each of the Big Five factors is composed of lower-order facets, providing a less parsimonious but more complete depiction of personality structure. For instance, the Big Five Inventory-2 (BFI-2; Soto & John, 2017) divides openness to experience into the three facets *intellectual curiosity*, *aesthetic sensitivity*, and *creative imagination*. Studies have demonstrated value in assessing differential relations between personality trait facets and variables such as wellbeing (Sun, Kaufman, & Smillie, 2018), creative achievement in the arts versus sciences (Kaufman et al., 2016), and prosociality (Zhao, Ferguson, & Smillie, 2016). Evidence suggests that ambiguity tolerance can also be subsumed by more fine-grained factors (Lauriola et al., 2016). As summarized in Section 1.2, these factors appear to be differentially related to personality traits. In the current study, we aim to explore empirically derived sub-dimensions

of our three ambiguity/uncertainty tolerance measures, and subsequently assess whether these differentially relate to facets of openness to experience, extraversion, and neuroticism. In so doing, we can (a) observe whether sub-components derived by Lauriola et al. (2016) are represented in our data, and whether they map onto personality traits in a similar fashion, and (b) explore new patterns of associations that may not yet have been discovered, from which future researchers may wish to conduct confirmatory investigations.

For this task, we employ a network model (Cramer, 2012; Costantini et al., 2015). A network model represents variables of interest as *nodes*, and correlations between variables as *edges*. It is possible to construct a network in which edges are computed between two nodes, controlling for all other nodes in the network. This comprises a network of partial correlations, where only the unique variance between variables is represented. This thus provides all the advantages of a traditional partial correlation analysis, but includes important checks on inferring signal from noise, such as the creation of sparse network structures via regularization, and estimation of bootstrapped confidence intervals around edge weights (Epskamp, Borsboom, & Fried, 2018). An additional benefit is easy interpretability: networks are able to condense a substantial amount of information into an intuitive visualization, allowing patterns of associations to be grasped efficiently.

1.5. The present study

To sum up, there is suggestive evidence that openness to experience, extraversion, and neuroticism may relate to ambiguity tolerance, in line with theoretical perspectives on psychological entropy offered by Hirsh et al. (2012) and DeYoung (2013). The aim of the present study is to strengthen this fledging literature through a comprehensive evaluation of these associations, across both self-reported and behavioral measures of ambiguity tolerance. In additional exploratory analyses, we assess the partial correlation network of key variables with a network analysis, aiming to further clarify how sub-components of ambiguity tolerance are related to facets of Big Five personality traits.

For self-report measures, we hypothesize that openness to experience, extraversion, and plasticity will relate positively to ambiguity tolerance, and will relate negatively to intolerance of uncertainty. We also expect that openness to experience will predict ambiguity tolerance even controlling for intelligence.

We hypothesize that the opposite pattern will appear for neuroticism: specifically, that neuroticism will negatively relate to ambiguity tolerance, and positively relate to intolerance of uncertainty. We also expect that neuroticism will be a better predictor of ambiguity tolerance when it is measured as uncertainty intolerance rather than openness to experience.[3] Finally, we explore whether extraversion continues to predict ambiguity tolerance controlling for openness to experience.

For behavioral measures, we hypothesize that openness to experience, extraversion, and plasticity will predict preference for an ambiguous (versus unambiguous) gamble; that the relation between openness to experience and choosing an ambiguous gamble will hold even when controlling for intelligence; and that neuroticism will predict choosing an unambiguous (versus ambiguous) gamble.

This study was preregistered, and all materials, data, and analysis code for this study are freely available on the Open Science Framework (OSF; https://osf.io/4mruh).

[3] This prediction can be found in the "Analysis plan" section of the preregistration, rather than the hypotheses section.

2. Method

2.1. Participants

Participants were United States residents who were recruited from Amazon Mechanical Turk in June of 2018. Our target sample was 300 individuals. In total, 327 participants began the study. After removing 19 participants who completed less than 90% of the survey (our pre-registered exclusion criteria),[4] the final sample was $N = 308$ ($M_{age} = 36.23$, $SD_{age} = 10.82$, 38% female). This provides > 90% power to detect a correlation of $r = .20$, the approximate average effect size observed in personality psychology (Gignac & Szodorai, 2016). Ethical approval for the study was obtained from the Melbourne School of Psychology Human Ethics Advisory Group (ID. 1851766.2).

2.2. Materials and procedure

Participants completed a battery of questionnaires and behavioral tasks (full survey questions available on the OSF) and were informed that they would be reimbursed $2.00 USD for their time, with an additional $0.50 USD conditional upon correctly completing attention checks. In addition, participants were told that they had the chance to win an additional $0.50 USD in the behavioral tasks. To maintain fairness among participants, all participants received this second bonus money after study completion. All scales included in the survey are described below. All used a 5-point scale from *Strongly Disagree* to *Strongly Agree.*

2.2.1. Big Five personality traits

The five major domains of personality (extraversion, neuroticism, conscientiousness, agreeableness, and openness to experience) were measured with the BFI-2 (Soto & John, 2017). Each domain is assessed using 12 items (e.g., *Is outgoing, sociable*), and can be divided into three facet scales, measuring narrower conceptualizations of the trait (e.g., extraversion divides into Energy Levels, Sociability, and Assertiveness). For an additional measure of openness to experience, we administered Openness/Intellect from the Big Five Aspect Scales (BFAS; DeYoung, Quilty, & Peterson, 2007), a 20-item measure of openness to experience which can be divided into two narrower aspect scales, Openness (appreciation of sensorial and perceptual complexity) and Intellect (appreciation of intellectual complexity).

2.2.2. Self-reported ambiguity/uncertainty tolerance

As mentioned earlier, the two scales of ambiguity tolerance used were the TfA (Herman et al., 2010), and the MSTAT (McLain, 2009). Of the many measures available, these appeared the most valid and reliable. Items also appeared relatively different from each other on face value (e.g., *I don't tolerate ambiguous situations well* from the MSTAT; *I would like to live in a foreign country for a while* from the TfA), allowing for an exploratory investigation of the construct space for these measures. In addition, participants completed the Intolerance of Uncertainty Scale-12 (Carleton et al., 2007), a 12-item measure with evidence of high internal consistency and evidence of convergent validity, discriminant validity and clinical validity.

2.2.3. Behavioral ambiguity tolerance

We used five variants of the Ellsberg paradigm (Ellsberg, 1961; described in Camerer & Weber, 1992). In this paradigm, partici-

[4] One additional participant completed more than 90% of the survey, but did not complete the study to obtain an identifying code that was necessary to obtain payment, and additionally failed both attention checks and a comprehension check. Their data was not included in the study.

pants are required to choose between two gambles. Both gambles are equally risky, but one is more ambiguous than the other. The five tasks are described below. To increase participant engagement, we altered the traditional task design from one in which participants were told they were choosing balls from urns, to a design in which participants were informed they were explorers moving through various rooms in a cave, with an aim to collect treasure (the equivalent of balls) from chests (the equivalent of urns) guarded by a trickster ghost. The online documentation contains the full script shown to participants.

The five variants were as follows. First, in the *two-color problem,* participants choose between a 50/50 probability of winning *or* a completely unknown probability of winning. Next, two versions of the *three-color problem* were presented. In the first, participants choose between a 3/9 chance of winning, or an unknown/9 chance of winning. In the second, participants choose between an unknown/9 chance at winning versus a 6/9 chance of winning. Finally, participants completed two versions of the *two-color problem with second-order probability.* Second-order probabilities refer to gambles where the participants are made aware of how ambiguous an option may be (Camerer & Weber, 1992). In the first of these tasks, participants choose between a 50/50 probability of winning, or a chance that is somewhere between 40/100 and 60/100. In the second of these tasks, participants have the same 50/50 chance for the first option, but the ambiguity of the second option was increased to a chance of winning that is anywhere between 20/100 and 80/100.

2.2.4. Intelligence

To assess whether any relation between openness to experience and ambiguity tolerance might be driven primarily by intelligence, we employed the publicly available International Cognitive Ability Resource (Condon & Revelle, 2014). This 16-item measure is an open-access intelligence test that has strong psychometric properties, including excellent internal consistency, and compelling evidence of construct validity, convergent validity, and discriminant validity.

2.3. Attention and comprehension checks

Participants were asked to complete a simple comprehension check following the behavioral ambiguity task (in which they were asked the number of gems possible to be drawn from a treasure chest in the final behavioral task), and two attention checks threaded into the survey questions (“Respond ‘strongly agree’” and “Respond ‘strongly disagree’”). Of the 308 participants whose data we included in the study, 14 failed the comprehension check, and following our pre-registered plan, their data was excluded from computations involving behavioral ambiguity tolerance. Seventeen participants failed the first attention check, and 15 failed the second attention check. Of these, seven participants failed both attention checks. As results based on self-report measures did not substantially change when we removed these participants, we followed our pre-registered plan to retain this data in order to maximize statistical power.

2.4. Data analysis

2.4.1. Indices

When we had multiple measures of the same construct, we computed a single factor using exploratory factor analysis. This was performed to avoid duplicating analyses for both scales, and to increase measurement precision (as assuming that the two scales are valid and reliable, a general factor combining these measures will be superior to one scale alone). Specifically, we employed ordinary least squares with a direct oblimin rotation, and saved factor scores with the correlation-preserving (“ten Berge”) method (ten Berge, Krijnen, Wansbeek, & Shapiro, 1999). This procedure was applied to (1) our two measures of openness to experience (BFAS and BFI-2), (2) our two measures of ambiguity tolerance (TfA and MSTAT), and (3) the meta-trait plasticity (BFI-2 Open Mindedness and Extraversion). These saved scores were used in the inferential analyses described below, except when specified. Finally, we also planned to use this approach with the five variants of the Ellsberg paradigm to create an overall measure of behavioral ambiguity tolerance, conditional on acceptable reliability amongst responses to these items (omega greater than .60). However, as reliabilities did not meet this threshold in our sample, we analyzed behavioral results separately (see Section 3.3.2).

2.4.2. Exploratory network analysis

Prior to commencing the network analysis, it was necessary to assess the dimensionality of our measures of ambiguity tolerance. The supplementary information (Section S3) contains full methodological details of this analysis. In brief, we used exploratory graph analysis (Golino & Epskamp, 2017), an alternative to exploratory factor analysis developed from the network approach. This method has previously been used to assess the dimensionality of personality measures (Christensen, Cotter, & Silvia, 2018; Christensen, Gross, Golino, Silvia, & Kwapil, in press) and simulation studies indicate it can successfully retrieve the correct number of dimensions in a dataset (Golino & Epskamp, 2017). Exploratory Graph Analysis is comparable to common methods of deriving the correct number of factors (e.g., parallel analysis), and can perform better than traditional methods when factors are highly correlated (Golino & Epskamp, 2017).

Subsequent to dimension reduction, we conducted the network analysis following the guidelines of Epskamp et al. (2018). Edge weights (i.e., partial correlations) were estimated with a Gaussian graphic model including LASSO regularization to create a sparse network structure. Regularization reduces false positives relative to partial correlations, such that a measured edge can be more confidently inferred to represent a true structural relation between two variables (Costantini et al., 2015; though note that a lack of edge may simply mean that the statistical power is not sufficiently high to detect an edge). To estimate the accuracy of edge weights, we used a nonparametric bootstrap with 1000 samples to construct 95% bootstrapped confidence intervals (CIs) around edge weights.

Network analyses often include additional tests from graph theory, such as measures of centrality (Fried & Cramer, 2017). However, as our main interest in the network analysis was viewing the partial correlation matrix rather than assessing which nodes were the most central in the network, we have not assessed these elements.

2.4.3. Packages

All analyses were deployed using *R* (version 3.5.0; R R Core Team, 2018), and making use of the following packages: bootnet (Epskamp et al., 2018), EGA (Golino, 2018), lavaan (Rosseel, 2012), lm.beta (Behrendt, 2014), lsr (Navarro, 2015), psych (Revelle, 2018), qgraph (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012), tidyverse (Wickham, 2017), and TOSTER (Lakens, 2017).

3. Results

3.1. Descriptive Statistics

Table 1 displays means, standard deviations, skew, kurtosis, and internal consistency values (omega hierarchical, omega total, and

Table 1
Descriptive statistics and internal consistency measures for all variables.

Variable	Mean	SD	Skew	Kurtosis	Internal consistency		
					Omega H	Omega T	Alpha
Behavioral AT	0.39	0.26	0.29	−0.72	.19	.47	.39
Ambiguity TfA	3.07	0.59	0.03	0.28	.40	.83	.76
Ambiguity MSTAT	3.13	0.80	0.06	−0.25	.73	.93	.91
Uncertainty Intolerance	3.06	0.83	−0.09	−0.49	.72	.92	.90
Intelligence	7.56	3.83	0.34	−0.77	.61	.84	.82
Extraversion	2.99	0.81	−0.11	−0.59	.62	.91	.88
Negative Emotionality	2.59	0.92	0.33	−0.51	.78	.94	.93
Conscientiousness	3.70	0.76	−0.35	−0.45	.76	.93	.91
Agreeableness	3.66	0.71	−0.36	−0.13	.64	.91	.88
BFI-2 Open Mindedness	3.78	0.78	−0.35	−0.44	.68	.93	.90
BFAS Openness/Intellect	3.75	0.65	−0.06	−0.68	.53	.93	.90

Note: SD = standard deviation, Omega H = Omega Hierarchical, Omega T = Omega Total, Behavioral AT = Behavioral Ambiguity Tolerance, TfA = Tolerance for Ambiguity Scale, MSTAT = Multiple Stimulus Types Ambiguity Tolerance Scale-II, Uncertainty Intolerance = The Short Form Intolerance of Uncertainty Scale. BFAS Openness/Intellect drawn from the Big Five Aspects Scale (DeYoung et al., 2007), with the remaining personality trait measures drawn from the Big Five Inventory-II (Soto & John, 2017). Behavioral AT is coded as 0 = Ambiguity avoidant, 1 = Ambiguity tolerant.

Cronbach's alpha) for all measured variables. All variables were normally distributed with minimal skew or kurtosis. Internal consistency was acceptable for most variables, with the notable exception of our behavioral measure of ambiguity tolerance ($\alpha = .39$, $\omega_h = .19$, $\omega_t = .47$). This falls short of the acceptable lower bound of reliability (.60) that we specified in our preregistration.

We speculated that participants' responses may have followed a different pattern for our fourth and fifth behavioral tasks, which both employ second-order probabilities. However, reliability for the first, second, and third items was even worse ($\alpha = .29$, $\omega_h = .03$, $\omega_t = .32$). As noted in our preregistration, drawing inferences from unreliable measures would be unwise. Thus, although we will present results as per our hypotheses, we consider these of descriptive rather than inferential value, and will not use them to derive evidence for or against our stated hypotheses.

Although our self-report measures demonstrated acceptable reliability, there were some interesting discrepancies between the ω_h and ω_t values across some of the variables (e.g., TfA $\omega_h = .40$ vs. $\omega_t = .83$; and Openness/Intellect $\omega_h = .53$ vs. $\omega_t = .93$). In one sense, it is unsurprising that omega hierarchical would produce a smaller internal consistency measure than omega total, as the former is the proportion of variance accounted for by the general factor only, whereas the latter includes the proportion of variance accounted for by the group and general factors (Zinbarg, Revelle, Yovel, & Li, 2005). Indeed, the large discrepancies between these measures may indicate the existence of a secondary factor structure. This is not surprising in the case of Openness/Intellect, subscales of which were designed to maximally distinguish between each of its two aspects (DeYoung et al., 2007). For TfA, however, this may imply a currently unknown multifaceted structure of ambiguity tolerance than as measured by the MSTAT.

3.2. Correlations

The zero-order correlation matrix depicted in Table 2 revealed that each measure of ambiguity tolerance was correlated with each measure of openness to experience at $r \geq .40$. Additionally, ambiguity tolerance was significantly correlated with extraversion and neuroticism.[5] Correlations between ambiguity tolerance and each of openness to experience, extraversion, and neuroticism appeared stronger when measured with the MSTAT than the TfA. We used a Fisher *r*-to-*z* transformation to test whether MSTAT produced significantly stronger correlations, and found that this was the case for extraversion ($z = -2.30$, $p = .021$) and neuroticism ($z = 3.57$, $p < .001$), but not for Openness to Experience (Open Mindedness $z = -1.55$, $p = .061$; Openness/Intellect $z = -1.96$, $p = .05$). Unsurprisingly, given its lack of reliability, behavioral ambiguity tolerance did not significantly correlate with any variable.

3.3. Regression analyses

3.3.1. Self-report measures

In a linear regression, openness to experience significantly predicted ambiguity tolerance, $\beta = 0.56$, $t(306) = 11.75$, $p < .001$, accounting for 31% of the variance in ambiguity tolerance; and continued to predict ambiguity tolerance even controlling for intelligence, $\beta = 0.55$, $t(305) = 11.31$, $p < .001$. (Intelligence did not significantly predict ambiguity tolerance in this model; $\beta = 0.02$, $t(305) = 0.48$, $p = .631$.)

Extraversion also significantly predicted ambiguity tolerance, $\beta = 0.43$, $t(306) = 8.41$, $p < .001$. Interestingly, this relation held when including openness to experience in the multivariate regression (extraversion, $\beta = 0.25$, $t(305) = 5.06$, $p < .001$, 95% CI [0.14, 0.37]; versus openness, $\beta = 0.46$, $t(305) = 9.20$, $p < .001$, 95% CI [0.36, 0.55]). Although openness appeared a stronger predictor, CIs between openness to experience and extraversion just overlapped, indicating that there was not a statistically significant difference in the size of the predictors. However, extraversion contributed only 5% of unique variance to this model ($R^2 = .36$).

We expected that openness to experience would negatively predict uncertainty intolerance, even controlling for intelligence; but that the effect would be weaker than for ambiguity tolerance, as the items in the Intolerance of Uncertainty scale seem on face value to be more conceptually related to neuroticism. Openness to experience did significantly negatively predict uncertainty intolerance, $\beta = -0.37$, $t(304) = 6.74$, $p < .001$, $R^2 = .15$; and when neuroticism was added as a predictor to this model, this trait was the stronger predictor, with the absolute value of CIs not overlapping (neuroticism $\beta = 0.54$, $t(303) = 11.70$, $p < .001$, 95% CI [0.46, 0.62]; versus openness to experience $\beta = -0.20$, $t(303) = 4.12$, $p < .001$, 95% CI [−0.28, −0.12]). The percentage of variance accounted for rose substantially to $R^2 = .41$; and the model with added neuroticism was significantly better fit than the model with only openness to experience and intelligence, as measured by an analysis of variance, $f(1) = 136.83$, $p < .001$.

Analyses presented here employ observed variables or, for openness to experience and ambiguity tolerance, latent factor

[5] In our preregistration, we mentioned that we would conduct two one-sided equivalence tests, setting −.17 and .17 as our equivalence bounds (Lauriola et al., 2017) for the associations between self-report openness to experience, extraversion, plasticity, and ambiguity/uncertainty tolerance. As we found very strong correlations between all of these variables, it was unsurprising that when testing equivalence between these measures, the relationships were statistically not equivalent to zero.

Table 2
Zero-order correlations between study variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Behavioural AT													
2. TfA	.02												
3. MSTAT	.04	**.66**											
4. Uncertainty Intolerance	−.05	**−.56**	**−.79**										
5. Intelligence	−.16	.12	.14	−.15									
6. Extraversion	.05	**.29**	**.45**	**−.41**	−.10								
7. Negative Emotionality	−.01	−.23	**−.48**	**.60**	−.02	**−.52**							
8. Conscientiousness	−.02	.10	**.24**	**−.27**	.03	**.33**	**−.53**						
9. Agreeableness	.05	.15	**.27**	**−.31**	.07	**.35**	**−.43**	**.46**					
10. BFI-2 Open M	.06	**.40**	**.50**	**−.34**	.18	**.37**	**−.24**	**.33**	**.43**				
11. BFAS O/I	−.01	**.43**	**.55**	**−.38**	**.25**	**.37**	**−.32**	**.39**	**.50**	**.85**			
12. BFAS Openness	.03	**.32**	**.34**	−.17	.14	**.25**	−.07	**.24**	**.49**	**.81**	**.85**		
13. BFAS Intellect	−.01	**.41**	**.60**	**−.46**	**.29**	**.37**	**−.46**	**.43**	**.36**	**.64**	**.86**	**.46**	
14. Plasticity	.07	**.42**	**.57**	**−.45**	.05	**.84**	**−.46**	**.40**	**.47**	**.82**	**.73**	**.63**	**.61**

Note: $rs > .18$ are significant at $p < .05$, and $rs > .23$ are significant at $p < .001$, Holm-Bonferroni corrected for multiple comparisons. $ps < 0.001$ are bolded. Behavioral AT = Behavioral Ambiguity Tolerance, TfA = Tolerance for Ambiguity Scale, MSTAT = Multiple Stimulus Types Ambiguity Tolerance Scale-II, BFI-2 Open M = BFI-2 Open Mindedness, BFAS O/I = BFAS Openness/Intellect. Plasticity is computed by averaging scores for BFI-2 Open Mindedness and BFI-2 Extraversion.

scores. As inferences concerning incremental validity can be misleading when using observed variables (Westfall & Yarkoni, 2016), the supplementary materials also includes a version of these analyses using structural equation modelling. Inferences were the same as presented here, and beta weights were highly similar or identical.

3.3.2. Behavioral ambiguity tolerance

Originally, we planned to test our predictions for behavioral ambiguity tolerance by computing a behavioral ambiguity tolerance index combining all five tasks. However, given the very poor internal consistency of our behavioral ambiguity tolerance measure, it was not appropriate to compute a combined index. Instead, we present a summary of analyses for each item in the supplementary materials (Table S1), and exploratory latent variable regressions to assess whether accounting for measurement error would provide additional insight (Table S2). Note that these analyses are included for completeness rather than for value in inferential conclusions, as the poor reliability casts serious doubt on our measurement of behavioral ambiguity tolerance. None of the variables listed above (openness to experience, extraversion, plasticity, and neuroticism) predicted behavioral ambiguity tolerance, either with any of the five behavioral ambiguity tolerance tasks, or with a latent variable approach. It therefore made no sense to test our third behavioral hypothesis (controlling for intelligence) or our exploratory research question (extraversion predicting behavioral ambiguity tolerance controlling for openness to experience).

3.4. Exploratory network analyses

An exploratory graph analysis produced three dimensions for the MSTAT ambiguity tolerance and two for Intolerance of Uncertainty (TfA was not included in the network analysis due to confusion surrounding its component structure). Supplementary materials Section S.3 contains further details of the exploratory graph analysis procedure. Assessing the item content within these dimensions, MSTAT included one dimension seemingly related to ambiguity *avoidant* items (M1; e.g., *I don't tolerate ambiguous situations well*), a second dimension related to ambiguity *tolerant* items (M2; e.g., *I am tolerant of ambiguous situations*) and a third that seemed to involve appreciation of complex problem solving (M3; e.g., *I would rather avoid solving a problem that must be viewed from several different perspectives*). For intolerance of uncertainty, the suggested dimensions were the same as the factors defined in the original scale by Carleton et al. (2007): prospective anxiety (IoU1; e.g., *I always want to know what the future has in store for me*) and inhibitory anxiety (IoU2; e.g., *when it's time to act, uncertainty paralyses me*).

Fig. 1 displays the partial correlation network of averaged scale sub-components, conditioning on all other nodes in the network. Importantly, the spatial arrangement of nodes is not directly interpretable, as this is a function of the plotting algorithm's attempt to derive a visually appealing graph with minimal overlap of nodes (Jones, Mair, & McNally, 2018). The reader should instead focus on the size of the edge connecting nodes, which confer information concerning the size of the partial correlation. A companion to this graph is Table S5 in the supplementary information, which includes exact values for partial correlations, including 95% bootstrapped CIs around edge weights.

The strongest partial correlation was between BFI-2 aesthetic sensitivity and BFAS openness, $r = .61$, 95% CI [.52, .69]. Following this in strength were sub-dimensions of scales, such as extraversion (sociability and assertiveness), $r = .39$, 95% CI [.27, .50]; and neuroticism (depression and anxiety), $r = .38$, 95% CI [.29, .47]. A large partial correlation could also be observed between M1 (ambiguity avoidance) and IoU1 (prospective anxiety), $r = -.38$, 95% CI [−.46, −.30]. This between-scale association is of a similar magnitude to within-scale relations, supporting the view that these scales measure highly similar phenomena; and specifically, suggesting that the common thread between the scales is intolerance for ambiguity.

The strongest connection between sub-domains of personality traits and ambiguity tolerance was between openness to experience—specifically, the intellect aspect—and M3, representing appreciation of complex problem-solving, $r = .23$, 95% CI [.13, .33]. Intellectual curiosity (the BFI-2 equivalent to intellect) also correlated with M3, $r = .15$, 95% CI [.07, .24]. All other sub-domains were only related to ambiguity tolerance via their connection with intellect (small connections remaining between openness to experience and ambiguity tolerance that are visible in Fig. 1 have CIs that encompass zero, and thus may not be accurate). To explore this pattern of associations further we conducted a traditional regression analysis predicting the MSTAT from openness and intellect. This found converging results, with intellect the only significant predictor of the MSTAT (intellect $\beta = 0.56$, $t(305) = 10.85$, $p < .001$, 95% CI [0.45, 0.66]; compared to openness, $\beta = 0.08$, $t(305) = 1.57$, $p = .117$, 95% CI [−0.03, 0.19]).

For neuroticism, the strongest correlation was between depression and IoU2 (inhibitory anxiety), $r = .21$, 95% CI [.12, .29]. Anxiety and volatility were also weakly negatively related to IoU2, but the CIs for both encompassed zero, indicating uncertain accuracy. No

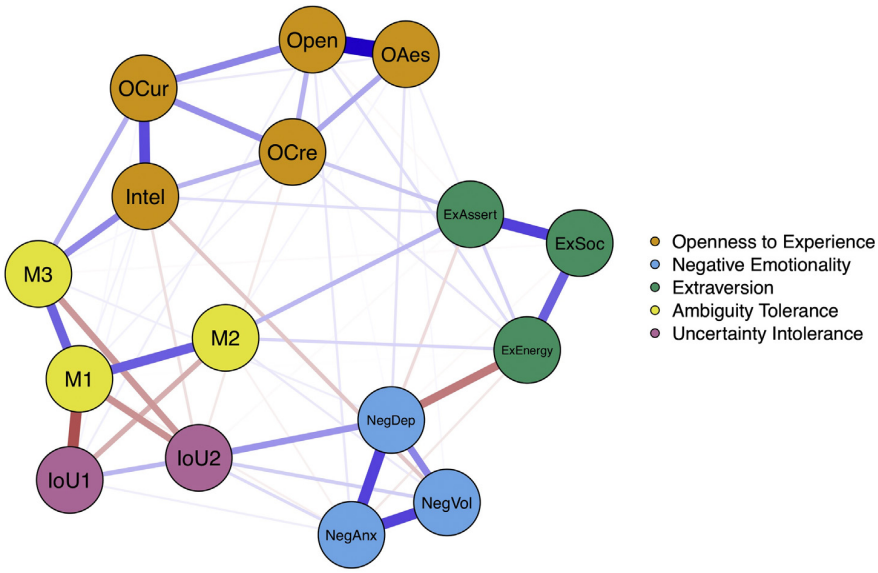

Fig. 1. A partial correlation network between sub-dimensions of openness to experience, extraversion, neuroticism, and ambiguity tolerance. Nodes are averaged subscale scores for each measure, and correlations between nodes are depicted by the line (or "edge") between items. Positive edges are blue, whereas negative edges are red. The size of the edge corresponds to the strength of the correlation. Items from a given scale or subscale are represented by different colors according to the legend. OAes = Open-Mindedness–Aesthetic Sensitivity; OCre = Open-Mindedness–Creative Imagination; OCur = Open-Mindedness–Intellectual Curiosity; Open = Openness/Intellect-Openness; Intel = Openness/Intellect–Intellect; NegDep = Negative emotionality–Depression; NegAnx = Negative emotionality–Anxiety; NegVol = Negative Emotionality–Emotional Volatility; ExEngergy = Extraversion–Energy levels; ExSoc = Extraversion–Sociability; ExAssert = Extraversion-Assertiveness; Mx = MSTAT Dimension x; IoUx = Intolerance of Uncertainty Dimension x.

relation between neuroticism and MSTAT existed where the CI did not encompass zero.

Finally, extraversion (assertiveness) was connected to ambiguity tolerance, and specifically to M2, the sub-component concerning positively-valenced attitudes towards ambiguity, $r = .14$, 95% CI [.05, .23]). Sociability and energy levels were only connected to ambiguity tolerance via their connections with assertiveness (except for a small relation between energy levels and M2 with CIs that encompassed zero, $r = .08$, 95% CI [−.01, .16]).

As we employed two measures of openness to experience, it is possible that strong relations between similar subdomains (e.g., the high correlation between openness and aesthetic sensitivity) could obscure any meaningful associations with other measures. Thus, we also created versions of the network models with either BFI-2 Open-Mindedness or BFAS Openness/Intellect. These can be found in the supplementary material (Figs. S2 and S3; Table S6). Promisingly, these alternative models yielded broadly similar results. We found identical $r = .14$ correlations between depression and M2 as for the main analysis, with only small variations in the CIs. For neuroticism, depression was correlated with IoU2 at $r = .19$ for the network with only BFI-2 Open-Mindedness, and $r = .22$ for the network with only BFAS Openness/Intellect, within $r = .02$ of the original effect size. Indeed, with only one measure of openness to experience, the associations between either intellect facets and M3 were *stronger* (intellect and M3 $r = .35$, 95% CI [.24, .45]; and intellectual curiosity and M3 $r = .28$, 95% CI [.19, .37]). For the network including only BFI-2 Open-Mindedness, aesthetic appreciation and creative imagination did not correlate with ambiguity tolerance. For the network considering BFAS Openness/Intellect, openness did weakly correlate with M3 ($r = .09$, 95% CI [.01, .17]), but this effect was far smaller than that linking intellect and M3, and included CIs that almost encompassed zero.

In summary, each of these Big Five traits were characterized by distinct relations to ambiguity tolerance, with neuroticism most related to emotive avoidant responses to ambiguity, openness to experience most related to complexity of problem solving, and extraversion most related to a positive attitude towards ambiguity tolerance. We additionally found, with our re-analyses including solely Open-Mindedness or Openness/Intellect, that the network was relatively stable to small changes in item content.

4. Discussion

In the present study, we investigated links between ambiguity tolerance and the traits openness to experience, extraversion, and neuroticism. We employed a comprehensive selection of ambiguity tolerance measures, encompassing multiple self-report and behavioral choice methods. In support of our hypotheses, we found that openness to experience and extraversion correlated positively, whereas neuroticism negatively correlated, with ambiguity tolerance. We also found that openness to experience continued to predict ambiguity tolerance even controlling for intelligence, and that extraversion continued to predict ambiguity tolerance controlling for openness to experience. Surprisingly, despite decades of research employing the Ellsberg paradigm as a behavioral index of ambiguity tolerance, this demonstrated very poor reliability in the form of low consistency of responding across the five variants of this paradigm used in the present study.

In a set of exploratory network analyses we examined how sub-dimensions of openness to experience, extraversion, and neuroticism related to ambiguity tolerance while controlling for all other variables. These results suggested that openness to experience was related to ambiguity tolerance via intellectual curiosity rather than aesthetic appreciation; that extraversion was most connected to ambiguity tolerance via assertiveness rather than sociability or energy levels; and that neuroticism had a strong connection to uncertainty intolerance, with no remaining reliable connections to any sub-dimensions of ambiguity tolerance.

4.1. Implications for psychological entropy theories of personality

One key aim of the current study was to assess the degree of support for predictions implied by the psychological entropy theories of personality (DeYoung, 2013; Hirsh et al., 2012). DeYoung (2013)

suggested that openness to experience and extraversion share variance because they both reflect a tendency to explore the unknown, either for sources of reward (in the case of extraversion) or information (in the case of openness to experience). Insofar as exploration of the unknown necessitates entering a more ambiguous state (the correspondence of which we outlined in Section 1.1), this theory predicts that extraversion and openness to experience will be related to tolerance for ambiguity. Conversely, individuals scoring highly on neuroticism would be more likely to anticipate potential threats lurking in the unknown, indicating that these persons would be more likely to display aversive attitudes toward ambiguity. We maintained that it was possible to test the initial stages of entropy theories of personality by measuring the relation between ambiguity tolerance and these basic domains of personality. Although prior studies provided suggestive evidence of the association between ambiguity tolerance and openness to experience, extraversion, and neuroticism, these associations emerged from secondary analyses and often involved scales with poor psychometric properties. However, the current study found strong evidence at the level of self-report that extraverts and those open to experience are more tolerant of ambiguity, and that those high in neuroticism are intolerant of ambiguity, thus supporting the assumptions inherent in the entropy theory of personality.

Note that the current study does not address other elements of entropy theory of extraversion and openness to experience outlined by DeYoung (2013): namely, that extraverts are motivated by rewards and that those higher in openness to experience are motivated by the reward value of any information, and that both of these drives are underpinned by dopaminergic mechanisms. We simply take the predictions that this hypothesis naturally evokes—that exploration necessitates engagement with ambiguity—and find that this is consistent with our empirical results. However, if extraverts *are* indeed motivated to explore by the potential for rewards, and individuals higher in openness to experience are motivated to explore for the rewarding value of information, then how might ambiguity tolerance assist these goals? We suggest that a greater tolerance for ambiguity may make it easier for these individuals to pursue these rewards, because it reduces any negative psychological burden involved in entering the unknown. This makes the exploration process more inherently enjoyable, and thereby, more positively reinforcing.

Testing mechanistic theories is a slow process, and we believe that it makes sense to first grasp the low hanging fruit. In other words, the connection between ambiguity tolerance and personality traits was something easily testable, where failing to find associations in the expected direction would call into question fundamental principles of the theory. Having now found evidence that supports the foundations on which entropy theories of personality are based, our study lays the groundwork for future researchers to test further predictions of this theory, such as the expectation that openness to experience relates to a greater motivation to obtain information.

4.2. Exploratory network analysis

The results of the exploratory network analysis offer some additional—if preliminary—insights, by allowing us to assess how individual facets of personality traits relate to particular dimensions of ambiguity tolerance. These analyses were intended to assess whether similar patterns of associations are uncovered as were previously reported by Lauriola et al. (2016), and to explore new patterns of associations that may not yet have been discovered, which may assist future confirmatory investigations.

For openness to experience, we found that holding constant all other nodes, the only relations between ambiguity tolerance and openness to experience were the intellect aspect and the intellectual curiosity facet; and that these connected to an empirically-derived factor representing appreciation of complex problem-solving. All other sub-domains were only related to ambiguity tolerance via their connection with intellect. Interestingly, this converges with Lauriola et al. (2016) who found that openness to experience was most strongly correlated with the component of ambiguity tolerance representing need for complexity and novelty. This finding has two key implications. First, it implies that those who tend to appreciate beauty and art (individuals higher in openness) are only more tolerant of ambiguity because they are also more likely to engage with abstract information and ideas. Furthermore, it implies that those higher in intellect are more tolerant of ambiguity primarily because they like to think about complex problems, which necessitates engaging with ambiguity.

Why might openness to be unrelated to ambiguity tolerance conditional on intellect? To speculate, it is possible that higher ambiguity tolerance permits individuals who are open to experiences to engage in deep intellectual musings without being burdened by the uncertainty of not uncovering an answer. Conversely, ambiguity tolerance may not influence an individual's openness to the same extent, because one can still appreciate art, literature, and poetry in a variety of forms, some which are more ambiguous (e.g., abstract art) than others (e.g., portraits). In this case, ambiguity tolerance would be a pre-condition for high intellectual curiosity, but not high openness. This would indicate that it is only when high openness is paired with high ambiguity tolerance that we would expect to find open individuals appreciative of ambiguous art. This is a prediction that could be tested in future research.

Extraversion demonstrated a contrasting pattern of results: assertiveness was the only facet that reliably related to ambiguity tolerance, and this was onto M2, the sub-component reflecting a general ambiguity-tolerant factor. This indicates that individuals who are enthusiastic or sociable are not primarily tolerant of ambiguity due to these factors; but rather, because they are also more likely to be bold, dominant, and socially powerful. Regarding the link to M2 that is apparent for extraversion but not openness to experience, this dovetails with Lauriola et al. (2016), who found that the general ambiguity tolerance sub-component was more strongly connected to extraversion than openness to experience (although note that formal comparisons of the strength of effect sizes were not conducted, meaning this difference may not be statistically significant).

Why do we find a link between ambiguity tolerance and assertiveness, but not sociability or energy levels? Perhaps higher ambiguity tolerance allows extraverts to display their bold, dominant tendencies with an optimistic expectation of positive outcomes and rewards. However, this would imply a similarly strong correlation between sociability and ambiguity tolerance, as extensive social engagement seems to necessitate a comfort with ambiguous scenarios (e.g., uncertain body language; misunderstood messages; shifting social hierarchy). It is possible that the high inter-correlations between assertiveness and sociability (zero-order $r = .60$; partial correlation .39) are obscuring any existing relation between sociability and ambiguity tolerance. To assess this, it may be useful to measure extraversion with a personality scale that maximally distinguishes between facets, such as the BFAS.

Finally, neuroticism had its strongest connection with intolerance of uncertainty (inhibitory anxiety) consistent with the theory that those higher in neuroticism will find ambiguity strongly aversive. This also fits with our regression analyses, in which we found that neuroticism was a stronger predictor of uncertainty intolerance than openness to experience. Thus, although we view ambiguity tolerance and uncertainty intolerance as conceptually interchangeable, it seems likely that individuals higher in neuroticism respond more strongly to the more negatively valenced items that characterize uncertainty intolerance scales.

4.3. Unreliability of behavioral ambiguity tolerance

One unexpected observation in this study was the very low reliability we observed for the well-established behavioral measures of ambiguity tolerance included in our study (Ellsberg, 1961). Interestingly, when revisiting the relevant literature we discovered that this has been previously documented, but the seriousness of this problem appears to have been overlooked. Stahl (2014) found that more than 60% of 101 individuals responded near randomly to 12 two-choice ambiguity tasks, with only 12% consistently choosing an ambiguity-averse response. Despite observing "significant heterogeneity and confusion" using these tasks (p. 97), Trautmann and Van De Kuilen (2015) justified the continued use of the measure based on the fact that individuals were, on average, ambiguity averse. A similar pattern of ambiguity aversion was evident in our study (Table 1), but the lack of consistency across different behavioral measures makes it nearly impossible to establish convergent validity with survey measures of personality, or indeed, ambiguity tolerance. In addition, if the Ellsberg Paradigm does measure ambiguity tolerance, it is likely capturing a much narrower aspect of ambiguity tolerance than is measured in self-report surveys, specific to decision-making for reward under risk. This may tap into different cognitive and emotional processes than the MSTAT or TfA scale: for example, a calculated reward assessment, rather than any comfort with exploring the unknown.

Why are responses to behavioral ambiguity tolerance so unreliable? These tasks require individuals to choose between, for example, a risky but unambiguous 50% chance of winning, versus an equally risky but *completely unknown* probability of winning. Thus, in this task economists define ambiguity as an *unknown probability* (Trautmann & Van De Kuilen, 2015), and this can be distinguished from risk in computational terms. However, there is no guarantee that individuals perform the same computations, and as a result *perceive* ambiguity separately from risk. A risky gamble means that the outcome is unknown—and unknown outcomes are also ambiguous outcomes. Thus, participants could view risky options as ambiguous. This would result in more random responding to behavioral gambles, providing an explanation for why we have observed poor reliability between the items. Future studies might directly investigate this possibility by having participants rate the perceived ambiguity of a series of gambles that differ in risk, holding constant ambiguity. If participants rate increasingly risky options as increasingly ambiguous, this would demonstrate that decision-makers do not differentiate ambiguity from risk.

If the Ellsberg tasks are not optimal for assessing individual differences in ambiguity tolerance, it would be valuable to identify an alternative behavioral paradigm to triangulate against self-report measures. One option could be to harness principles from marketing that exist on Internet websites. For example, some travel websites offer individuals the chance to stay in an unknown establishment for a slightly cheaper price—an inherently more ambiguous option. It could be possible to experimentally manipulate the degree of information available about these "unknown" travel options (e.g., star rating, number of bedrooms, closeness to nature or a beach, etc.) and observe whether individuals higher in openness to experience and extraversion were more likely to choose a more unknown alternative.

A complementary approach could be to retain the Ellsberg paradigm, but to vastly increase the trial numbers from 5 to 50 or beyond. Behavioral choices are inherently noisy data, and experiments from cognitive and mathematical psychology tend to manage this noise by running trial numbers in the hundreds or thousands, statistically aggregating these to account for noise in single observations. Given we did observe some consistency in responding (ω_t = .47) one could conceive that a task in which participants made repeated decisions between an ambiguous and unambiguous option over the course of a 30-minute experiment might shed light on the relation between personality traits and behavioral ambiguity tolerance.

4.4. Strengths, limitations, and constraints on generality

By directly addressing the question of relations between ambiguity tolerance and personality traits, and by employing two newer measures of ambiguity tolerance with acceptable psychometric properties—in addition to a measure of uncertainty intolerance—we provide compelling support for the relations between these traits and ambiguity tolerance at the zero-order level. Further, by finding that openness to experience predicted ambiguity tolerance even controlling for intelligence, this alleviates concerns that the relation observed between openness to experience and ambiguity tolerance may be driven by more intelligent individuals reasoning more meticulously about their choices when options are ambiguous, and thus being less affected by aversive properties in ambiguity.

Intriguingly, correlations between personality traits and ambiguity tolerance measured by TfA were uniformly smaller effects than for ambiguity tolerance measured by MTSAT. This is consistent with the poor omega hierarchical reliability observed for TfA, indicating that this form of ambiguity tolerance may tap a wide array of sub-traits. When computing separate TfA dimensions using exploratory graph analysis, it was unclear what the model suggested sub-domains might represent, and how they were related to ambiguity tolerance. This led us to drop TfA as a measure included in the network analysis. Thus, although TfA seems an adequate measure when considered as a unitary scale—and could be preferable for analyses of cross-cultural studies, for which it was original designed (Herman et al., 2010)—we would not recommend this scale for assessing relations with personality traits and subdomains of ambiguity tolerance.

We aimed to comprehensively measure ambiguity tolerance with different measures that tap different sub-components. However, it is possible that our measures were not sufficiently broad. For example, Lauriola et al. (2016) found three factors representing distaste for ambiguity, need for complexity, and moral absolutism. None of our chosen ambiguity tolerance measures assessed this final moral absolutism component, and thus it would be valuable to assess whether moral absolutism displays the same pattern of correlations with personality traits as for our current scales.

As may be clear from Section 4.3 above, we do not think that our non-significant findings related to behavioral ambiguity tolerance tasks are likely to generalize beyond the Ellsberg paradigm. It is highly possible that different behavioral measures could be devised that would better tap this construct, and would better assess relations with personality traits.

Within our sample, we had a reasonably wide distribution of income and age brackets, indicating that results may generalize across these groups. We also used a sample of United States participants from Amazon Mechanical Turk. There is no reason to expect that ambiguity tolerance would not generalize across cultures, so it is possible that conclusions are not limited to individuals in western countries—though of course, future studies would be necessary to confirm this intuition.

Finally, given the exploratory nature of the network analysis, our inferences drawn from this analysis should be followed up by a confirmatory analysis attempting to replicate the network structure.

5. Conclusions

Life presents us with many unknown possibilities and interpretations. Those who are open to experiences, or who are more extraverted, are more likely to tolerate the ambiguities inherent in life. Conversely, those higher in neuroticism are more likely to find

ambiguity aversive and fear-provoking. Our findings may provide a basis for future research to propose mechanistic explanations for personality traits, such as the support that we have found for the psychological entropy theories of Hirsh et al. (2012) and DeYoung (2013). The current study extends current understanding of how different people react to the unknown—an inevitable consequence of fully engaging with life.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrp.2019.02.003.

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Chapter 3
Testing the Information-Seeking Theory of Openness/Intellect (Studies 2 and 3)

3.1 Overview

Studies 2 and 3 were designed to assess whether the Big 5 and lower-level personality traits (in particular, uncertainty intolerance and curiosity facets *joyous exploration* and *deprivation sensitivity*) predict seeking information, in order to inform both personality and cognitive neuroscience explanations for information seeking. As previously described, DeYoung (2013) proposed that openness/intellect is grounded in enhanced sensitivity to the reward value of information, and thus these individuals should be more likely to seek information. However, the small body of existing research has not found that openness/intellect predicts information seeking (Smillie et al., Under Review), whereas it has found that neuroticism predicts information seeking (Bennett et al., 2020). Thus, given the links between neuroticism and uncertainty intolerance found in Study 1, current information-seeking research is consistent with uncertainty-reduction theories of information seeking but not with DeYoung's (2013) information-seeking theory. Yet crucially, existing paradigms that measured the choice to seek information did so with a task that operationalised information seeking via the choice to know about an upcoming financial gain or loss. Because information seeking within these tasks provides an opportunity to reduce one's uncertainty about the money that they would soon be winning or losing, this might be particularly likely to motivate individuals more *intolerant* of uncertainty, who might find the lack of information aversive and consequently seek information to reduce their negative emotions. To try to control for this confound, we altered the information-seeking paradigm to a version where participants immediately learn whether they win or lose a trial (thereby removing any uncertainty about the financial outcome) and then are asked if they would like to know some information peripheral to the trial.

Results of these studies found no significant effect of openness/intellect in predicting information seeking. However, people higher in joyous exploration, deprivation sensitivity, *and* uncertainty intolerance were more likely to seek information. Exploratory Bayesian model comparisons found that the strongest collection of predictors were joyous exploration and uncertainty intolerance, which each provided independent positive effects. As openness/intellect is correlated strongly positively with joyous exploration and strongly negatively with uncertainty intolerance, this may suggest two independent pathways to

information seeking. When their motivational force is relatively evenly balanced, then they may combine to cancel out any direct effect by openness/intellect. This finding becomes the guiding principle of the final chapter in Part 1, where I introduce an initial conceptual model of multiple motivations underlying information seeking, drawing on both cognitive neuroscience and personality perspectives.

3.2 Empirical Studies 2 and 3

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Testing the Information-Seeking Theory of Openness/Intellect

Hayley K. Jach and Luke D. Smillie

Abstract

Why are open people open? A recent theory suggests that openness/intellect reflects sensitivity to the reward value of information, but so far, this has undergone few direct tests. To assess preferences for information, we constructed a novel task, adapted from information-seeking paradigms within decision science, in which participants could choose to see information related to a guessing game they had just completed. Across two studies (one exploratory, n = 151; one confirmatory, n = 301), openness/intellect did not predict information seeking. Our results thus do not support a straightforward version of the theory, whereby open individuals display a general-purpose sensitivity to any sort of new information. However, trait curiosity (arguably a facet of openness/intellect) predicted information seeking in both studies, and uncertainty intolerance (inversely related to openness/intellect) predicted information seeking in Study 2. Thus, it is possible that the domain-level null association masks two divergent information-seeking pathways: one approach motivated (curiosity) and one avoidance motivated (uncertainty intolerance). It remains to be seen whether these conflicting motivations can be isolated and if doing so reveals any association between information-seeking and the broader openness/intellect domain.

Keywords

openness/intellect, information seeking, curiosity, intolerance of uncertainty, personality processes

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Introduction

Openness/intellect describes individual differences in the breadth, complexity, and depth of one's imagination and experience (John & Srivastava, 1999; Schwaba, 2019). High scorers on openness/intellect tend to be curious about the world (e.g., Kashdan et al., 2009; Kashdan et al., 2018; Kashdan, Rose, & Fincham, 2004; McCrae & Costa, 1997), creative (McCrae, 1987), artistic (Kaufman et al., 2016), intellectual (Mussel, 2013), and intelligent (DeYoung, Quilty, Peterson, & Gray, 2014; Kretzschmar, Spengler, Schubert, Steinmayr, & Ziegler, 2018). Two decades ago, McCrae and Costa (1997) observed that openness/intellect is the 'least researched and least understood of the five fundamental dimensions of personality' (p. 840). Since that time, there has been substantial research investigating how openness/intellect relates to attitudes and behaviours (e.g. Belke, Leder, Strobach, & Carbon, 2010; Gosling, Ko, Mannarelli, & Morris, 2002; Jost, Glaser, Kruglanski, & Sulloway, 2003; Kraaykamp & Van Eijck, 2005; Rentfrow & Gosling, 2003), cognitive processes and abilities (Antinori, Carter, & Smillie, 2017; Silvia, Nusbaum, Berg, Martin, & O'Connor, 2009), and neural indices (Beaty et al., 2016; DeYoung, Peterson, & Higgins, 2005). Further, there is a growing theoretical base concerning potential cognitive and biological processes underlying this trait (e.g. DeYoung, 2013; DeYoung, Grazioplene, & Peterson, 2012; Kaufman et al., 2016; Mussel, 2013; Denissen & Penke, 2008; Ziegler, Schroeter, Lüdtke, & Roemer, 2018). To our knowledge, however, none of these theories has yet been subjected to an explicit confirmatory test.

In the present research, we evaluate the evidence for one such theory that we term the *information-seeking theory of openness/intellect*. According to this theory, openness/ intellect is grounded in greater sensitivity to the reward value of information, and thus open individuals should be more motivated to seek information

Melbourne School of Psychological Sciences, The University of Melbourne, Melbourne, Victoria Australia

Corresponding author:
Hayley K. Jach, Melbourne School of Psychological Sciences, Melbourne University, Redmond Barry Building, Melbourne, Victoria, Australia 3010.
Email: hayleyjach@gmail.com

(DeYoung, 2013, 2015a, 2015b). Information can be operationally defined simply as *something you did not already know*. This aligns with dictionary definitions of information as knowledge obtained (e.g. Merriam-Webster online dictionary) and is consistent with an abstracted version of some definitions within information theory (Shannon, 1948). Additionally, it orients information to reflect the individual's internal model of the world, rather than any external stimuli/object. For example, a book is not inherently informative; rather, a reader gains information if they are unfamiliar with the contents.

We first describe the information-seeking theory of openness/intellect and the indirect existing evidence supporting it. Next, we review paradigms used in decision science to assess information-seeking preferences in a carefully controlled manner. We then discuss the small body of research that has explored individual differences using these paradigms, identifying factors that may have influenced results from these studies. We then provide two empirical tests of the theory, the first exploratory and the second confirmatory.

The information-seeking theory of openness/intellect: Summary and current evidence

The information-seeking theory of openness/intellect is one part of an overarching neurobiological theory of exploratory behaviour proposed by DeYoung (2013). According to this theory, the neurotransmitter dopamine mediates reinforcement sensitivity, and potentiates approach behaviour, to both rewards and information. DeYoung suggests that, just as the motivational value of *rewards* partially drives individual differences in extraversion (Depue & Collins, 1999; Pickering & Gray, 2001; Rammsayer, 1998), the motivational value of *information* partially drives individual differences in openness/intellect. This would mean that individuals scoring higher on openness/intellect should be (i) more sensitive to the reward value of information and (ii) more motivated to seek out information.

What evidence supports the information-seeking theory of openness/intellect? One might argue that clear evidence already exists: after all, people higher in openness/intellect undertake more years of formal education, visit art galleries more frequently, and consume and own a greater volume and variety of books, music, film, and other artefacts of culture (Chamorro-Premuzic, Reimers, Hsu, & Ahmetoglu, 2011; Gosling et al., 2002; Trapp & Ziegler, 2019; Van Eijck & de Graaf, 2004). However, these observations are simply part of our descriptions of what it means to be open: most openness/intellect scales include items that refer directly to such behaviours and interests (e.g. *is fascinated by art, music, or literature*; Soto & John, 2017). In contrast, we are seeking an *explanation* for these descriptions—to identify what makes open people open. It is circular to treat books, plays, and culture as examples of information seeking and then conclude that information seeking does indeed underpin openness/intellect. Moreover, people may seek out these stimuli for reasons that have little to do with the reward value of information. For instance, one may visit galleries to signal status or sophistication to others or collect cultural artefacts as a financial investment. To effectively test the information-seeking theory of openness/intellect, we must use stimuli that are not inherently attractive to people higher in openness/intellect, and that are not useful to achieve goals beyond information gains.

A second argument linking openness/intellect to information seeking is the connection to curiosity and related traits (e.g. interest and need for cognition). Curiosity can be defined as the motivation to pursue what is new, unknown, and/or complex and is sometimes conceptualized in terms of the drive to gain information or fill an 'information gap' (Lowenstein, 1994). Curiosity is strongly correlated with openness/intellect (e.g. Kashdan et al., 2004; Kashdan et al., 2009; Kashdan et al., 2018) and has been conceptualized as a narrower trait within the broader openness/intellect domain (McCrae & Costa, 1997; Woo et al., 2014). It is possible that if openness/intellect does relate to information seeking, it could do so via higher interest and curiosity to engage with stimuli.

Several studies have examined relations between state curiosity and information seeking, finding that when participants report being more curious about particular trivia questions, they are more willing to pay time or money to learn the answer (Gruber, Gelman, & Ranganath, 2014; Kang et al., 2009; Ligneul, Mermillod, & Morisseau, 2018; Marvin & Shohamy, 2016). As state curiosity is experienced more frequently and intensely by people higher in trait curiosity (Kashdan & Steger, 2007), this provides tentative, but indirect, encouragement for DeYoung's (2013) theory. Conversely, other studies have administered trait measures alongside information seeking, but these studies did not include a decision to seek information. For example, Lydon- Staley, Zhou, Blevins, Zurn, and Bassett (2019) asked participants to explore Wikipedia for 21 days and found that different facets of curiosity mapped onto different information-seeking strategies. Although these findings may reveal *how* people seek information, they do not directly address whether curious people are more likely to read Wikipedia articles in the first place. Another study measured experiences of interest in daily life, presumably across many situations in which information gain was possible (Ziegler et al., 2018). Although most interests were those we already know are attractive to individuals higher in openness/intellect (e.g. artistic interests), both state and trait openness/intellect predicted one item describing broad exploratory interests. Again, this finding

provides only indirect encouragement for the information-seeking theory of openness/intellect, as exploratory *intentions*, not exploratory *behaviour*, were assessed. One final study assessed four information-seeking paradigms in which participants browsed a website, studied trivia facts, and read articles (von Stumm, 2018). However, this study was focused on how openness/intellect relates to knowledge acquisition, not information-seeking preferences. Thus, although the study showed that openness/intellect predicted knowledge attainment in all four studies, it could not provide any evidence that open people were more motivated to seek information. Further, in all but the first study, the experimenter explicitly instructed participants to seek information, rather than measuring natural exploratory behaviour; and in the final two studies, participants were incentivised for high performance. The first study allowed participants to seek information at their leisure, but the information concerned beautiful lakes, a topic that high-open individuals would likely be attracted to. Further, the author did not report whether the time spent freely viewing the site correlated with openness/intellect.

In summary, although previous research seems broadly consistent with the information-seeking theory, there does not seem to be any direct test of the prediction that people higher in openness/intellect are more willing to seek information in and of itself. What is required is a study assessing how openness/intellect—and connected traits such as curiosity—relate to information seeking within a paradigm that (i) unambiguously assesses the decision to seek information and (ii) uses stimuli other than those people high in openness/intellect tend to prefer. We now introduce methods developed in decision science that may help to achieve this goal.

Information seeking in decision science

Information seeking has been extensively investigated by researchers within decision science and cognitive neuroscience (e.g. Bennett, Bode, Brydevall, Warren, & Murawski, 2016; Bennett, Sutcliffe, Tan, Smillie, & Bode, 2019; Blanchard, Hayden, & Bromberg-Martin, 2015; Bromberg-Martin & Hikosaka, 2009; Brydevall, Bennett, Murawski, & Bode, 2018; Charpentier, Bromberg-Martin, & Sharot, 2018; Kobayashi, Ravaioli, Baranès, Woodford, & Gottlieb, 2019). These researchers directly assess the decision to seek information with tasks where participants must make a choice to view information. Further, these studies only assess the preference for *non-instrumental* information; that is, information that provides no increased likelihood of receiving an extrinsic reward (such as money or food) that could confound apparent preferences for information. Additionally, the information used in this research typically bears no resemblance to art, poetry, or other cultural stimuli that are referenced within measures of openness/intellect, thus avoiding any methodological circularity in our measures. Finally, information seeking is typically assessed over tens or even hundreds of trials, which helps to minimise measurement error. Therefore, these tasks could be effective to test the information-seeking theory of openness/intellect.

One such task involves an array of cards in which the majority colour among a set of five cards (coloured black vs. red) determines the outcome of each trial (e.g. gain vs. no gain or loss vs. no loss; Bennett et al., 2016). Participants choose to see either an informative set of cards (i.e. the set on which the trial outcome will actually be based) or an uninformative set of cards (i.e. a random selection of black and red cards that has no relation to the trial outcome). On some trials, participants must pay a small proportion of their winnings to see this advance information. No matter their choice, participants learn if they win or lose after the trial ends, making the informative cards economically non-instrumental. Despite this, participants show reliable preferences for information in this task, and there are robust individual differences in the willingness to pay to see the information (Bennett et al., 2016; Bennett et al., 2019; Brydevall et al., 2018).

Interestingly, the information-seeking theory of openness/intellect was partly inspired by an animal analogue of this very task (see DeYoung, 2013, pp. 4-5). Specifically, Bromberg-Martin and Hikosaka (2009) found that primates will sacrifice primary rewards (food and juice) to learn the outcome of a gamble in advance (see also Blanchard et al., 2015). These researchers found that non-instrumental information elicits release of dopamine within the brain reward system, in a similar manner to primary rewards, suggesting that information has a reward value. DeYoung grounded his conception of information rewards, to which individuals high in openness/intellect are putatively more sensitive, in these studies. Thus, if openness/intellect predicts seeking even this form of information—devoid of any aesthetic or intellectual content—this would be consistent with the existence of a general-purpose sensitivity to the reward value of information. This would provide strong evidence in favour of the information-seeking theory.

To date, three studies have directly assessed the Big 5 personality correlates of non-instrumental information seeking using this task (Smillie, 2019, Studies 1 and 2; and Bennett et al., 2019, which used the same data set as Study 1 from Smillie, 2019). In these studies, participants were overwhelmingly likely to choose information when it was free, and individual differences emerged when participants were required to pay some small amount of money to see the informative set. However, in both studies ($N = 139$ and $N = 163$, respectively), correlations between openness/intellect and information seeking were non-significant and near zero (Study 1 $r = .03$; Study 2 $r = -.03$; Smillie,

2019). Conversely, measures of neuroticism and obsessive-compulsive tendencies, reported by Bennett et al. (2019), predicted a stronger preference to see information ($r = .31$ and $r = .25$, respectively).

These findings fail to support a straightforward prediction that people high in openness/intellect are more motivated to seek information. However, the way in which information seeking was operationalized might partially explain why. Specifically, information seeking within this task entails making a *choice to reduce one's uncertainty* about the money that they would soon be winning or losing. As such, this form of information might be particularly suited to motivate individuals higher in trait intolerance of uncertainty. These individuals might find the lack of information aversive and subsequently seek information as a strategy to reduce their negative emotions (Bennett et al., 2019; Carleton et al., 2012). As intolerance of uncertainty correlates negatively with openness/intellect and curiosity and is strongly associated with higher neuroticism (Carleton et al., 2012; Jach & Smillie, 2019; Kashdan et al., 2018), this may explain why neuroticism, rather than openness/intellect, was found to predict information seeking (Bennett et al., 2019; Smillie, 2019).

Aims of the present research

Building on these recent tests of the information-seeking theory of openness/intellect, we sought to examine forms of information seeking that do not lead to reductions in uncertainty about upcoming monetary outcomes and thus are less likely to be motivated by intolerance of uncertainty. To achieve this, we reversed the sequence of events within the task structure employed by Bennett et al. (2016) such that participants first learn the outcome of a guessing game (win or loss) and can then seek additional information. This information concerned an inconsequential detail of the just-completed game. This information is non-instrumental as it cannot affect their monetary outcome, and because it is made available *after* the game, a choice to view information cannot serve to resolve uncertainty regarding the game outcome. In all other aspects, this task retains the benefits described previously: it measures non-instrumental information; uses stimuli that are not, by definition, desirable to people higher on openness/intellect; and includes multiple trials. Whereas curiosity may still motivate information seeking, aversion to uncertainty related to the monetary prize should not, allowing us to assess whether openness/intellect predicts (possibly curiosity driven) information seeking.

Study 1 was designed to explore these potential questions. According to DeYoung's (2013) theory, we expected that openness/intellect would positively predict seeking information, and we also expected this to be the case for measures of trait curiosity. Conversely, we expected that intolerance of uncertainty would not significantly predict this form of information seeking. Study 2 adopts a confirmatory approach, providing a pre-registered test of hypotheses derived from Study 1. All study materials, deidentified data and analysis scripts for both studies, and preregistration for Study 2 are available on the Open Science Framework (project: https://osf.io/2hjfc/ preregistration https://osf.io/fsx5e). The supporting information includes a table listing our compliance to the preregistration. Ethical approval for both studies was provided by the University of Melbourne Human Ethics Advisory Group (ID 1953559.1).

Study 1

Method

Participants and procedure. We recruited 154 U.S. residents through the online marketplace Amazon Mechanical Turk (mTurk). We scaled the participant incentive to $7.25 per hour, the approximate U.S. minimum wage in early 2019. This equated to a $1.00 base payment plus 50c bonus for passing two simple attention checks, plus a second 50c bonus for winning the decision-making games. We excluded participants if they (i) completed less than 90% of the study, (ii) had a within-person standard deviation of less than 0.50 across the Likert-scale items or a sequence of equal to or greater than 20 consecutive responses (to prevent straight lining), or (iii) failed both a comprehension check at the end of the behavioural information-seeking tasks and an attention check embedded within the surveys. After removing three participants for failing any of these exclusion criteria, the final sample was 151 individuals ($mean_{age} = 36.68$, $SD_{age} = 9.85$, 47% female participants). A sample of this size—which was determined by financial constraints—provides approximately 70% power to detect a typical effect size within the context of personality psychology ($r = .20$; Gignac & Szodorai, 2016).

Materials and procedure

Behavioural information seeking. We assessed information seeking via a series of five guessing games, plus an additional information-seeking question after the games had ended, resulting in a 6-item measure of behavioural information seeking. To motivate participants, we informed them that their bonus for the experiment would be based on their performance for one randomly selected game. However, in reality, all participants were allocated the same winning amount (and were appropriately debriefed about this following the survey).

For each trial, participants made a guess as to the correct answer and were immediately told if they had won or lost that trial.[1] Following their guess and feedback, participants could choose to view non-

instrumental information about an earlier stage of the game. Choosing to view this information did not change the game outcome and could not be used to inform future behaviour. Additionally, choosing information required navigating to a new screen and therefore entailed a small time cost, which we believed would be salient to mTurk workers.

Game 1 (Figure 1) presented participants with a display of six fruits, and asked participants to guess which fruit was secretly rotten. After losing the game, participants were asked if they would like to know which fruit had indeed been rotten. The choice to see the rotten fruit was coded as seeking information. In Game 2, participants were told that the numbers 1 to 10 had been divided into two boxes, with one box containing the numbers 1 to 5, and the second box containing the numbers 6 to 10. Their task was to choose a box from which one number would be drawn: a number between 1 and 5 would mean a loss, and a number between 6 and 10 would mean a win. Following their win, participants were asked if they would like to see the specific number that had been selected from the box. For Games 3 through 5 (adapted from Jach & Smillie, 2019), participants were asked to imagine that they were explorers searching for two precious gems, chromite and zanium. In all three games, participants had to choose between two options with equal expected utility but where one option was more ambiguous than the other. In Game 3, following their choice, they were asked whether they would like to know which gem they selected. In Game 4, participants were asked if they would like to know the exact proportion of gems in the right chest. In Game 5, participants were asked if they would like to see how many zanium gems were in the chest. These choices were coded as information seeking.

Following the five games, participants were informed that they had won the bonus money. They were then asked if they would like to see which game was connected to winning the bonus or continue the survey without ever knowing. The choice to see this game was the final measure of information seeking.

Big 5 personality traits. The Big Five Aspect Scales (DeYoung, Quilty, & Peterson, 2007), a widely used measure of the Big Five traits and their lower level aspects, was used to measure openness/intellect, neuroticism, extraversion, agreeableness, and conscientiousness. Our primary focus was on the openness/intellect domain, which divides into *intellect*, describing engagement with semantic and abstract information (e.g. *Like to solve complex problems*), and *openness*, describing engagement with aesthetic and perceptual information (e.g. *Enjoy the beauty of nature*).

Curiosity. Curiosity was assessed using the five-dimensional curiosity scale (Kashdan et al., 2018). This scale divides into five factors, two of which are particularly pertinent to the current study: joyous exploration, describing enthusiasm for exploring and leaning in general (e.g. *I find it fascinating to learn new information*), and *deprivation sensitivity*, describing an intense hunger for specific knowledge (e.g. *I work relentlessly at problems that I feel must be solved*). Three additional dimensions are stress tolerance (e.g. *I cannot handle the stress that comes from entering uncertain situations* [reversed]), social curiosity (e.g. *I like to learn about the habits of others*), and thrill seeking (e.g. *Risktaking is exciting to me*). The scale's factor structure, temporal stability, internal consistency, and construct validity have been supported across three studies comprising 4000 participants.

Ambiguity and uncertainty tolerance. The Multiple Stimulus Types Ambiguity Scale-II (e.g. *I am tolerant of ambiguous situations*; McLain, 2009) and the intolerance of Uncertainty Scale-12 (e.g. *The smallest doubt can stop me from acting*; Carleton, Norton, & Asmundson, 2007) were employed to measure ambiguity tolerance and uncertainty intolerance. Note that the stress tolerance subscale from Kashdan et al.'s (2018) curiosity measure can also be considered a measure of uncertainty tolerance.

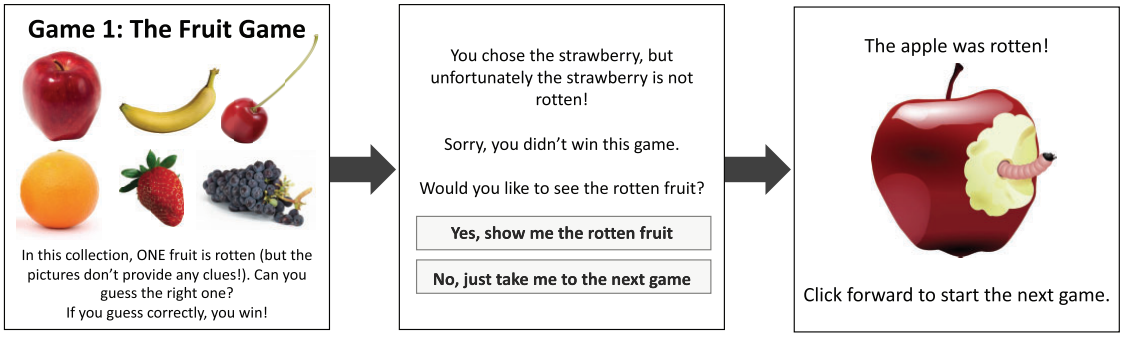

Figure 1. Behavioural information seeking, Game 1. In this example, the participant chooses to seek information and is shown an image of the fruit that was rotten (the apple). [Colour figure can be viewed online].

Analyses. R version 3.5.2 (R Core Team, 2019) was used for all pre-processing and analyses. Within R, we used the following packages: tidyverse (Wickham, 2017), careless (Yentes & Wilhelm, 2018), cowplot (Wilke, 2018), lm.beta (Behrendt, 2014), lavaan (Rosseel, 2012), apaTables (Stanley, 2018), psych (Revelle, 2018), and BayesFactor (Morey & Rouder, 2018).

Results

Descriptive statistics. Table 1 includes the mean, standard deviation, reliability (omega total), and correlations for all variables measured. Table S2.1 includes further descriptives (median, range, skew, and kurtosis) for these variables. Information seeking demonstrated high reliability ($\omega_t = .93$, $\omega h = .77$, $\alpha = .87$), indicating that participants were displaying consistent patterns in their choice behaviour. Figure S2.1 shows the pattern of responses for each information-seeking question. Despite the cost imposed in time from choosing to see information, more than half of participants chose to view information for each question. Indeed, for Question 1, 91% of participants chose information. In total, 60 individuals (40% of the sample) always sought information. This led to a somewhat non-normal distribution for information seeking, with acceptable skew (−0.34) but high kurtosis (−1.50). As non-normal dependent variables can cause biased estimates of standard errors and significance tests (Coxe, West, & Aiken, 2009), the supporting information includes alternate analyses using Poisson regressions, which yielded similar findings.

Considering interrelations between survey measures, openness/intellect was positively related to curiosity ($r = .49$, 95% CI [.36, .60]), positively related to ambiguity tolerance ($r = .52$, 95% CI [.40, .63]), and negatively related to uncertainty intolerance ($r = -.37$, 95% CI [−.50, −.23]), in line with previous research (Jach & Smillie, 2019; Kashdan et al., 2018). When assessing how openness/intellect related to subscales of curiosity, the strongest relationship was with joyous exploration ($r = .69$, 95% CI [.60, .76]), but there were also significant relations between openness/intellect and deprivation sensitivity ($r = .20$) and stress tolerance ($r = .39$).

Information seeking and personality. Information seeking did not significantly relate to openness/intellect ($r = -.10$, 95% CI [−.25, .06]). However, information seeking correlated with curiosity ($r = .16$, 95% CI [+.00, .31]) including its subscale deprivation sensitivity ($r = .18$, 95% CI [.02, .33]) but not the subscale joyous exploration ($r = .11$, 95% CI [−.05, .27]). Additionally, none of ambiguity tolerance, uncertainty intolerance, or stress tolerance significantly correlated with seeking information. As a lack of evidence for an effect does not provide evidence for a null effect, we employed a Bayes factor regression to

Table 1. Means, standard deviations, reliability, and correlations between Study 1 variables.

Variable	ω_t	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Information-seeking	.93	0.63	0.36															
2. Opeimess/Intellect	.92	3.65	0.49	−.10														
3. Opeimess	.88	3.44	0.44	.02	.67**													
4. Intellect	.91	3.85	0.75	−.14	.90**	.29**												
5. Agreeableness	.93	3.83	0.64	−.01	.37	.33**	.29**											
6. Conscientiousness	.92	3.58	0.67	−.03	.27**	−.05	.39**	.35**										
7. Neuroticism	.96	2.63	0.93	.05	−.36**	.12	−.54**	−.23**	−.54**									
8. Extraversion	.94	3.22	0.76	.03	.45**	.11	.52**	.25**	.45**	−.60**								
9. Curiosity	.89	3.37	0.51	*.16*	.49**	.27**	.48**	.08	.26**	−.43**	.65**							
10. Joyous exploration	.89	3.87	0.77	.11	.69** *	.42**	.65**	.28**	.30**	−.33**	.46**	.72**						
11. Deprivation sensitivity	.84	3.57	0.79	*.18*	*.20*	*.18*	.15	.06	.15	.07	.09	.52**	.43**					
12. Stress tolerance	.91	3.10	1.07	.00	.39**	.00	.50**	*.16*	.34**	−.75**	.66**	.52**	.32**	−.15				
13. Social curiosity	.89	3.59	0.82	.16	.12	*.20*	.03	.13	.03	.08	*.19*	.49**	*.19*	.29**	−.14			
14. Thrill seeking	.88	2.70	0.96	.05	.06	.06	.04	−.35**	−.08	*−.16*	.38**	.66**	.25**	.14	.25**	*.21*		
15. Uncertainty intolerance	.94	3.10	0.87	.08	−.37**	−.04	-.46**	−.14	−.25**	.66**	−.55**	−.42**	−.30**	.26**	−.85**	.14	−.26**	
16. Ambiguity tolerance	.92	3.06	0.75	−.06	.52**	*.18*	.57**	.10	*.18*	−.59**	.53**	.56**	.48**	−.11	.78**	−.05	.36**	−.86**

Note: M, *SD*, and Ω_t are used to represent mean, standard deviation, and internal consistency (omega total), respectively. Italics indicate $p < 0.05$. **$p < 0.01$.

assess evidence for models in which openness/intellect predicted information seeking against a null model with flat regression slopes. Bayes factors greater than 1 provide evidence that the variables are predictors of information seeking, whereas Bayes factors less than 1 provide evidence for the null hypothesis (Dienes, 2014). The current study takes the reciprocal of values <1 to provide more easily interpretable results concerning support for the null, such that all Bayes factors for and against the null are 1 or greater (as such, the term M_{01} indicates evidence in support of the null, whereas M_{10} indicates evidence for the alternative). We follow Jeffreys (1939/1961) who suggests conventional cut-offs with >3 considered substantial evidence for the alternative/reciprocal null.

For regressions predicting information seeking from openness/intellect, weak evidence for the null was obtained ($M_{01} = 2.99$), suggesting inconclusive evidence to state whether or not openness/intellect predicts informationseeking. We also used Bayes factor regressions to assess support for the null with our three scales measuring tolerance for uncertainty (ambiguity tolerance, intolerance of uncertainty, and stress tolerance) and found support for the null with all three scales measured separately ($M_{01} = 4.46$, 3.68, and 5.70, respectively) and even stronger support when they were all entered into the same regression equation ($M_{01} = 13.05$ in favour of the null). This tentatively suggests that our task was successful in eliciting curiosity-driven rather than uncertainty-driven information seeking.

Study 1 interim discussion

In this exploratory study, we found that curiosity was related to seeking non-instrumental information, whereas multiple measures of uncertainty intolerance were not. This suggests that our new task design may have successful reduced decisions motivated by intolerance of uncertainty.

Despite the strong correlation between openness/intellect and curiosity, we did not observe that openness/intellect predicted information seeking. However, we did not find decisive evidence against this relation, with a non-significant result and Bayes factors indicating only anecdotal evidence for the null.

There are several possible reasons for this outcome. First, although we observed a relation between information seeking and curiosity, when broken down by facet, it was significant only for the deprivation sensitivity subscale. It is possible that the design of the information-seeking task could be improved to increase the chance of tapping other factors of curiosity, such as joyous exploration. For example, we placed all information-seeking games together in the survey, which may have been repetitive and boring. Additionally, we did not explicitly tell participants that the information they could select would not be beneficial to them later in the experiment, so some participants may have suspected that the information they gained could help to win a future game. This may have explained the high numbers of people choosing to see information throughout the games and particularly

in Game 1 (around 90%). However, this seems unlikely given that, from Game 2 onwards, participants would see how different each of the games were from each other. Nevertheless, if people thought that the information might assist in future decision making, this may have increased pragmatic decision making.

Aims and hypotheses for Study 2

For Study 2, we aimed to address the potential issues in the task outlined above. To reduce the repetitiveness of these tasks, we interspersed them between sections of the surveys. To ensure participants were aware of the non-instrumental nature of the information they could obtain, we explicitly stated that the information for a given game would not be useful in subsequent games. We also included a single information-seeking question at the end of the games. Here, participants could choose to immediately know if they won the bonus money but incur a 30-second time delay before proceeding with the survey; or alternatively, they could wait until the end of the survey to see if they had won. Unlike our main task, this information serves to reduce uncertainty about the potential bonus and is thus analogous to the task used by Smillie (2019) and Bennett et al. (2019). We considered that including this task alongside our main information-seeking measure may help disentangle effects of curiosity-driven versus uncertainty-driven information-seeking.

We hypothesized that when information seeking was measured as it was for Study 1, openness/intellect, curiosity, and its facets deprivation sensitivity and joyous exploration would positively correlate with and predict information seeking. We also hypothesized that uncertainty intolerance, ambiguity tolerance, and neuroticism would *not* predict information seeking.

Further, we hypothesized that neuroticism and uncertainty intolerance would positively predict our new reward-related information-seeking question; that ambiguity tolerance would negatively predict it; and that openness/intellect would not be a significant predictor.[2]

Study 2

Method

Participants. Participants were 316 U.S. residents recruited through mTurk. As we found in Study 1 that a small proportion of participants required

more time to complete the study than we had expected, we increased the base study payment to $1.50, keeping the 50c bonus for winning the decision-making games (which we allocated to everyone) and the 50c attention-check bonus. The target sample for this study was $N = 300$. We excluded participants for the same reasons as stated in Study 1, and exclusion criteria led to the total loss of 15 participants, leaving a final study sample of 301 ($mean_{age} = 36.54$, $SD_{age} = 10.30$, min = 19, max = 69; 124 female participants, 175 male participants, and two responding 'other'). This sample provides approximately 94% power to detect a typical effect size within the context of personality psychology ($r = .20$; Gignac & Szodorai, 2016).

Materials and procedure. We used all measures from Study 1. As described previously, we also included an additional single-item information seeking question that provided *temporal reduction of uncertainty* about an upcoming reward. Specifically, after completing all trials of the main information-seeking task, participants were asked to choose between either (i) learning immediately if they won the bonus payment but incurring a 30-second time penalty; or (ii) waiting until the end of the experiment to learn this information, with no time penalty. Note that if participants asked to wait until the end of the study to find out their bonus, then we also waited until that time to assess the final information-seeking item from the main measure (see Study 1 Methods for full explanation of the original trials).

Analysis strategy. Mean (observed) scores were used for descriptive and inferential statistics. However, the supporting information contain several additional companion analyses. First, as inferences concerning parameter values from multiple regression can sometimes be misleading with observed variables, we computed regressions with latent variables, which account for measurement error and typically give a better estimate of the true effect size (Westfall & Yarkoni, 2016). Second, we computed tetrachoric factor scores for information seeking and conducted regular regressions with otherwise observed variables. Finally, similarly to Study 1, our information-seeking measure was non-normal (and thus could potentially lead to incorrect Type 1 error rates; Coxe et al., 2009). We thus employed Poisson regressions as were used for Study 1. Unless otherwise stated, inferences presented in the manuscript body were consistent for each of these measures.

We used Bayes factor regressions for several of our key hypotheses from which we intended to make inferences concerning null effects. For each regression, we tested the null hypothesis that regression slopes were 0 against the alternative that all slopes were non-zero. This package uses default mixture-of-variance priors that are calculated from a version of the multivariate Cauchy distribution (see Rouder & Morey, 2012 for a full description of this approach).

Results

Descriptive statistics. As in Study 1, information seeking demonstrated excellent reliability (Table 2). Figure 2 shows (a) the frequency of information seeking for each of the six items separately, (b) how often each person chose to seek information, and (c) responses to the reward-related information-seeking question. A large number of participants chose to view information on the first trial, but choices were more evenly divided for the remainder of trials. Participants appeared to seek information slightly less frequently than in Study 1, perhaps as a result of our assurance that information was not instrumentally useful for performance. For the single-item reward- related

Table 2. Internal consistency, means, standard deviations, and distribution information for all variables.

	ω_t	ω_h	Mean	SD	Min	Max	Skew	Kurtosis
Information−seeking	.94	.85	0.57	0.38	0	1	−0.15	−1.59
Reward information−seeking	NA	NA	0.36	0.48	0	1	0.60	−1.64
Openness/Intellect	.90	.42	3.59	0.48	2.25	4.65	−0.03	−0.64
Openness	.86	.57	3.41	0.45	2	4.6	−0.16	−0.08
Intellect	.87	.48	3.78	0.69	1.6	5	−0.22	−0.46
Agreeableness	.93	.69	3.73	0.67	2.4	5	0.09	−1.18
Conscientiousness	.93	.55	3.55	0.67	1.95	5	0.04	−0.70
Neuroticism	.95	.57	2.61	0.82	1	4.85	0.02	−0.47
Extraversion	.93	.53	3.21	0.72	1.15	4.95	−0.25	0.11
Curiosity	.88	.65	3.39	0.49	1.44	4.88	−0.23	0.98
Joyous exploration	.83	.69	3.90	0.73	1.2	5	−0.69	0.40
Deprivation sensitivity	.80	.70	3.64	0.79	1	5	−0.56	0.04
Stress tolerance	.86	.83	2.94	1.01	1	5	0.17	−0.87
Social curiosity	.86	.68	3.56	0.83	1	5	−0.59	0.09
Thrill seeking	.87	.80	2.94	1.02	1	5	−0.12	−0.87
Uncertainty intolerance	.94	.66	3.23	0.85	1	5	−0.22	−0.42
Ambiguity tolerance	.91	.65	3.02	0.72	1.23	5	0.26	−0.05

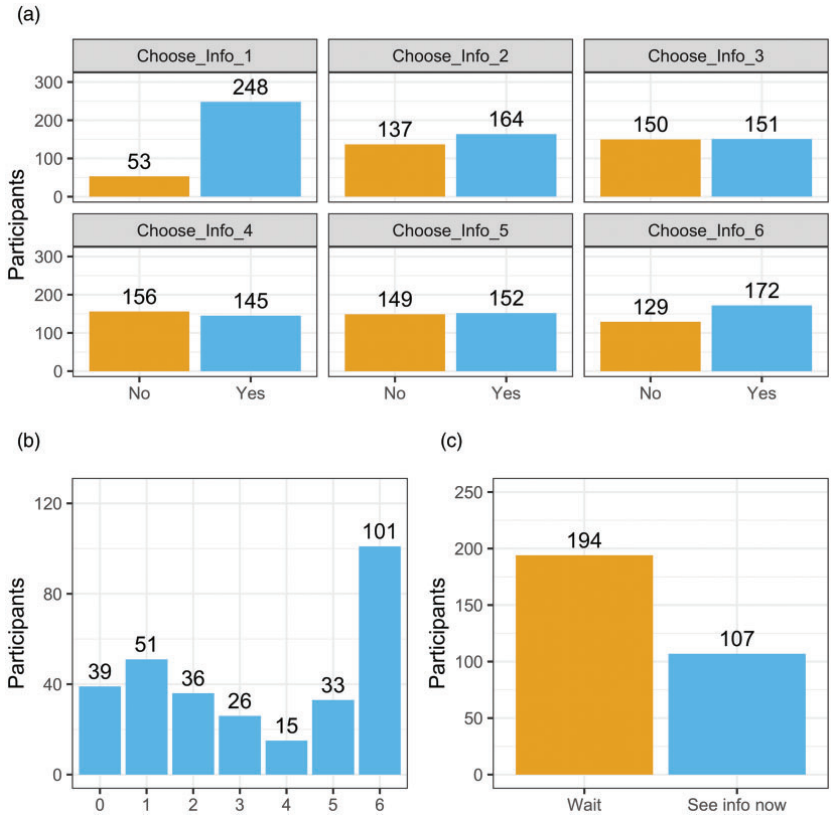

Figure 2. Responses to the customized information-seeking responses. (a) The frequency of responses for each individual item. No = participants chose not to view information, yes = participants chose to view information. Note that Choose Info 1 has a large proportion of participants choosing to view the information, but the remainder of the questions contain roughly equal responses. (b) Frequency of times out of six an individual chose to see information. Roughly a third of respondents always chose to see information. (c) Single-item information-seeking measure that reduces uncertainty about an upcoming reward. Here, most participants chose to wait rather than seek information. [Colour figure can be viewed online].

question (Figure 2c), a majority of people chose to wait until the end of the survey to find out if they won bonus money, rather than seeking this information immediately.

Table 3 illustrates the zero-order correlations between the battery of variables. Our central information-seeking measure correlated only moderately with reward-related information seeking ($r = .28$, 95% CI [.17, .38]), suggesting that we may be tapping partially dissociable forms of information seeking.

Openness/intellect, curiosity, and information seeking. In contrast to our hypotheses, but consistent with Study 1, openness/intellect did not significantly correlate with information seeking, either at the domain level ($r = -.05$, 95% CI [−.16, .06]) or the aspects openness ($r = .02$) or intellect ($r = -.08$). In addition, a Bayes factor regression indicated that the data were 5.59 times more likely to occur under the null hypothesis than under the alternative hypothesis, providing substantial evidence for a null effect of openness/intellect predicting information seeking (Jeffreys, 1939/1961).

Next, supporting our predictions, we found that curiosity sub-scales deprivation sensitivity and joyous exploration each positively related to information seeking (deprivation sensitivity $r = .20$, 95% CI [.09, .31]); joyous exploration $r = .15$, 95% CI [.04, .26]). However, in contrast to Study 1, curiosity as a whole did not significantly correlate with information seeking ($r = .09$, 95% CI [−.02, .20]). This was likely due to the moderate and negative correlation between information seeking and the curiosity sub-scale stress tolerance ($r = -.21$, 95% CI [−.32, −.10]). Indeed, when computing curiosity as a latent variable, it became a significant positive predictor of information seeking (see Table S3.1). This appeared to be due to the poor loading of stress tolerance on a general curiosity factor: the model evidently reduced the negative effect that stress tolerance was playing on predicting information seeking, allowing the remaining sub-scales to display their positive effect on information seeking. Thus, with the exception of stress tolerance,

Table 3. Correlation matrix, Study 2.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Information−seeking																
2. Reward information−seeking	.28**															
3. Openness/Intellect	−.05	−.16**														
4. Openness	.02	−.10	.75**													
5. Intellect	−.08	−.16**	.91**	.40**												
6. Agreeableness	−.12	−.16**	.49**	.35**	.45**											
7. Conscientiousness	−.04	−.11	.35**	.08	.43**	.40**										
8. Neuroticism	.13	.12	−.35**	.02	−.49**	−.39**	−.58**									
9. Extraversion	−.07	−.03	.40**	.17**	.44**	.15	.43**	−.50**								
10. Curiosity	.09	.09	.49**	.34**	.46**	.01	.17**	−.19**	.52**							
11. Joyous exploration	.15**	.07	.62**	.42**	.60**	.17**	.13	−.18**	.34**	.75**						
12. Deprivation sensitivity	.20**	.07	.30**	.26**	.25**	.00	.13	.27**	.04	.55**	.53**					
13. Stress tolerance	−.21**	−.18**	.37**	.04	.49**	.32**	.44**	.71**	.51**	.30**	.15**	−.31**				
14. Social curiosity	.12	.13	.14	.28**	.02	−.01	−.05	.23**	.11	.57**	.26**	.35**	−.23**			
15. Thrill seeking	.06	.17**	.03	.06	.00	−.41**	−.18**	.06	.39**	.69**	.32**	.17**	.04	.32**		
16. Uncertainty intolerance	.27**	.18**	−.34**	−.06	−.44**	−.34**	−.28**	.68**	−.46**	−.23**	−.13	.32**	−.85**	.26**	−.09	
17. Ambiguity tolerance	−.15**	−.12	.49**	.22**	.54**	.26**	.16**	−.48**	.49**	.49**	.40**	−.03	.69**	−.10	.31**	−.78**

Note: Italics indicates $p < 0.05$. **$p < 0.01$.

curiosity was positively associated with information seeking in Study 2.

Uncertainty attitudes, neuroticism, and information seeking. Contrary to our predictions, information seeking correlated significantly with uncertainty intolerance ($r = .27$, 95% CI [.16, .37]) and neuroticism ($r = .13$, 95% CI [.02, .24]) and correlated negatively with ambiguity tolerance ($r = -.15$, 95% CI [−.26, −.04]). Similarly, Bayes factors revealed substantial evidence in favour of associations between information seeking and ambiguity tolerance ($B_{10} = 3.46$) and intolerance of uncertainty ($B_{10} = 4898.79$), whereas there was indeterminate evidence for a relation between neuroticism and information seeking ($B_{10} = 1.53$ in favour of the alternative). This indicates that participants who were more intolerant of uncertainty were more likely to pay in time to view the informative option.

Reward-related information seeking. We next examined our single-item information-seeking measure that allowed participants to remove uncertainty about an upcoming reward. We predicted that we would observe similar information-seeking relations found by prior research using this version of the task (i.e. a positive relation with intolerance of uncertainty and neuroticism and no measurable relation to openness/intellect). Supporting the first predictions, reward-related information seeking significantly correlated with intolerance of uncertainty ($r = .18$, 95% CI [.07, .29]), ambiguity tolerance ($r = -.12$, 95% CI [−.23, −.01]), and neuroticism ($r = .12$, 95% CI [.01, .23]). A Bayes factor regression comparing a model in which each variable predicted information-seeking with a model in which there was no relationship found evidence that intolerance of uncertainty predicted information seeking ($B_{10} = 16.07$ in favour of predicting information-seeking) and anecdotal evidence for ambiguity tolerance ($B_{10} = 1.21$) and neuroticism ($B_{10} = 1.12$). Note that these effect sizes are on par or less than those observed from our main information-seeking task, indicating that we do not have evidence that our modified task more strongly elicited intolerance of uncertainty. That said, the relation between curiosity and information-seeking was absent for the altered task: neither joyous exploration nor deprivation sensitivity correlated with seeking advance information about an uncertain outcome, and Bayes factor regressions indicated substantial evidence for a null relation (deprivation sensitivity $B_{01} = 4.14$; joyous exploration $B01 = 3.79$).

Finally, in contrast to our prediction that openness/intellect would not relate to the choice to see uncertainty-reducing information, a negative correlation was observed ($r = -.16$, 95% CI [−.27, −.05]). This appeared to be driven primarily by the *intellect* aspect ($r = -.16$), suggesting that individuals higher in intellect were more likely to wait until the end of the

study to see their bonus payment. Convergent results were found with a Bayes factor regression: openness/intellect negatively predicted information seeking ($B_{10} = 5.90$), but assessing aspects, evidence for the alternative was substantial for intellect ($B_{10} = 5.51$), whereas indeterminate evidence for a null effect was found for openness ($B_{01} = 1.86$).

Exploratory analyses. To further explore combinations of variables that may relate to seeking information, we conducted a Bayesian model comparison predicting our original 6-item information-seeking measure from openness/intellect, joyous exploration, deprivation sensitivity, ambiguity tolerance, and uncertainty intolerance. We followed the guidelines of Rouder and

Morey (2012) and compared each predictor in turn, followed by all combinations of predictors. The supporting information contains figures and exact numerical values for each predictive model.

The model with the highest evidence was given by the predictors joyous exploration and uncertainty intolerance, indicating that this model was 208,067 times more likely than a null model. Sampling from the posterior distribution of this model in order to obtain parameter estimates of regression slopes, each predictor was positively related to seeking information (joyous exploration $\mu = 0.10$, 95% credible interval [0.04, 0.15]; intolerance of uncertainty $\mu = 0.13$, 95% credible interval [0.08, 0.17], which converges with a traditional frequentist multiple regression finding that both of these are significant predictors of information seeking (joyous exploration $\beta = 0.19$, $t(298) = 3.45$, $p < .001$; intolerance of uncertainty $\beta = 0.29$, $t(298) = 5.26$, $p < .001$). The second highest performing model (joyous exploration, intolerance of uncertainty, and openness/intellect) was not a substantially worse performer ($BF_{10} = 0.73$). However, given that the additional predictor did not result in a better fitting model, the former model could be favoured on grounds of parsimony. All other models were considered substantially worse (all $BF_{10} < 0.33$). Note that for the second highest performing model, openness/intellect was a negative predictor of information seeking ($\mu = -0.10$, 95% credible interval [−0.21, −0.02]) whereas the other variables were positive predictors.

Given the well-documented links among openness/intellect, uncertainty intolerance, and curiosity, we were interested to observe the evidence for these variables as predictors of openness/intellect. We thus performed an additional Bayes factor model comparison predicting openness/intellect from joyous exploration, deprivation sensitivity, intolerance of uncertainty, and 6-item information-seeking. The model with the greatest evidence was comprised of joyous exploration and intolerance of uncertainty ($M_{10} = 1.05e{+}37$), the same two variables that formed the highest performing model predicting information seeking. However, whereas both variables were positive predictors of information seeking, joyous exploration was a positive predictor of openness/intellect ($\mu = 0.38$, SD = .03, 95% credible interval [0.32, 0.44]) but intolerance of uncertainty was a negative predictor ($\mu = -0.15$, SD = 0.02, 95% credible interval [−0.20, −0.10]). This suggests that one reason openness/intellect was unrelated to information seeking in our study is because it relates positively to one driver of information seeking and negatively to another.

General discussion

The information-seeking theory of openness/intellect proposes that openness/intellect is grounded in greater sensitivity to the reward value of information and should, therefore, predict information-seeking behaviour (DeYoung, 2013). We tested this theory by investigating whether openness/intellect predicted the choice to pay a time cost to view non-instrumental information. Across two studies, individuals high in openness/intellect were no more likely to choose to view this form of information than their less open counterparts. However, curiosity predicted information seeking in both studies, and intolerance of uncertainty predicted information seeking in Study 2. To our knowledge, this is the first time that trait curiosity has been found to relate to information seeking. Because curiosity and intolerance of uncertainty relate in opposite ways to openness/intellect, their associations with information seeking may help account for the lack of such an association at the broader openness/intellect domain. Thus, our findings may help to refine DeYoung's information-seeking theory.

Is the information-seeking theory of openness/intellect supported?

Information seeking is sometimes mentioned in definitions of openness/intellect (e.g. Allen & DeYoung, 2017; DeYoung, 2015a, 2015b), giving the appearance that DeYoung's (2013) theory has been long since supported. However, there has been little research that has directly measured information seeking. To address this, we adapted a task from decision science assessing willingness to pay for non-instrumental information (Bennett et al., 2016). In an effort to reduce any motivation driven by intolerance of uncertainty, information within this task did not inform participants of an upcoming event or outcome. Instead, participants first learned if they had won a reward and were then asked if they would like to see some information that did not affect any outcome.

Some might argue that the information in this task is too trivial to capture individual differences in openness/intellect. But this triviality is exactly the point: If individuals higher in openness/intellect have a

preference to know things that they did not already know, then this should be evident *regardless* of the form of information. These stimuli allow for a strong test of the theory: if we found that openness/intellect predicts seeking even this form of information, this would have provided compelling evidence that open individuals have a general-purpose sensitivity to any sort of new information. Conversely, demonstrating that open individuals are motivated to view artworks or intellectual materials could simply reflect the content of the openness/intellect scale items.

Consistent with Smillie (2019), we found no relation between openness/intellect and information seeking in either study, with substantial evidence for a null effect obtained in Study 2. However, in both studies, curiosity—arguably a lower-level facet of the broader openness/intellect domain—positively predicted seeking information. Moreover, in Study 2, we observed that uncertainty intolerance positively predicted information seeking.[3] At the same time, consistent with prior research (Jach & Smillie, 2019; Kashdan et al., 2018), we found that these traits were both strongly related to openness/intellect but in opposite directions: openness/intellect was negatively related to uncertainty intolerance but was strongly positively related to trait curiosity. The difference between the domain-level and facet-level associations aligns with research showing that constructs measured at different levels of the trait hierarchy can produce unexpected results compared to when these are measured on the same level (Kretzschmar et al., 2018). If trait associations are specific to only particular facets or aspects of a trait, it might then be inappropriate to generalize these associations to the broader trait as a whole (Mõttus, 2016). Thus, the present findings suggest a potential refinement to DeYoung's (2013) information-seeking theory of openness/intellect, in that it may apply more narrowly to a specific facet of this domain (curiosity), but perhaps not to the domain more broadly.

In summary, the most straightforward version of the theory (i.e. higher openness/intellect leads to more information seeking) was not supported by our results. However, restricted support for the theory could be found via its relation to curiosity. Of course, as we did not pre-register this precise prediction, future studies are necessary to confirm these results.

Future research

One important implication of our results is that the task and stimuli used to measure information seeking matter: in both of our studies, curiosity predicted seeking information about inconsequential task details, but when the information reduced uncertainty about an upcoming reward, curiosity no longer predicted information seeking, and openness/intellect became a negative predictor. If curiosity is the process via which openness/intellect relates to information seeking, then we might observe a relation between openness/intellect and information seeking if we could find stimuli that elicit feelings of curiosity much more strongly than uncertainty. One promising option is to use trivia questions. Many studies have shown that state curiosity predicts paying a cost to see answers to trivia questions (Gruber et al., 2014; Kang et al., 2009; Ligneul et al., 2018; Marvin & Shohamy, 2016), but no study has assessed if state curiosity relates to trait curiosity or openness/intellect or how this may in turn predict information-seeking preferences. Recently, a rich, normed database of trivia questions has been made available to researchers (Fastrich, Kerr, Castel, & Murayama, 2018), providing an opportunity for future research to investigate these questions. An additional advantage of trivia questions is the ability to measure learning, thereby connecting information-seeking findings to theories of how openness/intellect relates to intelligence and knowledge acquisition (e.g. von Stumm, 2018; Ziegler et al., 2018).

An additional approach could be an information-seeking intervention measured with experience sampling (Scollon, Prieto, & Diener, 2009). These methods have been used to assess interests in everyday life (Ziegler et al., 2018) and could be built on by explicitly asking participants to seek information in their everyday life, examining potential effects of self-reported (or other-reported) openness/intellect throughout the intervention. If curiosity-driven information seeking underlies openness/intellect, then upregulating information seeking should theoretically lead to increased openness/intellect—particularly if participants are instructed to seek information via *fascination* (i.e. joyous exploration) rather than to reduce their anxiety at not knowing (intolerance of uncertainty). Experience sampling approaches have been previously used to assess the causal structure between extraversion and positive affect (Jacques-Hamilton, Sun, & Smillie, 2019) and processes that may drive volitional personality change (Hudson & Fraley, 2015), giving some precedence to this technique.

Finally, rather than upregulating curiosity, future information-seeking paradigms could attempt to hold constant uncertainty, or yoke uncertainty to information such that gains in information entail *increases* in uncertainty. This may seem a formidable goal, given that information is often equated with reductions in uncertainty by definition (e.g. Bennett et al., 2016; Gottlieb, Oudeyer, Lopes, & Baranes, 2013; Shannon, 1948). However, it is common for real-world information gains to accompany increases in uncertainty. Learning something can make you less certain about a prior belief (e.g. when reading a murder mystery, new evidence can come to light that makes you unsure about your previous suspect),

and uncertainty can immediately follow information gain (this new evidence can make you question the motives of the other characters in the novel). This connects to existing ideas and research surrounding openness/intellect. DeYoung (2013) proposed that temporary increases in uncertainty can be rewarding to some individuals, as exploring uncertainty may lead to long-term knowledge acquisition and understanding (i.e. an ultimate decrease in uncertainty, even if there are many short-term increases). Relatedly, Mussel (2013) proposed that personality traits related to intellectual achievements (including the *intellect* aspect of openness/intellect) are underpinned by dual motivations to *seek* and *conquer* information, where *seeking* involves exploring complex stimuli (i.e. engaging in temporary increases of uncertainty) before attempting to understand and thus *conquer* that stimuli (i.e. reducing uncertainty). Openness/intellect is also associated with more positive relations between the emotions of interest and confusion (Fayn, Silvia, Dejonckheere, Verdonck, & Kuppens, 2019). As confusion may arise from uncertainty, this suggests that individuals higher in openness/intellect may be better able to stay interested when exploring uncertain, confusing stimuli. We might thus expect curiosity and openness/intellect to relate to information seeking when uncertainty increases, whereas individuals who are intolerant of uncertainty might be unlikely to seek information that also increases uncertainty. A multi-trial experimental paradigm that can measure the objective and subjective uncertainties in the environment would be highly valuable to test this basic hypothesis, link to prior ideas, and ultimately further refine the information-seeking theory of openness/intellect.

Limitations

The primary limitation of the current studies is the use of cross-sectional designs from which we are attempting to draw evidence of causal mechanisms. Specifically, we have conceptualized curiosity and intolerance of uncertainty as mechanisms that cause people to seek information and potentially explain why the broad openness/intellect domain may not directly relate to information seeking. This is obviously not an inference that we can make given the nature of our variables. However, conducting such correlation-based research was a necessary first step towards gathering evidence for these hypotheses. If we did not observe any relation between curiosity and information seeking, or between intolerance of uncertainty and information seeking, that would suggest that our theorizing was *not* correct (Underwood, 1975). At the least, we have found that our results are not inconsistent with our theoretical conceptions and have paved the way for future studies, as suggested previously.

An additional limitation concerns the small number of trials used for our measure of information seeking: six choices for our main measure and only one for reward-related information seeking. Although we obtained high reliability for our main measure, it would be valuable to confirm these findings using a version of our task with many more trials (as in Bennett et al., 2016; Brydevall et al., 2018). It would also be useful to add a measure of intelligence to any such study, given that some theories of intelligence propose bidirectional effects of fluid intelligence and openness on seeking out and acquiring knowledge (e.g. Ziegler et al., 2018).

Finally, although participants were explicitly told that information would not be useful in subsequent games, this does not ensure that they believed us. If participants believed information was instrumental, this could have increased reward-driven motivation to seek information and reduced the impact of uncertainty-driven and curiosity-driven motivation. It might be particularly likely for participants to be suspicious about the value of information for the last three games, which all concerned a similar storyline (a 'gem quest'). However, if participants did believe that information was instrumental for those final three games, then we would expect to observe proportions of information seeking that were higher for the penultimate and final game compared with the first. We did not see this (Figure 2a), which may provide some reassurance that participants were following instructions as intended.

Conclusion

Openness/intellect—the putative trait of cognitive exploration—has itself been explored across multiple studies, but few direct tests of its proposed mechanistic underpinnings have been performed. To address this gap, we conducted some initial tests of the information-seeking theory of openness/intellect. We observed for the first time that trait curiosity, a facet of openness/intellect, predicted seeking non-instrumental information, and so too did intolerance of uncertainty. However, global openness/intellect did not predict choosing to view this form of information, perhaps because individuals scoring high on this trait tend to be both curious and tolerant of uncertainty. Our results thus fail to support any broad link between information seeking and the openness/intellect domain. However, the relation between information-seeking and curiosity arguably provides some support for a restricted version of the theory. We hope that this study can spur future research to disentangle these interrelated constructs and ultimately better understand the mechanistic underpinnings of curiosity, creativity, imagination, and exploration.

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Data accessibility statement

This article earned Open Data, Open materials and Preregistered + Analysis Plan badges through Open Practices Disclosure from the Center for Open Science: https://osf.io/tvyxz/wiki.The data are permanently and openly accessible at https://osf.io/2hjfc/, https://osf.io/mnw3d/ and https://osf.io/saqhe/. The permanent path to the registration is openly accessible at https://osf.io/fsx5e. Author's disclosure form may also be found at the Supporting Information in the online version.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Open Practices Disclosure Form

Data S1. Supporting Information

Notes

1. To reduce undesirable noise assessing individual differences, each game was rigged: participants won or lost the same games, and this deception was revealed to participants after they had completed the survey.
2. Additionally, given that we are linking motivations for information seeking (uncertainty driven vs. curiosity driven) to personality traits via attitudes to uncertainty, we pre-registered predictions to replicate the only (to our knowledge) existing pre-registered study of ambiguity tolerance and personality (Jach & Smillie, 2019). As these predictions are tangential to the main aims of this paper, we relegate these hypotheses and results to the supporting information. In short, findings from Jach and Smillie (2019) were replicated: ambiguity tolerance related positively to openness/intellect and extraversion and negatively to neuroticism; and the opposite pattern of findings occurred for intolerance of uncertainty.
3. Why did uncertainty intolerance continue to relate to information seeking in Study 2? Although participants were no longer uncertain about whether they had won or lost the game, they nevertheless remained uncertain about the specific piece of information that they could learn about that game. If attitudes to uncertainty concern anything that is unknown (Carleton et al., 2007), the knowledge that some currently unknown piece of information could be obtained may have led to uncertainty-motivated information seeking, even when the information was irrelevant to their monetary outcome.

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Chapter 4
Why Do People Seek Information? The Role of Personality Traits and Situation Perception
(Studies 4 and 5)

4.1 Overview

In this final section of Part 1, I draw together results from the first three empirical studies to propose an initial conceptual model of different motives underpinning information seeking. Results of Studies 2 and 3 suggested that there may be independent information-seeking pathways, the first linked to higher curiosity (related positively to openness/intellect), and the second linked to higher uncertainty intolerance (related positively to neuroticism). Further, Study 3 found that these dual relations were detected only in the altered information-seeking paradigm where participants already knew their upcoming reward. Alternatively, in a one-shot task where non-instrumental information informed participants about an upcoming reward, no significant link to relevant facets of curiosity (joyous exploration and deprivation sensitivity) was observed, whereas there remained a positive correlation to uncertainty intolerance. This suggests that elements of the particular information-seeking context may influence momentary emotions and motivations related to information seeking. Personality traits correspond closely to the properties of density distributions of psychological states (Section 1.3.1; Fleeson & Gallagher, 2009), and thus would be expected to influence the strength and frequency of emotional and motivational responses. But the perceived situation also plays an important role in experienced emotions, motivations, and cognitions; there is generally assumed to be an interaction between person and situation factors in predicting behaviour, whereby people higher in a given personality trait are more likely to experience personality-relevant states in situations that tend to elicit them (Funder, 2006; Furr & Funder, 2021; Lewin, 1936; Rauthmann et al., 2014). Perhaps the uncertainty-reduction explanation for information seeking is prevalent within cognitive neuroscience partially as a result of the experimental paradigms that have been used to assess information seeking.

I proposed a conceptual model that specified two main pathways to seek information, integrating literature describing the interactions between personality and situation perceptions with information seeking theory and research. When describing situation perceptions, I used terms from the DIAMONDS framework described in Section 1.3.2 (Rauthmann et al., 2014). The first *exploration* pathway is proposed to be elicited in situations that are perceived as higher in positivity (i.e., enjoyable, playful, humorous, simple, and easy) and intellect (i.e., offering opportunities for intellectual engagement and cognitive processing) and when people feel

stronger or more frequent states of curiosity; this is more likely to be experienced by people higher in trait curiosity (both joyous exploration and deprivation sensitivity) and openness/intellect. Conversely, the *safety* pathway is proposed to be elicited in situations that are perceived to be more negative (i.e., stressful, anxiety-provoking, or frustrating) and when people feel stronger or more frequent states of uncertainty-related anxiety; this is more likely to be experienced by people higher in trait uncertainty intolerance and neuroticism, and curiosity as a feeling of deprivation.

To test the predictions of this model, I compared information seeking across four stimulus sets. The first stimulus set was a version of the information-seeking task used most commonly in cognitive neuroscience, called here a *reward-outcome paradigm*. The second was a *trivia* paradigm, where participants had the option to pay in units of time to learn the answer to trivia questions. Two final stimulus sets controlled for potential confounds in the trivia paradigm. In principle, reward-outcome paradigms would be more likely to elicit safety-oriented information seeking because they contain cues that indicate whether participants will lose or fail to gain money, which could cause stress and anxiety related to this uncertainty. Meanwhile, trivia/related paradigms would be more likely to evoke exploration-oriented information seeking because they provide an opportunity for intellectual engagement with no threat to one's finances.

Results suggested evidence consistent with an exploration pathway connected to curiosity (and openness/intellect) across both studies. However, evidence for the safety pathway was more tentative across Study 4 and 5, with uncertainty intolerance predicting reward-outcome information seeking in Study 2 only. These results partly support the working model, but they also suggest that further refinements are necessary. Yet Study 4 and 5 demonstrate that information seeking shows distinct correlates with personality traits and situation perceptions depending on the context. This supports the crucial importance of combined person and situation factors in spurring motivated behaviour and emphasises the need to account for each of these factors when proposing explanations for information seeking.

Why Do People Seek Information? The Role of Personality Traits and Situation Perception

Hayley K. Jach[1]*
Colin G. DeYoung[2]
Luke D. Smillie[1]

* To whom all correspondence should be addressed: hayleyjach@gmail.com

[1]Melbourne School of Psychological Sciences, Redmond Barry Building, Melbourne University, 3010, Australia
[2] Department of Psychology, University of Minnesota, 75 East River Rd., Minneapolis, MN 55455, United States

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Author Note: Ideas and data appearing in this manuscript have not previously been presented or shared with the public. The preregistration for Study 1 can be found via the following link: https://osf.io/7k83t. Data, analysis code, and materials for this manuscript can be found via the following link: https://osf.io/9tqgn/

Abstract

The opportunity to learn new knowledge is ever present. How do people decide if information has sufficient value to counteract the cost of obtaining it? We proposed a conceptual model of information seeking that emphasizes how personality traits and perceptions of situations may influence motivations to seek information to *explore* (related to trait curiosity and openness/intellect, and situations evoking more positive emotions and opportunities for intellectual engagement) or *feel safe* (related to trait uncertainty intolerance and neuroticism, and situations that evoke more negative emotions). Across two studies (N = 436; N = 316), information seeking was assessed with two widely-used paradigms (advance knowledge of a reward outcome and answers to trivia questions), as well as two variations of the trivia paradigm in Study 1. In all contexts, the available information was *non-instrumental*, having no practical utility within the context of the task. Consistent with our proposed exploration pathway, curiosity and openness/intellect predicted the choice to seek information for trivia and related stimuli, but not reward-outcome stimuli, and trivia stimuli were generally rated as more intellectually engaging, more positive, and less negative than reward-outcome stimuli. However, evidence for the safety pathway was only partially in line with predictions, with uncertainty intolerance predicting reward-outcome information seeking in Study 2 only. We consider possible modifications to our initial model and implications for information-seeking research. These studies provide a proof of concept that people display both trait- and context-dependent preferences for non-instrumental information, both of which are commonly overlooked in studies of information seeking.

Each day brings opportunities to learn new knowledge, but gaining information often comes at a cost of time, effort, or money. How do we decide if information (for example, the weather forecast for the following day) has sufficient value to counteract this cost? Often, the information helps to gain rewards (e.g., learning if a trip to the beach can take place) or avoid punishments (e.g., whether to bring an umbrella to escape a drenching), but there are many circumstances where the information provides no clear benefit to the individual (e.g., looking at the various forecasts in other cities around the world). This latter form of information is commonly called *non-instrumental* (e.g., Bennett et al., 2016; Eliaz & Schotter, 2010). Why are individuals willing to pay a cost to obtain non-instrumental information? The current research draws on knowledge and theory from personality psychology to propose a conceptual model of motivations for information seeking. Specifically, we propose that decisions to seek information vary as a function of the degree to which the information-seeking situation affords the possibility of *exploration* or *safety.* Further, individuals who tend to be more *curious* are more likely to see opportunities for exploration, and individuals who tend to be more *anxious* are more likely to find uncertainty aversive and see opportunities for gaining safety. We present results from two studies that demonstrate the critical importance of the person and the situation for understanding information-seeking behavior.

The Value of Non-Instrumental Information

Information can be defined as data that cause a shift from one's prior to posterior knowledge (Lawrence, 1999)—or, more colloquially, learning something you did not know. Why do we seek information? Economists initially proposed that agents seek information that is perceived to provide some net financial benefit (Stigler, 1961; Hirschleifer & Riley, 1979). However, experiments have convincingly demonstrated that people will seek information that provides no such benefit, and many are even willing to pay time, effort, or money to gain non-instrumental information (Bennett et al., 2016b, 2020; Charpentier et al., 2018; Eliaz & Schotter, 2010b). Further, evidence that non-human animals such as primates (Bromberg-Martin & Hikosaka, 2009; Wang & Hayden, 2019) and starlings (Vasconcelos et al., 2015b) assign value to non-instrumental information speaks to the universality of this phenomenon. Understanding the basis of non-instrumental information seeking could provide clues to motivations underlying sub-optimal and counter-intuitive choice behavior (Gilovich et al., 2002), help to understand how primary rewards versus information rewards are computed in the brain (Bromberg-Martin et al., 2010; Bromberg-Martin & Hikosaka, 2009; Gruber et al., 2014; Jepma et al., 2012; Kang et al., 2009; Lau et al., 2020), and aid in uncovering

mechanisms that putatively underlie variance in conceptually related personality traits (DeYoung, 2013, 2015).

The fact that people are willing to seek and pay a cost for non-instrumental information, despite limited economic or practical value, suggests it can provide psychological value. One proposed benefit is the resolution of uncertainty (Bennett et al., 2016b; Bromberg-Martin & Monosov, 2020; Caplin & Leahy, 2001b; Crupi et al., 2018; Eliaz & Schotter, 2010b; Gottlieb et al., 2013b; Schwartenbeck et al., 2019; Wu, 1999). Although information does not always reduce uncertainty[3], the two terms tend to map directly to one another—for example, checking the weather before you head outside removes uncertainty you previously had about this state of the world. For advocates of uncertainty-reduction explanations of information seeking, uncertainty is often considered aversive and anxiety-provoking (as it could signal a potential threat lurking in the environment; Carleton et al., 2007; Hirsh et al., 2012), and resolving uncertainty can help to reduce this anticipatory anxiety (Bennett et al., 2020; Caplin & Leahy, 2001a; Wu, 1999). In support of this explanation, computational models based on uncertainty-reduction fit well to participant data, and information seeking has been found to correlate with indices of negative emotionality and anxiety, such as neuroticism and obsessive-compulsive tendencies (Bennett et al., 2020).

Despite the prevalence of this explanation, it seems unlikely that all instances of information seeking can be ascribed to motivations to reduce uncertainty-induced anxiety. Reflecting on your own information search patterns, do you sometimes seek information simply for the joy of learning something new? If so, then your information seeking may reflect an alternative anticipatory emotion elicited by uncertainty that has been proposed to drive information seeking: *curiosity* (Gottlieb et al., 2013b; Kidd & Hayden, 2015; van Lieshout et al., 2020). Curiosity can be defined as the desire and interest to explore new, uncertain, and/or complex events (Kashdan et al., 2018). As curiosity represents an expansive exploration of the unknown rather than fear of the unknown, it could be said to denote the opposite attitude to uncertainty-related anxiety. Studies assessing the relation between curiosity and information seeking find that participants will pay in time or money to seek information for stimuli (e.g., trivia questions) about which they report being curious (Kang et al., 2009; Marvin & Shohamy, 2016). A recent study even found that participants were

[3] For example, new knowledge can cause people to update their prior beliefs to become less certain about their previous knowledge. However, in the context of current information-seeking experiments, the choice to seek information always entails a reduction of uncertainty.

willing to undergo electric shocks to learn information that induced self-reported curiosity (Lau et al., 2020).

How can these two explanations for information seeking—uncertainty reduction and curiosity—be reconciled?[4] One clue may be gleaned from the experimental paradigms that tend to accompany them. Studies advocating an uncertainty-reduction explanation for information seeking often employ a class of experiments in which participants can seek advance knowledge of an upcoming outcome, almost always a reward (e.g., Bennett et al., 2020; Bromberg-Martin & Hikosaka, 2009; Eliaz & Schotter, 2007). These are often called *temporal reduction of uncertainty* paradigms (e.g., Kidd & Hayden, 2015), but to distinguish them from other information-seeking paradigms which also resolve uncertainty, we will call them *reward-outcome* paradigms. In reward-outcome paradigms, participants can choose between two options, one that delivers early knowledge about a small monetary or food reward, and another that delivers no knowledge of the reward. This information is non-instrumental as the participant's choice does not alter the total reward obtained at the end of the experiment. For example, in Bennett et al. (2020), participants can choose to pay a small sum of money to view a series of stimuli that reveal whether they will win or lose the trial, or else pay no money and view perceptually equivalent stimuli providing no information about the outcome. Whatever their choice, they will learn the outcome at the end of the trial.

Meanwhile, studies that assess how curiosity relates to information seeking often draw on very different experimental paradigms; most commonly *trivia* paradigms, where the information provided is the answer to general-knowledge questions (e.g., "Which bird is the international symbol of happiness?"; Kang et al., 2009; Marvin & Shohamy, 2016). As in reward-outcome paradigms, the information within trivia paradigms is non-instrumental (i.e., trivia answers do not alter the likelihood of receiving a specific extrinsic reward).

[4] Because curiosity has a long history and many different definitions, it is important to acknowledge that curiosity has sometimes been defined as a desire to reduce aversive feelings of uncertainty (Berlyne, 1954; Golman & Loewenstein, 2018; Jepma et al., 2012; Kobayashi et al., 2019; Lau et al., 2020; Ligneul et al., 2018). This perspective features in the influential "information gap" model of curiosity, whereby curiosity is considered an aversive state produced by awareness of explicit gaps in one's knowledge, which can be eliminated by successfully seeking information (Loewenstein, 1994). This would suggest that one way to reconcile the curiosity and uncertainty-reduction explanation for information seeking is to consider them the same construct. However, this explanation is arguably unsatisfying given the extensively documented neurobiological differences between states of exploration/curiosity versus anxiety/fear (Panksepp, 2004), the distinct personality traits related to tendencies to be curious and tendencies to be anxious about uncertainty (Jach & Smillie, 2019; Kashdan et al., 2018), and, indeed, the negative correlation observed between trait curiosity and uncertainty intolerance (Jach & Smillie, 2021). However, in the following sections we make some space for this interpretation by distinguishing between distinct *interest* versus *deprivation* facets of curiosity, and how they differentially relate to anticipation about outcomes and uncertainty intolerance.

An advantage of using similar experimental designs is that results can be built cumulatively from and compared closely to prior research. However, there are downsides to this consistency: no setting is truly neutral, and by aiming for uniform experimental environments and task structures, researchers may unknowingly constrain potential cognitive, emotional, or motivational affordances. For example, in reward-outcome paradigms, even though information doesn't alter the reward on each trial, it informs participants about whether or not they will soon gain a reward. This task structure may be particularly likely to provoke information seeking in order to reduce uncertainty, because participants' uncertainty about their future reward may elicit anxiety concerning their financial gains, which could lead to information seeking to reduce the aversion caused by this uncertainty. Further, it has been established that monetary rewards undermine intrinsic motivations (such as curiosity) to engage with a task (Deci et al., 1999; Murayama et al., 2010). Although the task structure of reward-outcome paradigms is not the same as those that typically demonstrate the undermining effect (i.e., by omitting and then including a monetary reward to perform the task), it is possible that by including reward-information as its only information stimuli, the focus on obtaining information to learn about upcoming rewards could have made it less likely to induce curiosity motivations compared to paradigms where information does not inform the participant about rewards. Moreover, as individuals differ in their tolerance of uncertainty (Carleton et al., 2012), this paradigm may evoke information-seeking only in people who are relatively high in uncertainty intolerance as a trait.

This can be contrasted with trivia paradigms. Trivia questions tend to include a variety of content and topics and consequently might be experienced as more intellectually stimulating and positive than reward-outcome paradigms. These elements may make trivia paradigms more likely to elicit curiosity-driven information seeking than other motivations, such as anxiety. Further, just as uncertainty intolerance is a trait-like individual difference, one's level of curiosity is also (Kashdan et al., 2018; Litman, 2008). Without measuring trait levels of curiosity, it's not possible to assess whether the individuals choosing to seek information in trivia paradigms are only those who are more generally curious.

Taken together, these considerations suggest that no one task purporting to measure information seeking may be sufficient to measure all motivations in all people: choices observed in a given task cannot be taken to be representative of all situations, and, even in identical situations, there are individual differences both in how situations are perceived and in the degree to which the same situational affordances matter. Instead, it may be beneficial to compare information seeking across people and contexts. This is the aim of the current

paper: we present a conceptual model that describes how different personality traits and contextual factors may drive different instances of information seeking, and test model predictions across multiple information-seeking paradigms.

A Conceptual Model of Information Seeking

Our model (Figure 1) specifies two pathways to information seeking: one characterized by the motivation to explore the unknown, and one characterized by the motivation to seek safety.

The motivations to explore or seek safety represent two fundamentally different action tendencies, one *approach*-oriented and one mostly *avoidance*-oriented[5] (Carver & Scheier, 1998). The contrast between exploration and safety, or approach and avoidance, has many similar comparisons across various literatures, including the behavioral activation and behavioral inhibition systems from personality neuroscience (Smillie, 2008), the SEEKING and FEAR systems from affective neuroscience (Panksepp, 2004), promotion and prevention focus from theories of self-regulation (Higgins, 1998), and self-direction versus security values from social psychology (Schwartz, 1992). The prevalence of these two motivational directions across such a wide gamut suggests an appropriate starting point from which to consider different motivations to seek information.

The degree to which a person seeks information via an exploration or safety motive is proposed to be a function of both situational factors (i.e., situation perception and momentary emotions) and personal factors (i.e., stable individual differences in personality). This aligns with foundational psychological theory that behavior is a function of both the person and the situation (Lewin, 1936). As we describe, state and trait curiosity are major drivers of the exploration pathway, and state and trait uncertainty intolerance are major drivers of the safety pathway. This suggests that both explanations for non-instrumental information-seeking that have emerged in the literature—uncertainty reduction and curiosity—may be correct, depending on the situation and the person. The remainder of this section outlines our logic.

[5] We write "mostly" avoidance-oriented because a drive to seek safety is grounded in an avoidance of the unknown, but also involves an approach of information to facilitate this avoidance of uncertainty. This is consistent with action tendencies being dynamic processes that involve cycles between approach and avoidance (Carver, 2006)

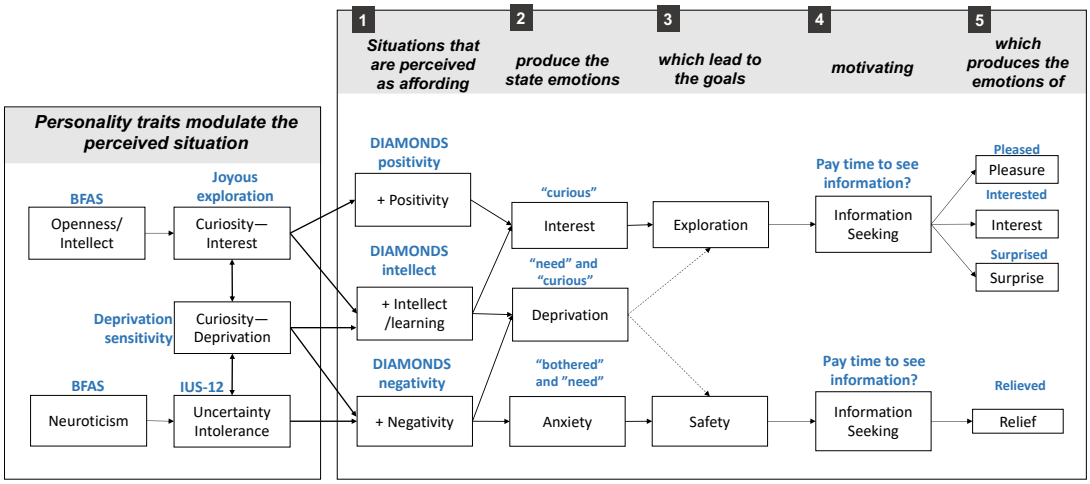

Figure 1. Conceptual model of how personality and situation perception relate to information-seeking motivations. The *exploration* pathway (top path) is evoked in situations that afford positivity and intellectual engagement and when people feel stronger and/or more frequent states of interest-based curiosity. The *safety* pathway (bottom path) is evoked in situations that afford greater negativity and when people feel stronger and/or more frequent states of anxiety related to uncertainty. Feelings of deprivation (induced in situations that afford greater negativity and intellectual engagement) evoke both pathways. The pathways are modulated by personality traits: the exploration pathway is more likely to be experienced by people higher in trait curiosity and openness/intellect. The safety pathway is more likely to be experienced by people higher in trait uncertainty intolerance and neuroticism. The blue text describes how we are operationalizing the constructs in the current research.

The Person

Personality traits describe typical patterns of emotion, behavior, thought, and desire (John & Srivastava, 1999). The most relevant personality traits for current purposes are curiosity and uncertainty intolerance. Curiosity describes the desire and interest to explore new, uncertain, and/or complex events (Kashdan et al., 2018; Spielberger & Starr, 1994). Trait curiosity comprises multiple dimensions, the two most relevant being deprivation sensitivity (representing *desire* to explore, involving feelings of deprivation and a pressing need to know) and joyous exploration (representing *interest* to explore, where you do not feel deficient of information but would nonetheless enjoy exploring something new; Kashdan et al., 2018; Litman, 2008). Conversely, uncertainty intolerance describes the tendency to find the negative possibilities in the unknown threatening and unacceptable (Carleton et al., 2007).

Personality traits are also hierarchically-organized, with higher-level traits formed from the shared variance of lower-level traits (often called *facets*). Curiosity, particularly joyous exploration, is often considered a facet of the broader personality dimension

openness/intellect, describing variance in imagination, creativity, and intellectual engagement (Kashdan et al., 2018; Silvia & Christensen, 2020; Woo et al., 2014). Further, trait uncertainty intolerance can be considered a facet of neuroticism, a broad personality dimension describing variance in negative emotionality and anxious/depressive tendencies (Berenbaum et al., 2008; de Bruin et al., 2007; Jach & Smillie, 2019; McEvoy & Mahoney, 2012; see Markon, 2009, for a discussion of how lower-order traits can be located within personality dimensions). As shown in Figure 1, deprivation sensitivity is not presented as a facet of either Big 5 trait, but instead an interstitial facet between joyous exploration and uncertainty intolerance. This is consistent with the positive correlations found between deprivation sensitivity and each of these other traits in the past (Jach & Smillie, 2021; Kashdan et al., 2018; Litman, 2005; Litman & Jimerson, 2004), though it diverges from typical definitions of deprivation-oriented curiosity as arising from negative affect related to uncertainty (Litman, 2005; Loewenstein, 1994), which we view as closer to uncertainty intolerance.

For any personality trait, each person's score can be thought of as approximating the mean in a density distribution of psychological states (Fleeson, 2001; Fleeson & Gallagher, 2009). For example, a person scoring relatively high on trait uncertainty intolerance is unlikely to feel an aversion to uncertainty in all situations in all times. However, they will tend to feel negative emotions toward uncertainty more frequently and more intensely than a person scoring lower on the trait. Likewise for curiosity, people who score higher in trait joyous exploration or deprivation sensitivity are more likely to experience more intense feelings of interest or deprivation, respectively, than a person scoring low on that trait. Thus, because personality traits summarize tendencies of psychological states, assessing trait scores should provide an indication of how likely a person is to experience emotions beyond that indicated by that particular situation.

The Situation

Different situations may *afford* (i.e., make possible or provide a context for) different thoughts, behaviors, and emotions (Stoffregen, 2004; Thielmann et al., 2020). A key development in the empirical study of situation effects has been to assess individuals' perceptions of situations (Horstmann et al., 2018), and researchers of individual differences have proposed several taxonomies of the main dimensions of situation perceptions that converge on the existence of five or six robust dimensions (Asendorpf & Rauthmann, 2020). From this literature we identify three key situation dimensions that may be relevant to information-seeking. First is the degree to which the situation affords *positivity,* describing

situations that are perceived to be enjoyable, playful, humorous, simple, and easy. Second is the degree that the situation affords *negativity,* describing how stressful, anxiety-provoking, or frustrating the situation is thought to be. Third is to what degree the situation is perceived to afford *intellect,* describing whether the situation offers opportunities for intellectual engagement and cognitive processing.

We propose that in situations where an opportunity to gain information exists, perceptions of these situations play an important role in influencing emotions and attitudes toward potential information gain, which has flow-on effects to motivations to seek information. Specifically, when the situation is perceived to be positive, they are more likely to experience positive emotions (e.g., eagerness, happiness). When the situation is both positive and intellectually engaging, they will be likely to experience feelings of interest-oriented curiosity. These positive emotions spur exploration-oriented information seeking as the person is optimistic about the possibilities for growth and understanding that may be afforded by transforming the unknown into the known (DeYoung, 2013).

Conversely, when people are in situations that they perceive to be negative, they are more likely to feel negative emotions (e.g., stress, anxiety, fear) in that situation. When these negative emotions are related to the lack of information itself, then this will be experienced as anxiety related to uncertainty, and will spur safety-oriented information seeking to reduce the negative emotions evoked by the unknown (Hirsh et al., 2012).

Finally, when momentary anxiety toward uncertainty is felt in situations that people *also* rate as intellectually engaging, then this is likely to spur dual information-seeking motivations both to reduce negative emotions induced by uncertainty *and* to approach the new knowledge available from the unknown. This reflects a combination of both approach and avoidance tendencies and will be experienced as a feeling of deprivation-oriented curiosity. The dual requirement of intellectual engagement alongside anxiety about uncertainty is consistent with the existing view that feelings of deprivation are mildly negative (because the uncertainty created by a perceived knowledge gap is aversive) and arise when the information to be gained is perceived to be "substantive, meaningful, and capable of increasing subjective feelings of competence" (Litman, 2005, p. 799).

Which elements of the situations (i.e., situational *cues*; Rauthmann et al., 2014) might create a context where information gain is perceived as more intellectually engaging, positive, or negative? If the information provides an opportunity to learn more about the world, consider complex topics, or question one's existing assumptions, then we predict this will influence the situation to be perceived as higher in intellect. Further, if the information is

novel, easy to understand, and contains high variety and surprise, it may be perceived more positively. Similar to appraisal theories of interest (Silvia, 2005, 2008), we predict these elements may lead the situation to be rated as higher in positivity and intellectual engagement, spurring interest-oriented curiosity. This collection of cues is likely to describe trivia paradigms, which sample from a variety of content and topics and allow participants to learn new things (and thus expand their internal model of the world). Thus, trivia paradigms would be expected to elicit interest-oriented curiosity and to be rated as higher in positivity and intellect.

Second, we propose that contexts that signify possible threats to one's safety are likely to lead the situation of uncertainty to be perceived as more negative and less positive. "Safety" here is relative and does not mean to imply that only life-threatening outcomes are relevant. Instead, any chance of losing or failing to gain something can impact one's perceived safety. This means that monetary and social threats are relevant in addition to physical threats.

When information informs the person about their safety, this provides psychological utility even when the information will not change the eventual outcome, because knowing the outcome a little in advance allows the person to either become less anxious (as they know they will be safe) or allows them to mentally prepare for a negative outcome (Wu, 1999). Thus, the information facilitates self-regulatory processes rather than being intrinsically valuable. An example of where information may serve this purpose may be compulsively checking the news to gain more information about world disasters, such as wars or pandemics. This context signifies a potential threat to oneself and loved ones, and although news-checking does not change the current state of the world, information may allow one to temporarily alleviate the anxiety elicited by uncertainty about one's safety. In experimental paradigms, the stakes are clearly far lower than for real-world scenarios. Nevertheless, when the paradigm provides information about one's safety or lack thereof, we posit that this cues attention to these factors and may cause the situation to be perceived as somewhat stressful and anxiety-provoking; emotions that can be eliminated by early information gain. As information in reward-outcome paradigms informs participants about their upcoming monetary status, participants may be anxious about the upcoming reward and thus more likely to seek information to reduce the anxiety induced by uncertainty.

Finally, what cues would we expect to elicit deprivation-oriented curiosity? The drive to know the answer is conceived of as an intellectual and approach-oriented (to approach information for its own sake) but also as a way of escaping the aversive properties of

uncertainty. Hence, we might expect that in all situations where information reduces uncertainty, deprivation-oriented curiosity would be relevant. This encompasses both the reward-outcome and trivia paradigms.

Connecting the Person and the Situation

Personality traits influence how a situation is perceived: openness/intellect predicts perceiving a situation as higher in intellect, whereas neuroticism predicts perceiving a situation as higher in negativity and lower in positivity (Rauthmann et al., 2014, 2015). As previously outlined, the way a situation is perceived will influence state emotions and the likelihood of seeking information via an exploration or safety pathway. Thus, personality traits are crucial variables to consider in relation to information seeking both because they describe tendencies toward psychological states (including emotional states) and because they change the way a situation is construed, which in turn influences state emotions. This makes it important to measure personality traits and to obtain a sample of sufficient size to obtain reliable estimates of the trait's correlates (Schönbrodt & Perugini, 2013).

Information Receipt and Reward

Finally, we expect that the receipt of information will elicit different emotional responses depending on the motivation to seek information. For those who sought information to explore, receipt of information might be more likely to activate positive emotions such as pleasure, interest, and surprise. In line with existing reinforcement learning models of curiosity (Murayama et al., 2019), these emotions act as reward signals, increasing the likelihood that information will be sought on the following trials. Conversely, for those who sought information to reduce the aversive feelings of uncertainty, a sense of relief from the elimination of anxiety may be felt. This reinforces behavior as people learn that they can reduce their anxiety by continuing to seek information.

Relations to Existing Research

As the majority of information-seeking studies have not explicitly considered situational or person-specific factors for choice motivation, there is minimal direct existing evidence for our full conceptual model. However, several studies support elements of the theory. One study assessed individual differences related to information seeking in a reward-outcome paradigm (Bennett et al., 2020). They found that neuroticism and obsessive-compulsive tendencies correlated with seeking information. A second paper using the same paradigm across two studies found that openness/intellect did *not* predict seeking information (Smillie et al., 2021). The results of these studies are in line with our assertion that reward-outcome tasks will typically elicit safety motivations but not exploration motivations.

Further, Jach and Smillie (2021) assessed information seeking with a paradigm that amalgamated reward-outcome and trivia paradigms. Here, participants were immediately informed that they had won or lost a trial, and then were allowed to pay (in units of time) to learn more information about that trial. Thus, uncertainty related to participants' monetary status was removed, but the information that they gained provided a greater context to their reward-related outcome. In this paradigm, the authors observed that both joyous exploration and uncertainty intolerance independently predicted seeking information. Taken together, these studies provide initial evidence for the impact of personality traits on information seeking preference. However, none of these studies assessed state emotions or situation perceptions in their results, and so cannot speak to this component of our model. On the other hand, studies using trivia paradigms have nearly always included measures of state curiosity and observed that momentary curiosity strongly predicted information seeking (Kang et al., 2009; Lau et al., 2020; Marvin & Shohamy, 2016). But as these studies did not include measures of trait curiosity, it remains unknown to what degree state and trait curiosity correlate in these tasks. Finally, substantial prior research has focussed on the structure of curiosity and possible emotional or situational processes spurring curious exploration (e.g., (Ainley, 1987; Berlyne, 1954; Lau et al., 2020; Litman, 2005; Loewenstein, 1994; Marvin & Shohamy, 2016). But this research has rarely considered person, emotion, and situation factors together, or conducted experiments where these elements can be jointly measured and manipulated.

Testing This Theory Across Situations

No prior study has included both a reward-outcome paradigm and a trivia paradigm within the same study, nor measured the divergent validity of trait curiosity and uncertainty intolerance across paradigms. We therefore present the first studies of choice preferences across two paradigms that each purport to measure non-instrumental information seeking.

Trivia paradigms are not as tightly controlled as reward-outcome paradigms because the amount of expected information can neither be held constant across trials (i.e., some questions will be more or less difficult than other questions) nor across participants (i.e., some participants will know more about certain content or topics than other participants). Further, due to their popularity in everyday life (e.g., pub quizzes) trivia questions may have established scripts and associations to games and social rewards for correct answers, and hence provide an alternative motive for the answer. To improve on these limitations, we generated two novel stimulus sets.

First, midway through each trial of the Trivia paradigm we asked participants if they would like to know some "bonus" information. This information provides more context to the trivia question but, crucially, does not help to answer the trivia question. As the bonus information is a complete unknown on each trial, the amount of expected information is constant across trials and participants. Moreover, as the bonus information does not help to answer the trivia question, it is entirely non-instrumental in the context of the task.

Despite these advantages, a possible confound remains: individual differences in general knowledge mean that the information gained from bonus information will not be equal between people, even if expected information is held constant. Although this cannot affect choice preferences for the first trial, it might affect choices on later trials (e.g., a participant might be less willing to pay for bonus information if they didn't gain much new knowledge initially). Thus, we included a final stimulus set that accounts for this confound. Midway through each trial of the reward-outcome paradigm, we presented a coin featuring a word written in Chinese characters, and asked participants if they would like to know the translation of this character. Within a participant sample who cannot read Chinese, both the predicted and received information is equivalent across participants and trials. Moreover, by using simple words as stimuli, choices will not relate to existing interest niches as they could for trivia and bonus information. Finally, by embedding this task within the reward-outcome paradigm, all peripheral situational elements of the two measures are identical.

Aims and Hypotheses

Our aims for this research are twofold. First, we will explore how non-instrumental information-seeking preferences differ across four stimulus sets (hereafter termed the Trivia stimuli, Bonus stimuli, Reward-Outcome stimuli, and Character stimuli). Second, we will evaluate evidence for our working model via model-derived predictions regarding how information-seeking preferences relate to personality traits, situation ratings, and state emotions.

For our first aim, we expect that there will be a difference in choice distributions between the Reward-Outcome stimuli and other stimulus sets due to differences in how this situation is perceived, as previously described. As no prior study has compared information preferences simultaneously across reward-outcome paradigms and other paradigms that do not involve rewards, we have no specific predictions for the distribution of information-seeking responses.

For our second aim, our model yields clear predictions regarding how information seeking should map to situation ratings, state responses, and personality traits. Specifically,

information from the Trivia, Bonus, and Character stimulus sets will be chosen more often by individuals higher in trait curiosity (joyous exploration and also, with the exception of the Bonus stimuli, deprivation sensitivity) and openness/intellect, and these stimuli will be accompanied by states reflecting interest-oriented curiosity and be perceived as comparatively positive, intellectually engaging, and not negative. This represents a general exploratory motivation for obtaining information. In contrast, information from the Reward-Outcome stimuli will be chosen more often by individuals higher in uncertainty intolerance, deprivation sensitivity, and neuroticism, and these stimuli will be accompanied by negative emotions and be perceived as comparatively negative, not positive, and not intellectually engaging. This represents a general safety motivation for obtaining information.

These predictions can be operationalized with two broad hypotheses, each of which houses several specific predictions (see Table 1). Our hypotheses, method, analysis plan, and conceptual model were pre-registered on the Open Science Framework (OSF; https://osf.io/7k83t).

Note that we specified a third broad hypothesis concerning how pre- and post-information state ratings would correlate with epistemic emotions, situation ratings, and Big 5 personality traits. Results for this hypothesis are included in the supplementary materials rather than the main text because high intercorrelations between state ratings made them relatively uninformative.

Table 1

Study 1 Hypotheses

Broad Hypothesis	Precise Hypothesis
1. Trait emotions and Big Five traits will predict information-seeking preferences depending on the particular context.	Openness/intellect and joyous exploration will positively predict information seeking for Trivia, Bonus, and Character stimuli, and will continue to do so when controlling for intelligence. The relation between openness/intellect and information seeking will be mediated by state curiosity. Deprivation sensitivity will positively predict seeking information for the Reward-Outcome, Trivia, and Character stimuli. Openness/intellect, joyous exploration, and intelligence will not positively predict seeking information for the Reward-Outcome stimuli: the relation may be non-significant or negative. Neuroticism and uncertainty intolerance will positively predict seeking information for the Reward-Outcome stimuli, but not the Character, Trivia, or Bonus stimuli.
2. The different information-seeking paradigms will be rated differently by participants on average.	For situation ratings, on average, participants will rate Trivia and Character stimuli as higher on intellect and positivity and lower on negativity than the Reward-Outcome stimuli. The adapted item from the intellect sub-scale "the [task] provided an opportunity to learn about unusual ideas or points of view" will be endorsed more for the Trivia and Character than for Reward-Outcome stimuli. Prior to receiving information, people will report on average being less bothered, uncertain, and needing to know the answer for Trivia and Character compared to Reward-Outcome stimuli. Conversely, they will report higher average curiosity for Trivia and Character than for Reward-Outcome stimuli. For post-information responses, people will report higher average pleasure, interest, and surprise for Trivia, Character, and Bonus stimuli than for Reward-Outcome stimuli. Conversely, when participants make the correct answer, there will be higher average reported relief for the Reward-Outcome stimuli compared to Trivia and Character.

Study 1

Method

Participants

Ethical approval was provided by The University of Melbourne Human Ethics Advisory Group (ID 2056233.2). In total, 449 participants from the online platform *Prolific Academic* completed the study or required compensation despite non-completion (e.g., technical difficulties). Participants were required to be English-speaking monolinguals to ensure that they could not read Chinese characters used in one part of the study. Participants were paid £6.70 plus a £0.50 bonus, which equated to an average payment of £5.45 per hour.

As preregistered, participants were excluded from analyses if they (1) provided an average response time faster than 1 second per questionnaire item from the BFAS questionnaire (n = 6); (2) provided non-sensical text, an irrelevant response, or no response to an open-ended question asking them to list some current hobbies or interests, (n = 0); (3) provided a mean of less than 4 out of 7 to a 6-item self-report survey of data quality (Wood et al., 2017; e.g., *I exerted sufficient effort on this survey; n* = 0); (4) provided a response of more than 2 years' discrepancy to two separate questions about participant age (n = 1) or (5) completed less than 90% of the study or did not reach the end of the study (n = 2)[6]. Additionally, we detected two participants who had attempted to complete the survey twice, entering a different Prolific ID than their automatically-provided ID for their second attempt. These four entries were removed as they indicated dishonest responding.

Following participant exclusion, our final sample comprised 436 participants (49% female, 49% male, and 1.8% non-cisgender), which exceeded our prespecified minimum sample of 350. Age ranged from 18 to 78 (mean = 34.22, SD = 11.92). Participants were currently living in the United Kingdom (n = 222), the United States (n = 173), Canada (n = 29), Australia (n = 5), Ireland (n = 3), or New Zealand (n = 3).

Procedure

Participants were asked to complete an online survey that included three "games" (one of which was a cognitive ability test), ratings of their personality, and demographic information. Following each game, participants also rated their perception of that situation

[6] Note that Criterion 5 slightly deviates from our pre-registration, where we only wrote that we would remove participants who completed less than 90% of the study. Two excluded participants completed more than 90%, but due to technical difficulties, we could not recover their survey responses in the correct format. Consequently, these participants were excluded prior to analyses.

and provided an optional open-ended comment on the game. The survey was created with Qualtrics software and can be viewed in our OSF documentation.

The two games from which we collected state ratings and information-seeking decisions were a Trivia paradigm (including the Trivia and Bonus information-seeking stimulus sets) and a Coin Flip paradigm (including the Reward-Outcome and Chinese Character stimulus sets; Figure 2). Each game comprised 20 trials, the first 10 of which were "no-choice" trials that automatically revealed information following a 2-second delay. This design was chosen to permit full-sample analysis of post-information ratings, as only those who see information can rate emotions evoked by that information. On the remaining 10 trials, participants could choose to pay time (5 seconds) to seek information, else proceed immediately to the next part of the game. No-choice trials were presented in a block before choice trials, and trials were randomized within each block. Participants first completed the Trivia paradigm, followed by personality surveys, the cognitive ability test, and finally the Coin Flip paradigm, after which they were fully debriefed and reimbursed for their time.

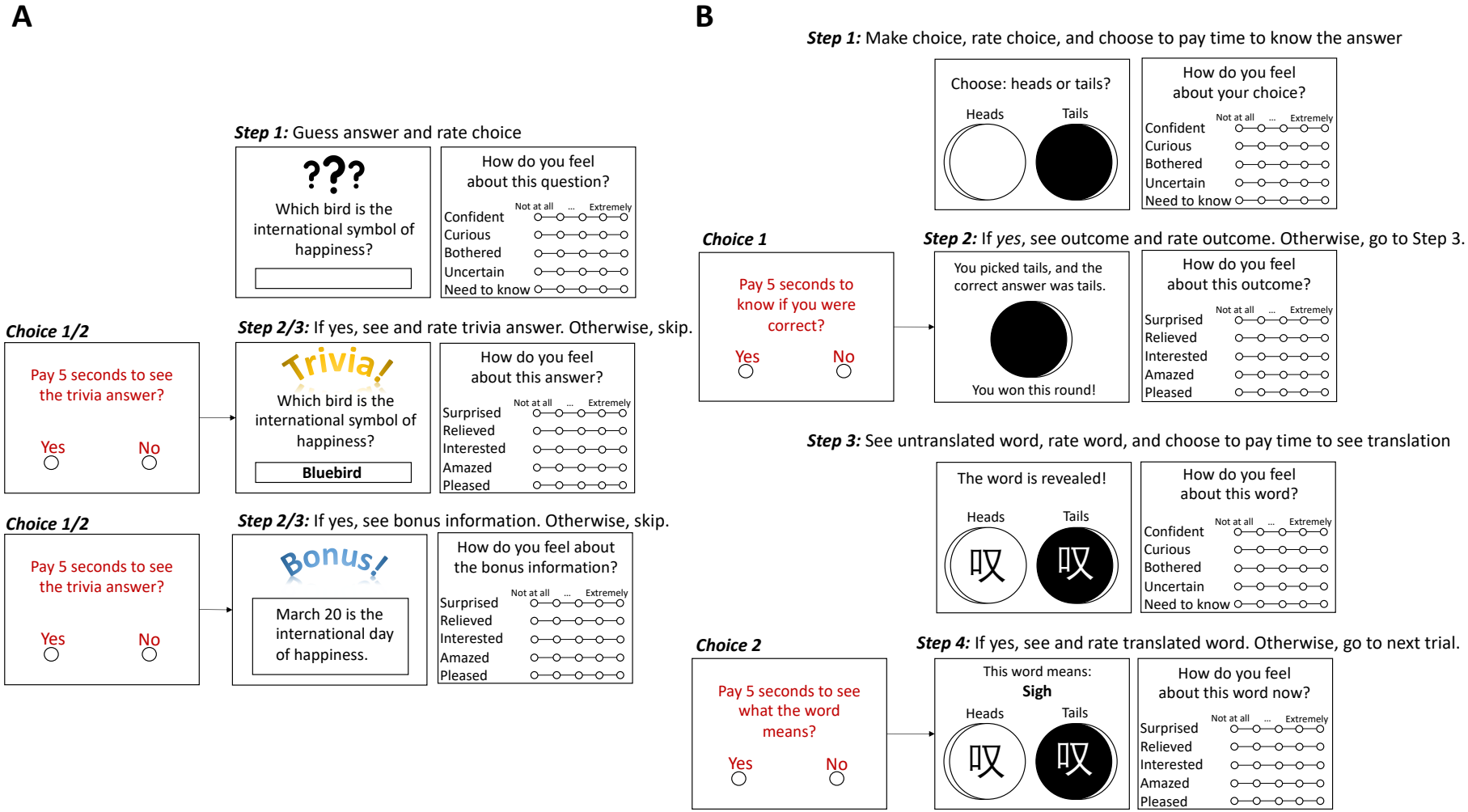

Figure 2. Example trials for the two experimental paradigms in which participants can seek information. (A) The trivia questions paradigm (including both Trivia and Bonus stimulus sets). (B) the Coin Flip paradigm (including Reward-Outcome and Character stimulus sets).

Trivia Game (Trivia and Bonus Stimulus Sets). On each trial, participants were shown a trivia question (e.g., *What disability did Thomas Edison suffer from?*) drawn from an existing database of trivia questions (Fastrich et al., 2018). They entered a free-text answer, and then provided *pre-information* emotion and cognition ratings (described in the *Materials* section below). The trivia game included two stimulus sets in which information could be provided to participants: the *answer* to the trivia question (Trivia stimuli), and *bonus* information (Bonus stimuli). The Trivia stimulus set allows participants to learn the answer to the trivia question (e.g., in the case of Thomas Edison's disability, *deafness*), whereas the Bonus stimulus set provides some additional context to the question (e.g., *Edison set up his first lab in his parent's basement at the age of 10*). Participants were explicitly told that bonus information would not provide any clues to the answer. The order of trivia answer information and bonus information within each trial was counterbalanced across trials. Finally, following information, participants provided *post-information ratings* of their emotions.

Coin Flip Game (Reward-Outcome and Character Stimulus Sets). Participants were informed that on each trial, the computer would flip a virtual coin that had 50% chance of falling on heads and 50% chance of falling on tails, and their task was to guess which side the coin would land on. For each trial where they guessed correctly, they would win 5p that would be added to their total at the end of the study (to ensure equal success and failure, we set each participant to win 50% of their trials but randomized the occurrence of this outcome across trials).

As in the Trivia game, the Coin Flip included two distinct information stimulus sets. First, participants had the option to learn the outcome of the coin flip (Reward-Outcome stimulus set), thereby learning whether they had guessed correctly for that trial. Importantly, participants were explicitly informed that their final winnings would be revealed at the end of the game, making this information economically non-instrumental.

Second, a word written on the coin was revealed to participants. This word was written in Chinese characters and could thus not be understood by our English-speaking monolingual participants. Participants were given the option to see the English translation of this word (Character stimulus set) or continue immediately to the next trial. Thus, the Character stimuli provided some additional contextual information but did not provide any clues to the outcome of the trial.

Materials

Information Seeking. Information-seeking choices were assessed using four different stimulus sets, as described above: (1) the answer to trivia questions (Trivia stimuli), (2) bonus trivia information (Bonus stimuli), (3) the reward-outcome of a heads/tails coin flip guess (Reward-Outcome stimuli), and (4) the translation of the Chinese characters written on the coin (Character stimuli). Each stimulus set included 10 trials, producing 40 information-seeking choices per participant. The cost to seek information was always a 5-second time delay.

State Emotion and Cognition Ratings. For the Trivia, Reward-Outcome, and Character stimulus sets, prior to the choice to seek information, participants responded to the following items on a 5-point Likert scale from 1 (*not at all*) to 5 (*extremely*): *I am confident I know the answer; I am curious about the answer*; *I am bothered by not knowing the answer*; *I feel uncertain about the answer*; and *I need to know the answer*. For the Character stimuli, "*about the answer*" was modified to "*what the word means*" (e.g., *I am confident I know what the word means*). We did not collect pre-information ratings for the Bonus stimuli as we thought this would be confusing for participants, given there was no question posed or context for them to consider prior to the choice to seek information.

After receiving information, participants were asked *How well does each word describe how you feel*? and rated how *surprised*, *relieved*, *interested*, *amazed*, and *pleased* they were on a scale from 1 (*not at all*) to 5 (*extremely*). Post-information ratings were collected for all four stimulus sets. Because participants cannot provide post-information ratings on trials for which they chose not to seek information (i.e., post-information rating data from trials 11-20 were incomplete), all assessments of state ratings were performed on trials 1-10.

Situation Perception Ratings. Participants rated their perceptions of the information-seeking situations for the Trivia, Reward-Outcome, and Character stimulus sets using the DIAMONDS (Rauthmann et al., 2014), a taxonomy of perceived psychological characteristics of situations. The 32 items are divided into eight four-item dimensions that form the DIAMONDS acronym (Duty, Intellect, Adversity, Mating, pOsitivity, Negativity, Deception, and Sociality). Responses were collected on a 5-point Likert scale from 1 (*Not at all*) to 5 (*Extremely*). To reduce the total survey length, we chose to only measure the dimensions that we judged could be relevant: Intellect (e.g., *affords an opportunity to demonstrate intellectual capacity*), pOsitivity (e.g., *situation is playful*), Negativity (e.g., *situation entails frustration*), and Duty (e.g., *a job needs to be done*). As *Duty* is not an

element of our conceptual model, we do not include results for this dimension within the manuscript, but it can be accessed via our open data.

We altered DIAMONDS items in the following ways: (1) We changed the scale from the present to the past tense and related it to the task that had just been completed (e.g., "Situation is enjoyable" became, "The [task] was enjoyable"); (2) For the Intellect sub-scale, we did not included the item *Situation evokes values concerning lifestyles or politics* because it was not relevant, and we altered the item *Situation affords an opportunity to express unusual ideas or points of view* to *the [task] provided an opportunity to learn about unusual ideas or points of view.* Finally, we changed the Negativity item from *Situation could entail stress or trauma* to *the [task] was stressful*. The Trivia and Bonus stimuli included a combined situation perception option (as we assumed participants would not accurately distinguish between the two parts of the paradigm) whereas the Reward-Outcome and Character stimuli included separate situation perception surveys.

Personality Traits. All trait responses were collected on a 5-point scale from 1 (*Strongly disagree*) to 5 (*Strongly agree*).

Big 5. We measured broad personality dimensions with the Big Five Aspect Scales (DeYoung et al., 2007), a 100-item measure that assesses both broad traits (openness/intellect, neuroticism, extraversion, agreeableness, and conscientiousness), as well as each trait's two lower-level *aspects*. The traits included in our hypotheses included openness/intellect, composed of the *intellect* (e.g., *Like to solve complex problems*) and *openness* aspect (e.g., *Enjoy the beauty of nature*); and neuroticism, composed of the *withdrawal* (e.g., *Worry about things*) and *volatility* (e.g., *Get easily agitated*) aspect. For present research questions, we focused on the trait- and facet-level rather than aspects.

Curiosity. Participants completed the Five Dimensional Curiosity Inventory (5DCI; Kashdan et al., 2018) and the Epistemic Curiosity Questionnaire (Litman, 2008). The 5DCI is a broad scale including five distinct factors, each composed of five items. For current purposes, our research questions concern joyous exploration, describing an interest in exploring things that are novel or unknown (e.g., *I find it fascinating to learn new information*), and deprivation sensitivity, describing an intense need to know (e.g., *I work relentlessly at problems that I feel must be solved*). These are also the two subscales that feature in Litman (2008; called *Interest-type* and *Deprivation-type*). As many of the items from Litman (2008) overlap closely or exactly with the joyous exploration and deprivation sensitivity subscales of Kashdan et al. (2018) we added the non-overlapping items from

Litman (2008) into an overall 8-item measure of joyous exploration and a 6-item measure of deprivation sensitivity, as preregistered.

Uncertainty intolerance. Uncertainty intolerance was measured with the 12-item Intolerance of Uncertainty scale (Carleton et al., 2007). Additionally, we included a 13-item measure of ambiguity tolerance (McLain, 2009), which can be considered an alternate measure of uncertainty intolerance. However, predictions made were specific to the Intolerance of Uncertainty scale, and ambiguity tolerance was included only for exploratory future research with our open data, given that it has been previously assessed in studies of information seeking (Jach & Smillie, 2021).

Cognitive Ability. Individuals who are more intelligent tend to have superior general knowledge and reasoning abilities, which could influence choices in unforeseen ways (e.g., they could have a higher baseline likelihood of knowing the trivia answers or the bonus information; they might try to recognize symbols from the Chinese characters to remember for later trials). As intelligence tends to be correlated with openness/intellect (DeYoung, 2020), of which curiosity can be considered a facet, this relation to intelligence might provide an alternative explanation for why the desire to know information may be linked to curiosity. Thus, it is important to measure and control for intelligence when predicting information-seeking choice across these stimuli. The international cognitive ability resource (ICAR) sample test (Condon & Revelle, 2014) is a 16-item open-source intelligence test measuring letter and number reasoning, matrix reasoning, three-dimensional rotation, and verbal reasoning. Due to time constraints, we did not include the four 3-dimensional rotation questions, leading to a 12-item test. This is consistent with reduced versions of the scale used in several prior studies (Dworak et al., 2020). During the experiment, participants were told that the task was a decision-making game with correct answers; the debrief statement later revealed they had completed an intelligence test.

Data Analysis

All analyses were conducted in *R* Version 4.0.1 (R Core Team, 2020). Within R, the following packages were used: bain (Gu et al., 2020), BayesFactor (Morey & Rouder, 2018), corrplot (Wei & Simko, 2017), cowplot (Wilke, 2019), lavaan (Rosseel, 2012), lme4 (Bates et al., 2015), lmerTest (Kuznetsova et al., 2017), plyr (Wickham, 2011), psych (Revelle, 2019), RColorBrewer (Neuwirth, 2014), reshape2 (Wickham, 2007), rstatix (Kassambara, 2020), semTools (Jorgensen et al., 2020), and tidyverse (Wickham et al., 2019).

Except where noted, confirmatory analyses followed our pre-registered plan. For Hypothesis 1, we employed structural equation models predicting information seeking across

the four stimulus sets from our variables of interest[7]. Both personality traits (predictors) and information seeking (outcomes) were represented as latent variables, thereby explicitly accounting for measurement error and providing a more accurate estimate of mean values and resultant effects (Westfall & Yarkoni, 2016). As information seeking was non-normally distributed (Table 2), a robust maximum likelihood estimator with a Sartorra-Bentler scaled test statistic and robust standard errors was used. Further, for predictions of null effects in Hypothesis 1, the R package *bain* (Gu et al., 2020) was used to compute Bayes Factors from the regression coefficients derived from the aforementioned structural equation models[8]. These analyses compare a hypothesis in which the regression coefficient is zero to an unconstrained hypothesis where the regression coefficient is nonzero. The Bayes Factor (BF_{01}) quantifies the support for the first (null) hypothesis relative to the second (alternative), using default uninformative priors (described further in Hoijtink et al., 2019; Van Lissa et al., 2020). Bayes Factors of 1 indicate no preference for either hypothesis, whereas Bayes Factors greater than 1 provide evidence for the null hypothesis and Bayes Factors less than 1 provide evidence for the alternative hypothesis. Bayes Factors greater than 3 or less than 1/3 have been proposed to provide substantial evidence for the null and alternative hypotheses, respectively (Jeffreys, 1961), and we preregistered these thresholds for the current study.

For Hypothesis 2, we used repeated-measures ANOVAs on mean-scored variables. For these analyses, the categorical independent value is the particular information-seeking stimulus set, and the dependent variable is the relevant rating (pre- and post-information state ratings and situation ratings). We used post-hoc Wilcoxon signed-rank-tests to test our directional predictions, which were Bonferroni-corrected for multiple comparisons.

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[7] In our pre-registration, we stated that we would use latent multilevel models for Hypotheses 1 and 3 contingent on model convergence. However, it became apparent that a multilevel approach would not be necessary for our research questions. This is because, although our outcome variables (information seeking/state emotion and cognition ratings) include multiple trials and can hence be represented at Level 1 (within-person) or 2 (between-persons), our predictor variables (i.e., traits/situation ratings) were measured only at Level 2. When a predictor is only measured at Level 2, the Level 1 outcome is aggregated to Level 2 for analyses. Thus, all that differs from a single-level model is that a multilevel approach explicitly models each individual's mean outcome, rather than solely the group's mean. This could affect the overall model fit, but for data where trials are nested within persons—and thus are automatically already clustered—it will not impact predictor parameter estimates, even when using a latent approach that accounts for sampling error (this is because the outcome is modeled a function of the predictor's sampling error, which is nil if it is only measured at Level 2; see equations in Lüdtke et al., 2008). Indeed, for Hypothesis 1, a single-level fully latent approach is arguably a better choice than a latent multilevel approach because it models information seeking as a latent variable (not an aggregated mean), thereby accounting for measurement error.

[8] This also diverges from our preregistration, where we wrote that we would compute separate Bayesian regressions on observed variables (Rouder & Morey, 2012). The current method is better as the Bayes factors are computed directly from parameter estimates that account for measurement error, thus providing more accurate estimates of relative evidence for the null or alternative hypotheses. However, to be consistent with our preregistration, the supplementary information contains all analyses under the method originally planned.

Results

Descriptive Statistics

Trait Scores, State Scores, and Situation Ratings. Table 2 shows descriptive statistics for information-seeking within each stimulus set, mean personality traits, and mean situation ratings. All variables demonstrated high internal consistency (ω and α). Skew and kurtosis values indicated that trait scores were approximately normally distributed, but information-seeking choices were often not normally distributed. On average, participants correctly guessed 30% of trivia questions.

Table 2
Reliability and Descriptive Statistics for Information Seeking, Intelligence, Trait Measures, and Combined Situation Ratings

Variable	ω	α	*M*	*SD*	Min	Max	Skew	Kurtosis
Info Seeking (Trivia)	.87	.87	0.54	0.33	0	1	-0.13	-1.27
Info Seeking (Bonus)	.90	.90	0.18	0.28	0	1	1.91	2.69
Info Seeking (RO)	.97	.97	0.41	0.43	0	1	0.43	-1.61
Info Seeking (Char)	.93	.93	0.10	0.24	0	1	2.68	6.49
Correct Trivia Guesses	NA	NA	5.95	4.21	0	18	0.68	-0.23
Intelligence	.77	.77	0.60	0.25	0	1	-0.20	-0.92
Openness/Intellect	.44	.80	3.71	0.54	2.20	4.90	-0.21	-0.33
Neuroticism	.82	.94	2.94	0.87	1	5	-0.05	-0.83
Extraversion	.74	.92	3.14	0.75	1.25	4.80	-0.16	-0.48
Conscientiousness	.63	.89	3.49	0.67	1.60	5	-0.17	-0.42
Agreeableness	.71	.87	3.90	0.55	1.40	4.90	-0.64	0.48
Uncertainty Intolerance	.86	.86	3.31	0.73	1.17	5	-0.22	-0.30
Joyous Exploration	.84	.85	3.86	0.66	1.88	5	-0.42	-0.11
Deprivation Sensitivity	.75	.83	3.57	0.74	1	5	-0.49	0.03
pOsitivity	.68	.83	2.68	0.69	1.42	4.92	0.93	0.80
Negativity	.71	.90	1.74	0.71	1	4.92	1.39	1.94
Intellect	.80	.88	2.35	0.87	1	5	0.95	0.50

Note. Info = Information, RO = Reward-Outcome, Char = Translated Character, ω = Omega, *a* = alpha, *M* = Mean, *SD* = Standard deviation. The way in which Omega is calculated in this column depends on the putative internal factor structure and data type. Omega categorical is used for information seeking and intelligence, Omega hierarchical is used for Big 5 personality traits and situation ratings, and unidimensional Omega is used for uncertainty intolerance and curiosity. This is consistent with recent recommendations (Flora, 2020).

Information-Seeking Choices. Figure 3, Panel A shows choice preference across stimulus sets. Choices for the Trivia stimuli were uniformly distributed, indicating substantial variability in how often people paid a time-cost for the answer. Meanwhile, responses were

positively skewed for the Bonus stimuli, with most people choosing not to seek information. The positive skew was even stronger for the Character stimuli, with the vast majority never seeking to know the translation of the Chinese character, and a tiny minority seeking information some or all of the time. Finally, responses for the Reward-Outcome stimuli were bimodal, with most people either never choosing to know if they had won the trial or always choosing to know if they had won the trial.

For each stimulus set, choices to seek information demonstrated high reliability (Table 1, Lines 1-4, ω and *a*), indicating that within a stimulus set choices to seek information were generally consistent across trials relative to other participants. However, despite this consistency, there were general differences in choice behavior across time. Figure 3, Panel B shows the average choice to seek information over time, from the first trial in which participants could choose (Trial 11) to the last (Trial 20). As seen visually and as estimated by multilevel models predicting information seeking by trial, the proportion of participants choosing to seek Bonus and Reward-Outcome information declined over time (Bonus $t(3923) = -5.29$, $p < .001$; Reward-Outcome $t(3923) = -10.31$, $p < .001$) whereas the choice to seek the answer to trivia questions or translated characters remained relatively stable (Trivia $t(3923) = -1.41$, $p = .157$; Character $t(3923) = -0.98$, $p = .330$. Further, Figure 4 displays statistically significant zero-order correlations for most variables of interest. All four information-seeking choices were positively intercorrelated, but not so strongly as to suggest a single information-seeking construct: associations ranged from $r = .30$ (Reward-Outcome and Character; Trivia and Character; Bonus and Reward-Outcome) to $r = .54$ (Bonus and Character). The strength of association between responses to the Bonus and Character stimuli is striking given that these choices occurred in different games on opposite ends of the study survey, and echoes their similar distributions displayed in Figure 3, Panel A. Taken together, these patterns of choice behavior suggest that not all forms of non-instrumental information seeking are interchangeable, but rather are preferred by different people to different degrees. The following sections assess which factors may play a role in these mean differences and individual differences.

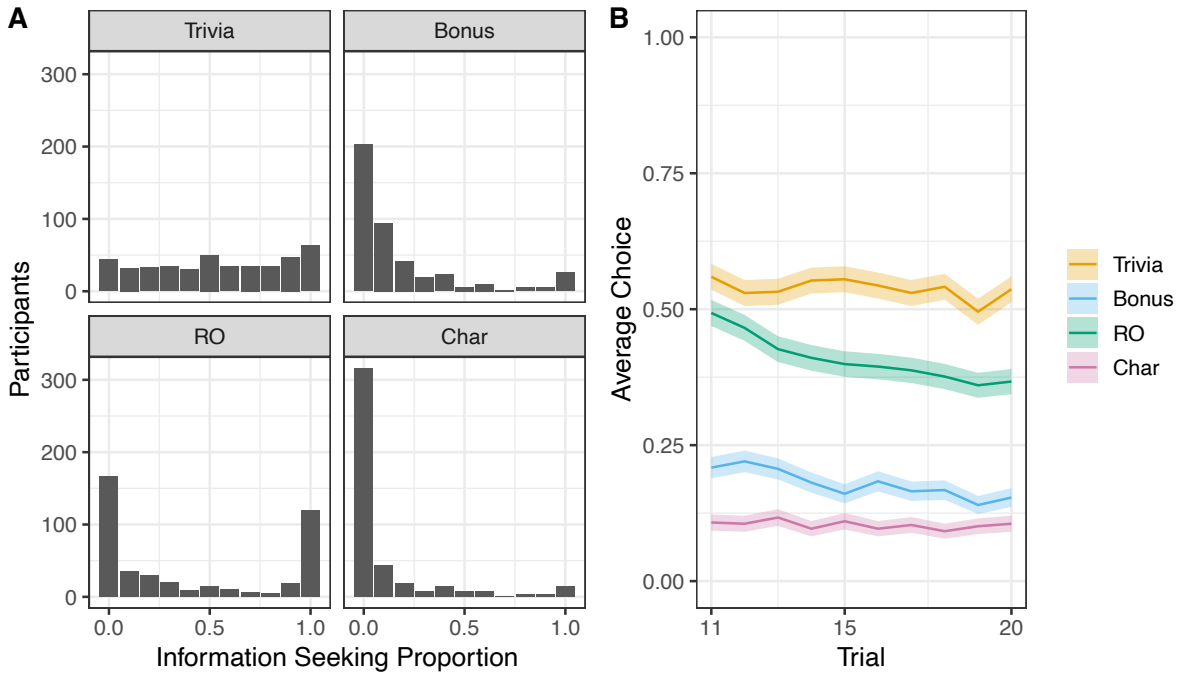

Figure 3. Information-seeking responses. RO = Reward-Outcome, Char = Character. (A) Proportion of information seeking across the four stimulus sets. (B) Mean post-information state ratings for each trial. The ribbon surrounding each mean depicts the standard error of the mean.

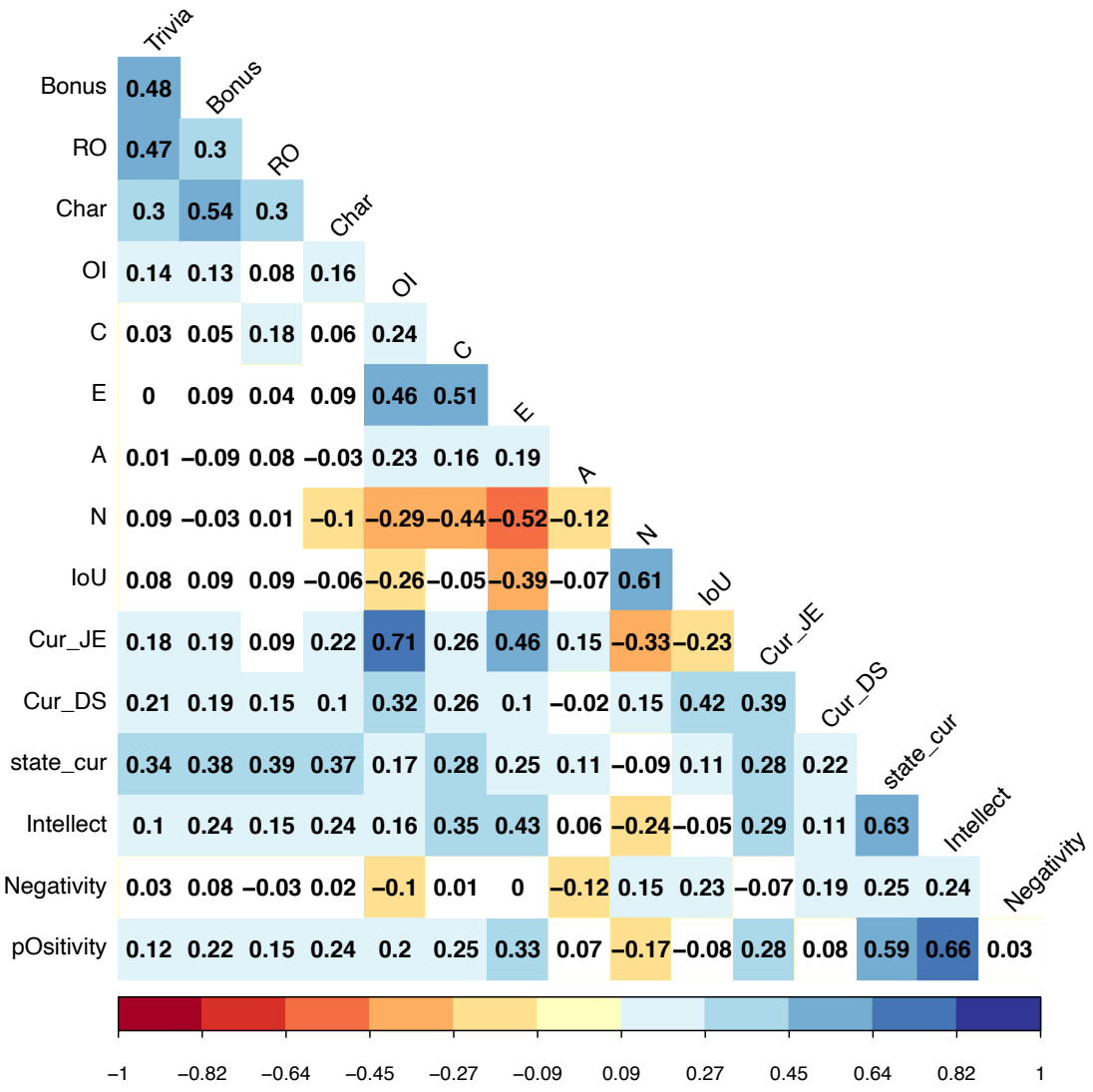

Figure 4. Pearson zero-order correlations of information seeking, personality trait scores, state curiosity, and situation ratings. Unshaded correlations are statistically non-significant. State curiosity and situation ratings (pOsitivity, Negativity, and Intellect) are averaged over three stimulus sets (Trivia, Reward-Outcome, and Character). RO = Reward-Outcome, Char = Character, OI = Openness/Intellect, C = Conscientiousness, E = Extraversion, A = Agreeableness, N = neuroticism, IoU = Uncertainty intolerance, Cur_JE = trait Curiosity—Joyous Exploration, Cur_DS = trait curiosity—Deprivation Sensitivity.

Inferential Analyses: Pre-registered Hypotheses

Hypothesis 1. We hypothesized that openness/intellect and the joyous exploration facet of trait curiosity would positively predict information seeking in response to the Trivia, Bonus, and Character stimuli, and would continue to do so when controlling for intelligence. Meanwhile, we hypothesized that openness/intellect, joyous exploration, and intelligence would *not* predict information seeking for the Reward-Outcome stimuli. Finally, we predicted that the deprivation sensitivity facet of curiosity would positively predict seeking information for the Reward-Outcome stimuli in addition to the Trivia and Character stimuli. These hypotheses were supported (Table 3): openness/intellect and joyous exploration significantly predicted seeking information for the Trivia stimuli, the Bonus stimuli, and the Character stimuli, but relations were not significant for the Reward-Outcome stimuli. Further, all results held when controlling for intelligence (Models 2 and 8, Table 3). Bayes Factors indicated substantial evidence for the null for openness/intellect predicting Reward-Outcome information seeking, both as a sole predictor (BF_{01} = 6.52) and when intelligence was added to the model (openness/intellect BF_{01} = 4.92; intelligence BF_{01} = 14.10). Joyous exploration followed a similar pattern, finding substantial evidence for the null as a single predictor (BF_{01} = 3.65), and anecdotal evidence for the null as a multivariate predictor (joyous exploration BF_{01} = 2.76; intelligence BF_{01} = 14.12). Meanwhile, deprivation sensitivity significantly predicted information seeking for the Reward-Outcome stimuli as well as all other stimulus sets. These results converged with straightforward zero-order correlations (Figure 4).

Table 3

Parameter Estimates and Model Fit Statistics of Structural Equation Models Predicting Information Seeking from Personality Trait Measures.

			Parameter Estimates						*Fit Indices*		
Model	Stimuli	Predictor/s	*β*	95% CI		*SE*	*Z*	*p*	CFI	RMSEA [95% CI]	SRMR
1. Openness/ Intellect	**Trivia**	**Openness/Intellect**	**0.14**	**[0.03,**	**0.25]**	**0.05**	**2.50**	**.012**	.90	.04 [.04, .04]	.06
	Bonus	**Openness/Intellect**	**0.15**	**[0.04,**	**0.26]**	**0.06**	**2.67**	**.008**			
	RO	Openness/Intellect	0.08	[-0.02,	0.18]	0.05	1.53	.127			
	Char	**Openness/Intellect**	**0.18**	**[0.08,**	**0.28]**	**0.05**	**3.57**	**< .001**			
2. Openness/ Intellect and Intelligence	**Trivia**	**Openness/Intellect**	**0.13**	**[0.02,**	**0.24]**	**0.06**	**2.35**	**.019**	.90	.04 [.03, .04]	.05
	Trivia	Intelligence	0.08	[-0.04,	0.19]	0.06	1.33	.182			
	Bonus	**Openness/Intellect**	**0.15**	**[0.04,**	**0.26]**	**0.06**	**2.64**	**.008**			
	Bonus	Intelligence	-0.01	[-0.14,	0.11]	0.06	-0.21	.832			
	RO	Openness/Intellect	0.08	[-0.02,	0.18]	0.05	1.48	.138			
	RO	Intelligence	0.02	[-0.09,	0.12]	0.05	0.30	.761			
	Char	**Openness/Intellect**	**0.18**	**[0.09,**	**0.28]**	**0.05**	**3.66**	**< .001**			
	Char	Intelligence	-0.07	[-0.19,	0.05]	0.06	-1.20	.231			
3. Mediation model 1: Predicting Trivia via state curiosity	Trivia	Openness/Intellect (c)	0.04	[-0.06,	0.14]	0.05	0.75	.454	.76	.06 [.06, .07]	.07
	Curiosity	**Openness/Intellect (a)**	**0.23**	**[0.13,**	**0.32]**	**0.05**	**4.48**	**< .001**			
	Trivia	**Curiosity (b)**	**0.44**	**[0.35,**	**0.53]**	**0.05**	**9.44**	**< .001**			
		Indirect Effect A*B	**0.10**	**[0.05,**	**0.15]**	**0.02**	**3.99**	**< .001**			
		Total Effect C+(A*B)	**0.14**	**[0.03,**	**0.24]**	**0.05**	**2.50**	**.013**			
4. Mediation model 2: Predicting Bonus via state curiosity	Bonus	Openness/Intellect (c)	0.08	[-0.03,	0.18]	0.05	1.43	.152	.82	.05 [.05, .06]	.07
	Curiosity	**Openness/Intellect (a)**	**0.23**	**[0.13,**	**0.32]**	**0.05**	**4.48**	**< .001**			
	Bonus	**Curiosity (b)**	**0.32**	**[0.22,**	**0.42]**	**0.05**	**6.55**	**< .001**			

		Indirect Effect A*B	**0.07**	**[0.03,**	**0.11]**	**0.02**	**3.62**	**< .001**			
		Total Effect C+(A*B)	**0.15**	**[0.04,**	**0.26]**	**0.06**	**2.68**	**.007**			
5. Mediation model 3: Predicting Character via state curiosity	Char	Openness/Intellect (c)	0.05	[-0.04,	0.14]	0.05	1.11	.268	.83	.07 [.07, .07]	.08
	Curiosity	**Openness/Intellect (a)**	**0.25**	**[0.16,**	**0.34]**	**0.05**	**5.36**	**< .001**			
	Char	**Curiosity (b)**	**0.52**	**[0.41,**	**0.62]**	**0.05**	**9.54**	**< .001**			
		Indirect Effect A*B	**0.13**	**[0.07,**	**0.19]**	**0.03**	**4.28**	**< .001**			
		Total Effect C+(A*B)	**0.18**	**[0.08,**	**0.28]**	**0.05**	**3.58**	**< .001**			
6. Mediation model 4: Predicting Reward-Outcome via state curiosity	RO	Openness/Intellect (c)	0.03	[-0.06,	0.12]	0.05	0.71	.481	.87	.07 [.07, .07]	.07
	Curiosity	Openness/Intellect (a)	0.09	[-0.02,	0.19]	0.05	1.66	.096			
	RO	**Curiosity (b)**	**0.52**	**[0.44,**	**0.59]**	**0.04**	**13.15**	**< .001**			
		Indirect Effect A*B	0.05	[-0.01,	0.10]	0.03	1.64	.102			
		Total Effect C+(A*B)	0.08	[-0.02,	0.18]	0.05	1.53	.127			
7. Joyous Exploration	**Trivia**	**Joyous Exploration**	**0.21**	**[0.11,**	**0.32]**	**0.05**	**3.90**	**< .001**	.97	.03 [.02, .03]	.04
	Bonus	**Joyous Exploration**	**0.21**	**[0.10,**	**0.32]**	**0.05**	**3.85**	**< .001**			
	RO	**Joyous Exploration**	0.10	[-0.00,	0.20]	0.05	1.87	.062			
	Char	**Joyous Exploration**	**0.25**	**[0.16,**	**0.34]**	**0.05**	**5.51**	**< .001**			
8. Joyous Exploration and Intelligence	**Trivia**	**Joyous Exploration**	**0.21**	**[0.10,**	**0.32]**	**0.06**	**3.79**	**< .001**	.96	.03 [.02, .03]	.04
	Trivia	Intelligence	0.07	[-0.04,	0.19]	0.06	1.28	.200			
	Bonus	**Joyous Exploration**	**0.21**	**[0.10,**	**0.32]**	**0.06**	**3.81**	**< .001**			
	Bonus	Intelligence	-0.02	[-0.14,	0.10]	0.06	-0.25	.800			
	RO	Joyous Exploration	0.10	[-0.01,	0.20]	0.05	1.83	.067			
	RO	Intelligence	0.02	[-0.09,	0.12]	0.05	0.30	.764			
	Char	**Joyous Exploration**	**0.25**	**[0.17,**	**0.34]**	**0.05**	**5.62**	**< .001**			
	Char	Intelligence	-0.07	[-0.19,	0.04]	0.06	-1.26	.207			

9. Deprivation Sensitivity	**Trivia**	**Deprivation**	**0.24**	**[0.12,**	**0.35]**	**0.06**	**4.08**	**< .001**	.98	.03 [.02, .03]	.04
	Bonus	**Deprivation**	**0.24**	**[0.14,**	**0.34]**	**0.05**	**4.56**	**< .001**			
	RO	**Deprivation**	**0.18**	**[0.07,**	**0.28]**	**0.05**	**3.38**	**.001**			
	Char	**Deprivation**	**0.14**	**[0.04,**	**0.24]**	**0.05**	**2.82**	**.005**			
10. Neuroticism	Trivia	Neuroticism	0.10	[-0.01,	0.20]	0.05	1.82	.068	.91	.04 [.04, .05]	.05
	Bonus	Neuroticism	-0.04	[-0.14,	0.07]	0.05	-0.71	.479			
	RO	Neuroticism	0.01	[-0.09,	0.11]	0.05	0.26	.796			
	Char	**Neuroticism**	**-0.12**	**[-0.21,**	**-0.03]**	**0.05**	**-2.50**	**.013**			
11. Uncertainty Intolerance	Trivia	Uncertainty Intolerance	0.08	[-0.03,	0.19]	0.06	1.49	.136	.95	.03 [.03, .04]	.05
	Bonus	Uncertainty Intolerance	0.09	[-0.02,	0.20]	0.06	1.56	.119			
	RO	Uncertainty Intolerance	0.07	[-0.03,	0.18]	0.05	1.39	.164			
	Char	Uncertainty Intolerance	-0.09	[-0.20,	0.02]	0.06	-1.58	.114			

Note. For mediation models, state curiosity was computed from trials in the relevant stimulus set (Bonus and Trivia = curiosity in the Trivia game; RO = curiosity for the Reward-Outcome stimuli; Char = curiosity for the Character stimuli).

As we proposed that openness/intellect predicts seeking information partially because these individuals tend to feel greater instances of state curiosity, we hypothesized that the relation between openness/intellect and information seeking would be statistically mediated by state curiosity for the Trivia, Bonus, and Character stimuli. Table 3, Models 3-6 present formal latent mediation models testing the indirect effect of openness/intellect on information within each stimulus set. For Trivia, Bonus, and Character stimuli, openness/intellect was no longer a direct predictor of information seeking when accounting for state curiosity. However, openness/intellect significantly predicted state curiosity, and state curiosity was a strong and significant predictor of information-seeking choices. Further, a significant indirect effect of openness/intellect on information seeking via state curiosity was observed, suggesting a full mediation, consistent with our theory. Conversely, for Reward-Outcome stimuli (Model 6), only reported curiosity was a predictor of information preference; no significant indirect or total effect was observed, and openness/intellect did not significantly predict state curiosity. This aligns with findings that openness/intellect significantly correlated with state curiosity for the Trivia/Bonus stimuli ($r = .20$, $p < .001$) and Character stimuli ($r = .19$, $p < .001$), but not the Reward-Outcome stimuli ($r = .06$, $p = .248$).

The second half of our predictions grouped under Hypothesis 1 concerned effects related to neuroticism and uncertainty intolerance. We hypothesized that these traits would positively predict seeking information for Reward-Outcome stimuli. However, neither neuroticism nor uncertainty intolerance significantly predicted seeking information, and Bayes Factors indicated evidence for the null (neuroticism $BF_{01} = 10.10$; uncertainty intolerance $BF_{01} = 3.96$). Second, we hypothesized that neuroticism and uncertainty intolerance would not positively predict seeking information for the remaining three stimulus sets. These predictions were mostly supported. No significant positive effects were observed (Table 3, Models 10 and 11). For neuroticism, Bayes Factors found substantial evidence for the null for the Bonus stimuli ($BF_{01} = 8.13$), and anecdotal evidence for the null for the Trivia stimuli ($BF_{01} = 1.98$). While there was anecdotal evidence for the alternative hypothesis for the Character stimuli ($BF_{01} = 0.46$), this reflected the finding that neuroticism *negatively* predicted seeking information for this stimulus set. For uncertainty intolerance, Bayes Factors found evidence in support of a null for the Bonus ($M_{01} = 3.09$), Trivia ($M_{01} = 3.44$), and Character ($M_{01} = 2.99$) stimuli.[9]

[9] As shown in the correlation matrix of Figure 4, the only personality correlate of seeking Reward-Outcome information was conscientiousness ($r = .17$). Although we had not predicted this outcome, it converges with prior research that the *orderliness* aspect of conscientiousness, when combined with other indicators of

Hypothesis 2. Our conceptual model specifies that information-seeking preferences should differ depending on how three key elements of the situation—positivity, negativity, and intellect—are perceived, which should, in turn, relate to the degree to which state emotions of joyous exploration, deprivation sensitivity, and uncertainty intolerance/anxiety and subsequent post-information emotions are transiently evoked. Consequently, we hypothesized that the different information-seeking stimulus sets would produce different situation and state emotion ratings by participants on average.

Figure 5 displays box plots for pre-information state ratings, post-information state ratings, and situation ratings across the different tasks. Repeated-measures ANOVAs found significant differences in all three ratings (Figure 5). Breaking down ratings by stimulus set, Bonferroni-adjusted Wilcoxon tests for mean differences are visualized in Figure 5. A summary of which hypotheses were (or were not) supported is included in Figure 5, Panel D. Supplementary Table 1 includes exact *p*-values for each comparison.

In line with our predictions, the Reward-Outcome stimuli were perceived to be more negative than both the Trivia[10] ($p = .002$) and Character ($p < .001$) stimuli. Similarly, the Reward-Outcome stimuli was perceived as less intellectually engaging than the Trivia and Character stimuli, both for the mean Intellect situation rating (Trivia $p < .001$; Character $p < .001$) and the adapted item from the Intellect sub-scale *the task provided an opportunity to learn about unusual ideas or points of view* (Trivia $p < .001$; Character $p < .001$). Further, participants reported higher pOsitivity ($p < .001$) and higher ratings of state curiosity for the Trivia stimuli compared to the Reward-Outcome stimuli. Further, for both Trivia and Bonus stimuli, participants reported higher post-information ratings of interest, amazement, and surprise than for the Reward-Outcome stimuli (*p*s all < .001). This suggests that these stimulus sets evoke greater positive emotions, consistent with the possibility that they afford more instances of state joyous exploration, leading to exploration-oriented information seeking.

We expected that the Character stimuli would be rated similarly positively to the Trivia and Bonus stimuli. However, against predictions, situation ratings of pOsitivity for the Character stimuli were the lowest of all tasks (*p*s <.001) and this pattern continued for the Character stimuli across the pre-information and post-information state ratings: although the

obsessive-compulsive tendencies, predicts seeking information for this form of information (Bennett et al., 2020). However, given that this finding was unpredicted and was not replicated in Study 2, we do not consider this result further.

[10] For the trivia task, situation ratings referred to the whole task (Trivia and Bonus stimulus sets), so results should be considered to reflect attitudes toward both of these.

Character stimuli produced low mean ratings of *bothered, need,* and *relief*—which we proposed signified aversive and deprivation-oriented responses to the unknown or, for relief, quiescence from having this uncertainty removed—it also produced the lowest mean ratings of putatively more positively-oriented emotions of curiosity, interest, pleasure, amazement, and surprise. Thus, it appeared that on average, participants felt little negativity or positivity toward the Character stimuli. This aligned with the optional feedback we obtained at the completion of each game: 32 participants reported boredom and related low positive emotions toward these stimuli (e.g., "Having absolutely no knowledge about Chinese characters the game was boring and not engaging"), compared to only six indicating higher positive emotions (e.g., "Interesting character choices - fun trying to guess what the words might be"). This lack of interest may provide an explanation why few participants sought information for these stimuli (Figure 3, Panel A).

Despite the average absence of positive feelings toward the Character stimuli, joyous exploration (and openness/intellect) predicted seeking information. Notably, pOsitivity ratings for the Character stimuli correlated with joyous exploration ($r = .21$, $p < .001$) and openness/intellect ($r = .17$, $p = .001$), and so too did ratings of state curiosity for the Character stimuli (joyous exploration $r = .31$, $p < .001$; openness/intellect $r = .19$, $p < .001$). Thus, it seems that even though mean positive emotion ratings were low for the Character stimuli, participants higher in curiosity and openness/intellect tended to construe these stimuli as more engaging, which may have flow-on effects to decisions to seek information. This is important because our theoretical model specifies that it is necessary for a situation to be perceived as having both Intellect and pOsitivity to evoke states of joyous exploration and exploration-oriented information seeking.

As predicted, reports of relief for the Reward-Outcome stimuli were higher than for the Trivia, Bonus, or Character stimuli (ps < .001). However, we predicted that the Reward-Outcome stimuli would have the lowest pleasure rating, but there was no significant difference between ratings for the Reward-Outcome stimuli and Trivia stimuli ($p > .999$), and pleasure ratings for the Character and Bonus stimuli were significantly lower than these (ps < .001). Finally, unlike the Character stimuli and against expectations, there were no significant differences in mean ratings of needing the information or being bothered by the lack of information for the Trivia stimuli compared to the Reward-Outcome stimuli (Figure 5, Panel B).

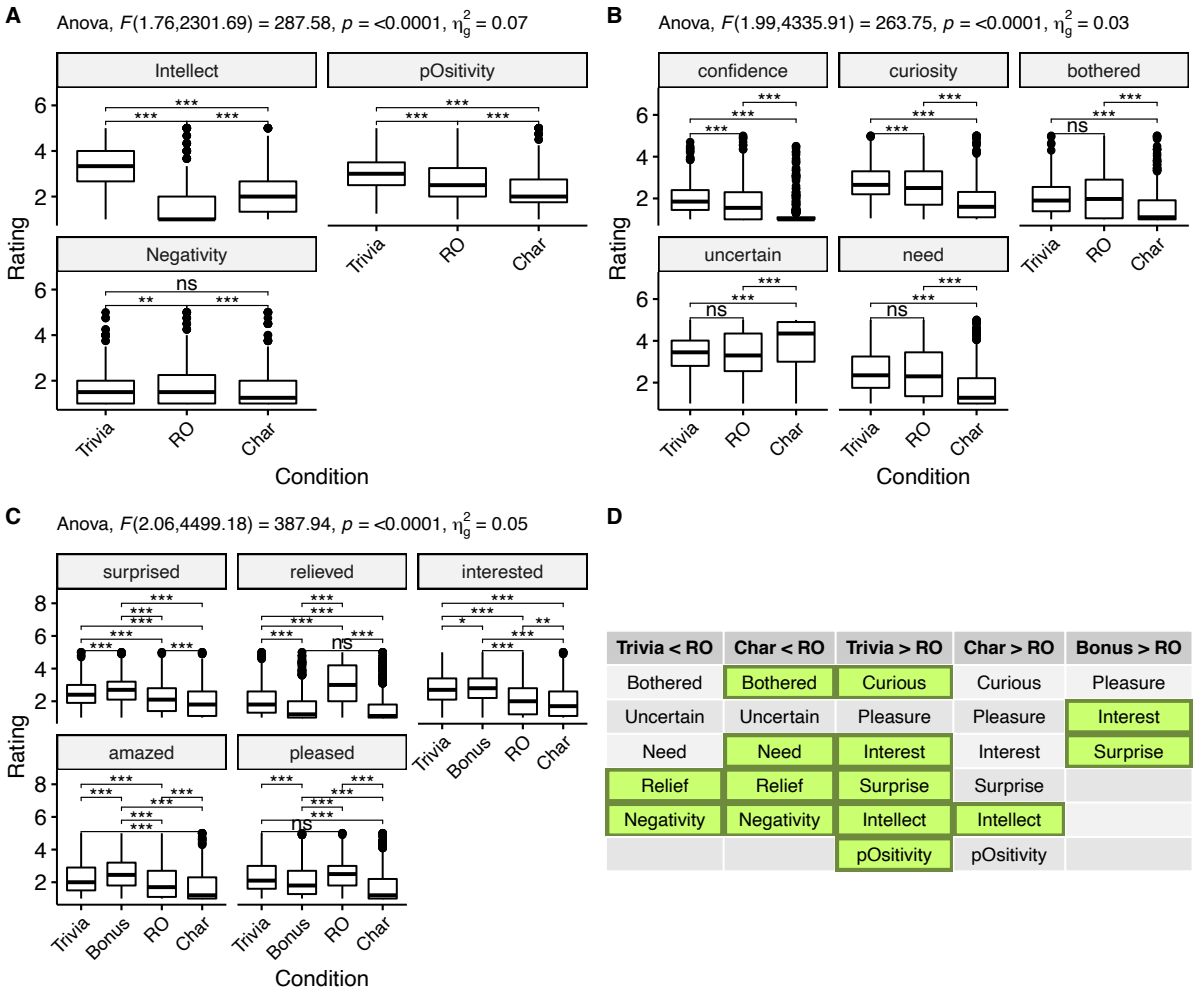

Figure 5. Tests of Hypothesis 2. *A*. Mean situation ratings. B. Mean pre-information ratings. *C*. Mean post-information ratings. *D.* Summary of which predictions from Hypothesis 2 that were supported (green highlight and box outline) or not supported (no emphasis) by results depicted in panels A, B, and C.

Study 1 Discussion

Study 1 assessed non-instrumental information-seeking preference, momentary emotions, and situation perception across four sets of stimuli. We found that preferences differed markedly across stimulus sets, both in proportion of choice responses and mean ratings over time (Figure 3). Further, participants rated their perceptions of and emotions toward the stimulus sets differently despite all including a choice for non-instrumental information. This suggests that these stimulus sets, each representing different situations, contain differing affordances and emotional responses that could partially drive differences in information seeking.

In this study, we tested predictions from our working model of information seeking, which featured two key motivations to seek information. The *exploration pathway* is more likely to be chosen by individuals higher in curiosity and openness/intellect and in situations evoking positive emotions and opportunities for intellectual engagement. The *safety* pathway is more likely to be chosen by individuals higher in uncertainty intolerance and neuroticism and in situations evoking more negative emotions. Several broad hypotheses were specified to test key elements of this model. Hypothesis 1 stated that personality traits (openness/intellect, neuroticism, curiosity, and uncertainty intolerance) would predict information-seeking preferences depending on the particular situation, and Hypothesis 2 stated that the information-seeking situations would be rated differently be participants on average.

Our results were supportive of an exploration pathway. For Hypothesis 1, openness/intellect and joyous exploration predicted choice preference for the Trivia, Bonus, and Character stimuli, but not the Reward-Outcome stimuli, whereas deprivation sensitivity predicted choice preference for all stimulus sets. These results held controlling for intelligence. Further, state curiosity was a statistical mediator in the relation between openness/intellect and information seeking, consistent with the possibility that individuals higher in openness/intellect tend to seek information due to feeling stronger instances of momentary curiosity. Note that, like all other results presented herein, the mediation analyses are conducted on cross-sectional data and don't provide direct causal evidence. Further, given the high intercorrelations between state curiosity and other state measures putatively assessing different emotions, this result should be considered highly tentative until the state measures can be adequately disentangled.

For Hypothesis 2, we found that situation perceptions of positivity were higher for the Trivia than Reward-Outcome stimuli, and that, although the Character stimuli produced the lowest positivity ratings, individual differences in these ratings were associated with trait measures of joyous exploration and openness/intellect, in line with predictions from our model. Further, ratings of intellect were higher for the Trivia and Character than the Reward-Outcome stimuli. Findings related to state emotions were more variable and may reflect the failure to disentangle these constructs (see Supplementary Materials for more information).

For the safety pathway, results for situation perception were in the predicted direction: the Reward-Outcome stimuli were rated as lower in intellect and higher in negativity than other stimulus sets. This supports the idea that situations in which non-instrumental information is provided in advance of reward are perceived to evoke more negative emotions,

and provide fewer possibilities for intellectual engagement, than tasks where the non-instrumental information is not linked to a reward but instead provides knowledge about the world more generally. Unexpectedly, however, neuroticism and uncertainty intolerance did not predict information seeking for the Reward-Outcome stimuli. Thus, we failed to find support for key predictions within Hypothesis 1 related to the safety pathway.

Given the prevalence of the uncertainty-reduction explanation of information seeking in the literature, and previous studies relating uncertainty intolerance or neuroticism to information seeking (Bennett et al., 2020; Jach & Smillie, 2021), we considered whether elements of our experimental design could provide an alternative explanation for these results. One possibility is related to the number of trials before participants are given the choice to seek information. In the experimental design of Study 1, participants first completed 10 trials in which they were automatically shown all information without a choice. Following these no-choice trials, they completed 10 trials where they had a choice to seek information. Participants were told at the beginning of the reward-outcome paradigm that the coin flip provided a 50% chance of a reward on all trials. Thus, in an economic sense, there is no change in ambiguity throughout the task; only an unambiguous risk of 50% (Trautmann & van de Kuilen, 2015). However, there is a difference between being told this in the experiment instructions and physically observing it for oneself. Participants may be suspicious about the researcher's intentions and any possibility of deception; they may question whether a 50% chance of success is truthful. Thus, the payout structure of earlier trials may be perceived as more ambiguous even if it technically is not. For participants who are more intolerant of uncertainty, the higher perceived ambiguity in earlier trials may influence their decisions, whereas on later trials, having learnt through experience that a 50% chance of reward is accurate, there is no longer any ambiguity in their choice.

If this explanation holds, then we might expect that the relation between uncertainty intolerance and state reports of uncertainty to decline over time. Indeed, a multilevel model found support for this prediction, revealing a negative interaction between time and uncertainty intolerance when predicting state uncertainty ratings (b = -0.005, t(8,282) = -2.34, p = .020). This suggests it could be useful to assess personality correlates of Reward-Outcome information-seeking without first presenting the 10 no-choice trials. We therefore added such a version of this task to a separate ongoing project including many of the same measures in this study. This allowed us to explore whether uncertainty intolerance predicts information seeking for the shortened Reward-Outcome stimulus set, as well as divergent validity with information-seeking preference for the Trivia stimulus set.

Study 2

Method

Participants, Procedure, and Materials

Ethical approval was provided by The University of Melbourne Human Ethics Advisory Group (ID 2056503.2). Three hundred and eighty-six undergraduate students at an Australian university participated in this study for course credit. Participants were excluded for the same reasons as pre-registered for Experiment 1, except (1) timing for the BFAS questionnaire could not be assessed as it was not recorded, and (2) participants reported their age via their birth year and age range (e.g., "*19-24*") rather than their birth year and age in years, so we used a discrepancy between these responses to assess this criterion. Following exclusions, a final sample of $n = 316$ was obtained ($mean_{age} = 20.04$, $SD_{age} = 3.25$, 75% female, 24% male, 1% other).

Participants first completed the latter 10 trials of the Reward-Outcome stimulus set (i.e., only the trials wherein participants could choose to seek information). Because undergraduates participated for course credit, we were limited in possible monetary incentives, and so our reward-outcome information was knowledge of whether the participant had won an entry into a raffle to be drawn at the end of the academic term. All other elements were identical to Study 1.

Participants next completed the Trivia paradigm. This version differed slightly from Study 1: it included 25 questions, the final 5 of which allowed participants the choice to seek information. Questions were again drawn from an existing database (Fastrich et al., 2018), with questions overlapping partially from those included earlier in the manuscript. Due to time constraints and the focus on the Reward-Outcome stimulus set, we did not include the Character or Bonus stimuli.

Finally, participants completed DIAMONDS situation perception ratings (pOsitivity, Negativity, Intellect, Duty) in response to the Reward-Outcome stimulus set, and personality trait measures assessed in Study 1 (Big 5, curiosity, and uncertainty intolerance). Several additional measures were included for different research projects and were not analyzed for the current study (see Ryakhovskaya, Jach, & Smillie, Under Review, for further details).

Data Analysis

Study 2 was not pre-registered as it followed up unexpected findings from Study 1. However, we aimed to be as consistent with Study 1 as possible, and data were analyzed with the same methods, using the same packages, performed once again in *R* Version 4.0.1 (R Core Team, 2020).

Results and Discussion

Table 4 shows descriptive statistics for variables of interest. Most variables, including information seeking for the Trivia and Reward-Outcome stimuli, demonstrated adequate reliability. Other descriptive statistics were also on par with what was observed in Study 1.

Table 4

Descriptive Statistics and Internal Consistencies for Study 2 Variables

Variable	ω	*α*	*M*	*SD*	Min	Max	Skew	Kurtosis
Info Seeking (Trivia)	.78	.77	0.59	0.34	0	1	-0.24	-1.17
Info Seeking (RO)	.90	.91	0.50	0.37	0	1	0.10	-1.49
Openness/Intellect	.57	.79	3.59	0.50	2.35	5	0.24	-0.13
Neuroticism	.76	.90	3.14	0.64	1	4.7	-0.05	-0.12
Extraversion	.67	.88	3.35	0.57	1.4	4.85	-0.04	0.39
Conscientiousness	.57	.83	3.18	0.52	1.8	4.65	-0.04	-0.12
Agreeableness	.72	.87	3.91	0.51	2.3	5	-0.26	-0.41
Uncertainty Intolerance	.84	.86	3.08	0.67	1.25	4.75	-0.16	-0.15
Joyous Exploration	.83	.83	3.83	0.63	2.12	5	-0.19	-0.42
Deprivation Sensitivity	.78	.85	3.40	0.75	1	5	-0.15	-0.03
pOsitivity RO	.73	-.61	2.85	0.73	1	5	0.34	0.13
Negativity RO	.86	.86	1.73	0.78	1	5	1.18	0.91
Intellect RO	.81	.81	1.74	0.80	1	4.33	1.08	0.45

Note. Omega reliability values (ω) are calculated in an identical fashion to Study 1.

Figure 6, Panels A and B display proportion of information seeking and average choice preference over time, respectively. Similar to Study 1, the distribution of Reward-Outcome information preference was approximately bimodal; however, there appeared to be more variability in choice preference, and in Study 2 more participants chose to seek information than not seek information. Meanwhile, Panel B shows that information preferences for the Reward-Outcome stimuli dropped sharply over time, and statistical evidence supported the visual trend, with a multilevel model predicting Reward-Outcome information seeking by trial; $b = -0.04$, $t(2,843) = -16.96$, $p < .001$.

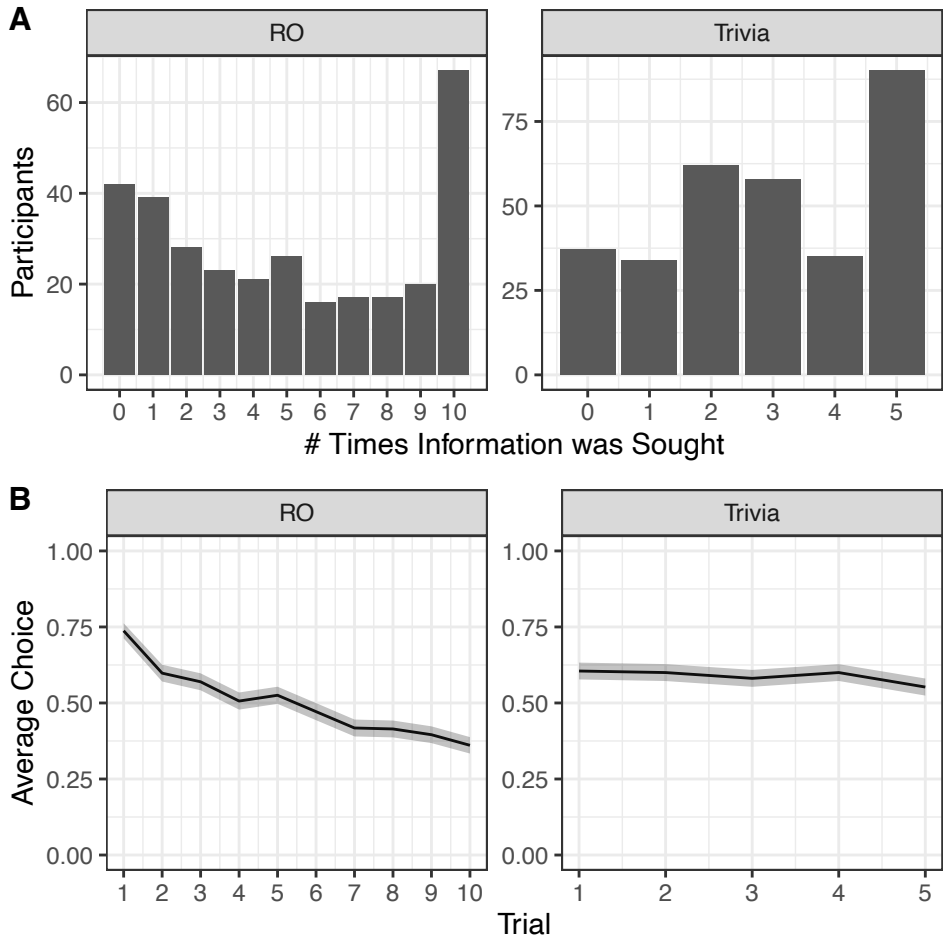

Figure 6. Information choice preference correlations for Experiment 2. (A) Number of participants who chose information. (B) Mean choice preference for information across trials. The ribbon surrounding each mean depicts the standard error of the mean.

Figure 7 displays correlations between variables of interest. Consistent with Study 1, openness/intellect and joyous exploration correlated significantly with seeking information for the Trivia stimuli but not the Reward-Outcome stimuli, whereas deprivation sensitivity correlated positively with seeking information in both stimulus sets. Further, uncertainty intolerance did not significantly correlate with Trivia information seeking. Neuroticism did not significantly correlate with Reward-Outcome information seeking, and though the correlation between uncertainty intolerance and Reward-Outcome information seeking was $r = .10$, this was also statistically non-significant ($p = .081$).

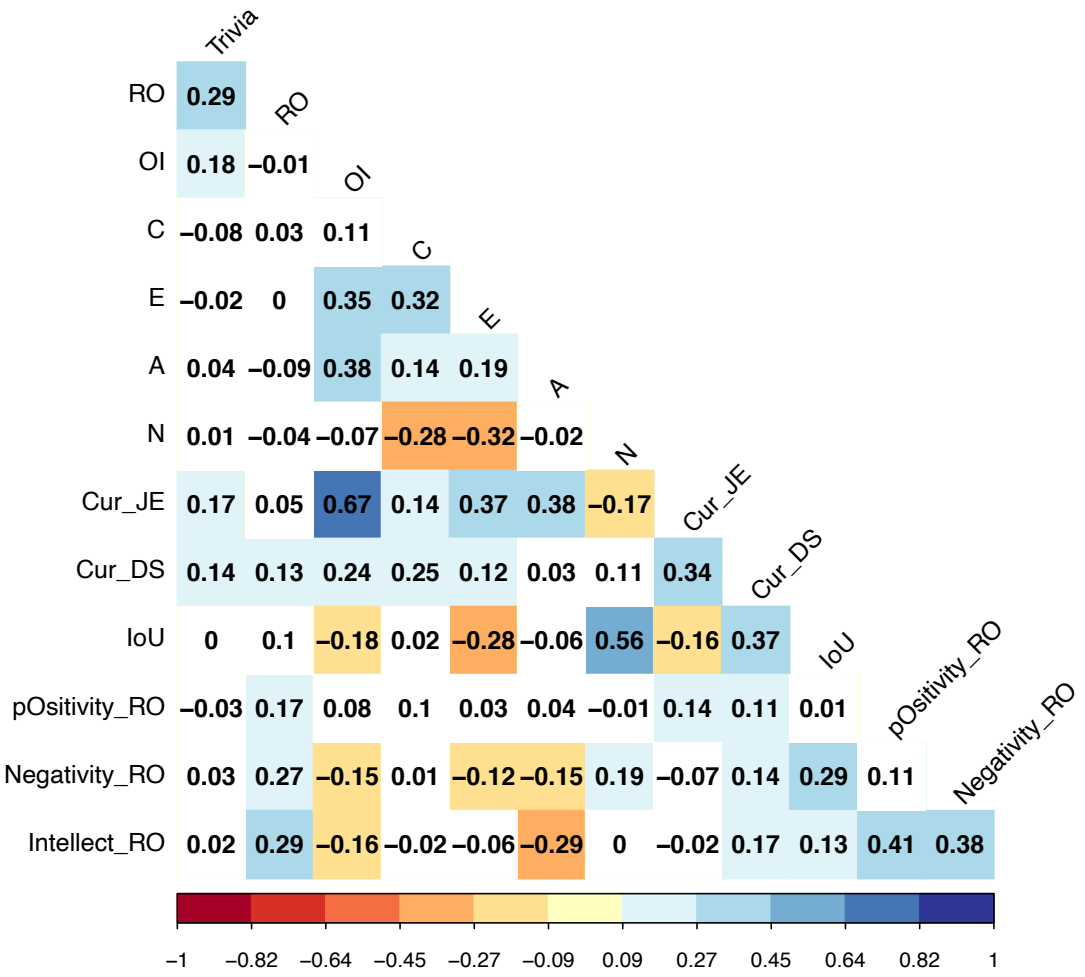

Figure 7. Zero-order correlation matrix of information-seeking for the Trivia and Reward-Outcome stimulus sets, personality traits, and situation ratings (for the Reward-Outcome stimuli only). Unshaded correlations are statistically non-significant.

Table 5 displays latent variable regressions predicting information seeking for the Trivia and Reward-Outcome stimuli. Joyous exploration and openness/intellect significantly predicted information seeking for the Trivia stimuli but not the Reward-Outcome stimuli, and Bayes Factors found converging evidence predicting the null for Reward-Outcome information seeking (joyous exploration, BF_{01} = 14.80; openness/intellect, BF_{01} = 17.38). Meanwhile, deprivation sensitivity significantly predicted information seeking for both stimulus sets. These results replicated Study 1 and support the proposed exploration pathway.

Concerning evidence for the safety pathway, in support of our hypotheses, uncertainty intolerance significantly predicted Reward-Outcome information seeking, and uncertainty intolerance and neuroticism did not significantly predict Trivia information seeking (and Bayes Factors found substantial evidence for the null predicting Trivia information seeking: uncertainty intolerance BF_{01} = 12.38; neuroticism BF_{01} = 11.97). Further, when considering uncertainty intolerance and joyous exploration jointly (Table 5, Model 5), joyous exploration predicted Trivia information seeking but not Reward-Outcome information seeking (BF_{01} = 5.10), and uncertainty intolerance predicted Reward-Outcome information seeking but not Trivia information seeking (BF_{01} = 7.13). Thus, after altering the Reward-Outcome task presented in our Study 1 by removing the first 10 no-choice trials, results do partially support our proposed safety pathway. However, contrary to our hypotheses, neuroticism did not significantly predict information seeking for the Reward-Outcome stimuli (Table 5, Model 5; BF_{01} = 10.22). Further, for uncertainty intolerance, Bayes Factors found weak and mixed evidence in predicting information seeking for Reward-Outcome stimuli: as a univariate predictor (Model 4) there was indeterminate evidence in support for the null despite a significant regression coefficient (BF_{01} = 1.43), and as a multivariate predictor (Model 6) there was indeterminate evidence in support of the alternative (BF_{01} = 0.66). Given only partial support across the set of hypotheses related to the safety pathway, we consider evidence for this pathway tentative but inconclusive, in contrast to the exploration pathway, where results were consistently in support of our hypotheses across both studies.

Table 5.
Latent Variable Regression Models for Study 2

			Parameter Estimates						*Fit Indices*		
model	Outcome	Predictor	*β*	95% CI		*SE*	*Z*	*p*	*CFI*	*RMSEA [95% CI]*	*SRMR*
1. Openness/ Intellect	RO	Openness/Intellect	-0.01	[-0.14,	0.12]	0.06	-0.14	.888	.73	.07 [.07, .08]	.09
	Trivia	**Openness/Intellect**	**0.24**	**[0.10,**	**0.37]**	**0.07**	**3.49**	**< .001**			
2. Joyous Exploration	RO	Joyous Exploration	0.04	[-0.09,	0.17]	0.07	0.58	.559	.97	.03 [.02, .04]	.05
	Trivia	**Joyous Exploration**	**0.23**	**[0.10,**	**0.37]**	**0.07**	**3.43**	**.001**			
3. Deprivation Sensitivity	**RO**	**Deprivation Sensitivity**	**0.14**	**[0.01,**	**0.27]**	**0.07**	**2.17**	**.030**	.98	.03 [.003, .04]	.04
	Trivia	**Deprivation Sensitivity**	**0.16**	**[0.01,**	**0.30]**	**0.07**	**2.16**	**.031**			
4. Uncertainty Intolerance	**RO**	**Uncertainty Intolerance**	**0.13**	**[0.01,**	**0.25]**	**0.06**	**2.08**	**.038**	.96	.03 [.02, .04]	.05
	Trivia	Uncertainty Intolerance	-0.01	[-0.14,	0.13]	0.07	-0.07	.940			
5. Neuroticism	RO	Neuroticism	-0.04	[-0.17,	0.09]	0.06	-0.62	.534	.88	.05 [.05, .06]	.06
	Trivia	Neuroticism	0.02	[-0.11,	0.15]	0.07	0.27	.788			
6. Joyous Exploration and Uncertainty Intolerance	**RO**	**Uncertainty Intolerance**	**0.14**	**[0.02,**	**0.27]**	**0.06**	**2.28**	**.023**	.93	.04 [.03, .05]	.06
	RO	Joyous Exploration	0.07	[-0.06,	0.20]	0.07	1.04	.297			
	Trivia	Uncertainty Intolerance	0.05	[-0.09,	0.19]	0.07	0.64	.519			
	Trivia	**Joyous Exploration**	**0.24**	**[0.10,**	**0.38]**	**0.07**	**3.42**	**.001**			

General Discussion

Despite nearly a century of theory and research suggesting that behavior is a function of both the person and the situation (Furr & Funder, 2021; Horstmann et al., 2020; Lewin, 1936; Sherman et al., 2015), researchers have rarely considered how person and situation factors may jointly drive variation in information seeking. In the current studies we sought to address this oversight by relating choice preference to personality traits across multiple information-seeking paradigms capturing different situational affordances. We were guided by a novel conceptual model of information seeking that includes different situation and person elements, and specifies two information-seeking pathways, one concerned with exploration and the other concerned with safety. Across two studies we found consistent support for the exploration pathway, and more tentative support for the safety pathway.

Results and Evidence for our Conceptual Model

Our first aim in this research was to assess whether information seeking varied across different experimental paradigms. We thus employed two predominant paradigms from the literature: a *Reward-Outcome* paradigm where participants could gain advance knowledge of a financial reward and a *Trivia* paradigm where information provided knowledge about the world but had no connection to an external reward. Further, we included two additional variations on the Trivia paradigm (Bonus and Character stimulus sets) that helped to rule out counter-explanations for choice preference. Across two experiments, we observed distinct information-seeking distributions between the stimulus sets (see Figures 3 and 6). Further, participants rated their emotions and perceptions of the situations differently across stimulus sets (Figure 5). Thus, despite both purportedly measuring non-instrumental information seeking, participants thought and acted differently in these different paradigms.

Our second aim in these studies was to evaluate our conceptual model that synthesized literature describing the interactions between personality and situation perception (Funder, 2006; Furr & Funder, 2021; Rauthmann et al., 2015) with information-seeking theory and research (Bennett et al., 2016b; Bromberg-Martin & Hikosaka, 2009; Lau et al., 2020; Sharot & Sunstein, 2020a). Our theory specified two main pathways to seeking information. The *exploration* pathway is evoked in situations that afford positivity and intellectual engagement and when people feel stronger and/or more frequent states of interest-based curiosity; this is more likely to be experienced by people higher in trait curiosity and openness/intellect. Conversely, the *safety*

pathway is evoked in situations that afford greater negativity and when people feel stronger and/or more frequent states of anxiety related to uncertainty; this is more likely to be experienced by people higher in trait uncertainty intolerance, neuroticism, and curiosity as a feeling of deprivation (Figure 1). Following the principles of this theory, we derived specific pre-registered hypotheses to test initial support (Table 1).

In line with our predictions, information from the Trivia, Bonus, and Character stimulus sets was chosen more often by individuals higher in trait curiosity and openness/intellect, even when controlling for intelligence, and these stimuli were perceived as more intellectually engaging, less negative, and (barring the Character stimuli) more positive than the Reward-Outcome stimuli. Further, in these stimulus sets, momentary reported curiosity correlated with trait curiosity, openness/intellect, and pOsitivity/Intellect ratings; and the joyous exploration facet of trait curiosity related to greater pleasure and interest ratings after receiving information (Supplementary Materials, Section 3). Study 2 replicated personality-information seeking results in an independent sample. Thus, we found evidence consistent with an exploration pathway connected to curiosity across both studies.

In contrast, evidence for the safety pathway was mixed. In Study 1, as predicted, the Reward-Outcome stimuli were rated as more negative and less positive and intellectually engaging than the Trivia stimuli, and deprivation sensitivity successfully predicted Reward-Outcome information seeking. Unexpectedly, however, uncertainty intolerance and neuroticism did not significantly predict the choice to seek Reward-Outcome information. In Study 2 we removed the first 10 no-choice trials as we thought these could have reduced general task ambiguity; we then observed that uncertainty intolerance emerged as a significant predictor of Reward-Outcome information seeking, and deprivation sensitivity remained a predictor. However, neuroticism failed to predict information seeking for the Reward-Outcome stimuli, and Bayes Factors suggested that evidence for uncertainty intolerance predicting information seeking for the Reward-Outcome stimuli was inconclusive.

In summary, results partly support our working model but also suggest further refinements are necessary. Nevertheless, our findings clearly confirm our broad claim that non-instrumental information-seeking paradigms can be perceived differently and that preferences for information are different in different tasks and correlate with different personality traits. Thus,

the model's general principles of the importance of person and situation factors in eliciting motivated behavior were borne out in our empirical results.

Implications for the Safety Pathway

We found tentative and inconsistent evidence for the safety pathway across experiments. This could suggest that uncertainty reduction—or, at least, anxiety-related uncertainty reduction—is not as strong a motivator for reward-outcome information seeking as has been previously proposed in the literature. Indeed, the few studies that have included uncertainty intolerance alongside information-seeking paradigms also found mixed evidence: for example, Bennett et al. (2020) found an effect that fell short of significance after correcting for multiple comparisons, and Jach and Smillie (2021) found a significant correlation in Study 2, but not Study 1. If correct, this would necessitate altering or removing the safety pathway from our conceptual model.

However, it is perhaps more likely that we simply did not create the optimal context to elicit anxiety related to uncertainty. For example, in most reward-outcome experiments, participants passively wait for information to be revealed (e.g., Bennett et al., 2020), whereas in the current studies participants guessed an answer before making a choice to seek information. In this context, participants may have felt greater perceived agency and been more invested in learning the result as soon as possible to find out whether they chose correctly and "won" the trial, leading this motivation to trump others such as uncertainty-reduction. Intriguingly, a large proportion of participants always chose to see reward-outcome information (Figure 3; Figure 6), even though this preference was only weakly related to uncertainty intolerance and did not appear to relate to the exploration pathway. This suggests additional motivations could have predicted choice preference. One possibility is the desire to "savor" a good result, which has been proposed to motivate choices in some prior literature (Bromberg-Martin & Monosov, 2020; Charpentier et al., 2018; Iigaya et al., 2016; Kobayashi et al., 2019). We observed that reported pleasure was higher for Reward-Outcome and Trivia stimuli than for Bonus and Character stimuli. As Reward-Outcome and Trivia stimuli are the only ones that permit participants to make guesses and then discover whether they were correct, this provides tentative support for savoring as a motivator of reward-outcome information seeking, and perhaps an additional motivator of Trivia information seeking, and could suggest a need to expand the conceptual model to incorporate savoring as an alternative motivator. To reduce perceived agency that

could be increasing savoring motives at the expense of uncertainty reduction motives, guesses prior to information-seeking choice should be removed.

Further, compared to states of interest proposed to drive the exploration pathway, uncertainty about one's sense of safety may be difficult to elicit in an experiment, where potential threats to safety are far weaker than in the wider world. For example, as this manuscript is being written in 2021, one salient real-world threat is the COVID-19 virus, where uncertainties include whether oneself or one's family will be affected, when a vaccine will be widely distributed, and when life will return to normal. This threat is orders of magnitude more serious than what is found in experiments, which may only include the threat of losing some small amount of money. This suggests the utility of more ecologically valid future study designs, where researchers could assess signs of anxiety-related information seeking via, for example, compulsive news checking. Alternatively, increasing the potential monetary loss per trial may make any threats to their monetary status more salient to participants.

Finally, we proposed that any sort of threat, including social threats, could drive information seeking to reduce uncertainty. Social threats can be readily assessed in experiments (e.g., through the Trier Social Stress Test or variations thereof; Allen et al., 2017) without raising significant ethical concerns and without a large financial costs. For example, if participants believe that their choices will be rated by a panel of other participants, they may wish to pay to know these ratings in advance even if they have no utility for the task.

Taken together, the tentative but inconsistent evidence across multiple studies, coupled with possible suggestions for why effects may not have emerged consistently, suggests that it is too early to say whether the safety pathway should be altered or removed from our conceptual model, and more broadly, whether the uncertainty-reduction explanation for information seeking is supported. Future studies should tackle this uncertainty with targeted attempts to address the issues as summarized above.

Multi-Disciplinary Implications of Results

Information Seeking Theory and Research

Our results indicate that information-seeking paradigms cannot be freely mixed and matched and expected to elicit the same motivations for behavior. Perhaps most striking is the reduction in exploration-oriented emotions and personality traits when employing reward-outcome paradigms. We suggested that this may occur in contexts that signal possible threats to

individual safety, which includes possible loss of financial gain. Further, this is in line with similar research that finds rewards undermine intrinsic motivation (Murayama et al., 2010). This outcome has implications for researchers advocating an uncertainty-reduction explanation for information seeking, who often assess information seeking with reward-outcome experiments, or devise computational models that simulate reward-outcome experiments or include extrinsic rewards in model equations (Bennett et al., 2016b, 2020; Caplin & Leahy, 2001b; Eliaz & Schotter, 2010b; Wu, 1999). Such studies may simply be unlikely to elicit cognitive, emotional, or motivational affordances related to exploration, leading important pieces in the information-seeking puzzle to remain unnoticed. Thus, although consistency of experimental design is important when building cumulatively from prior research, the current research demonstrates how it is important to be wary of overgeneralizing results from a particular experiment to all instances of a given behavior. Our results suggest that it is possible to gain some insight into generalizability with the use of multiple experimental paradigms coupled with situation perception or personality measures.

Curiosity Research

An information gap is defined as a specific question that one becomes aware of and recognizes that one does not know the answer to; it reflects a known lack of knowledge of a specific quantity (Golman & Loewenstein, 2018). Some theories of curiosity propose that it is necessary to specify an information gap before the feeling of deprivation-oriented curiosity is evoked (Golman & Loewenstein, 2018; Loewenstein, 1994). However, information seeking choices in the present studies were correlated with deprivation sensitivity for the Bonus and Character stimulus sets, neither of which contained a quantifiable information gap. This suggests that deprivation-oriented curiosity may not require an information gap.

Additionally, the fact that deprivation sensitivity was correlated positively both with joyous exploration (representing the exploration pathway) and uncertainty intolerance (representing the safety pathway) supports our framing of deprivation sensitivity as an interstitial facet comprising both positive emotions (e.g., enjoying learning) and negative emotions (e.g., finding the feeling of not knowing aversive). Deprivation sensitivity has been traditionally thought to reflect dopamine-mediated desire for information, in contrast to joyous exploration, which is proposed to reflect opioid-mediated liking of information (Litman, 2005). However, to our knowledge this proposition has never been directly tested in humans, and a more

parsimonious explanation could be that both facets of curiosity involve dopaminergic and opioid activity (providing the motivation to explore and the rewarding feeling of gaining knowledge, respectively), but deprivation sensitivity is additionally accompanied by negative emotions that make the experience of seeking information somewhat unpleasant, even while it is desired. A suitable test could be a dopamine drug manipulation on one portion of the sample; this approach has been used successfully in prior research to test hypotheses relating dopamine to other personality traits (Mueller et al., 2014).

Theory of Openness/Intellect

Our results offer additional insight into a theory of the personality trait openness/intellect (DeYoung, 2013). This theory proposes that openness/intellect is grounded in greater sensitivity to the reward value of information, leading individuals higher in openness/intellect to explore and seek information. Until now openness/intellect has not been found to predict information seeking directly (Jach & Smillie, 2021; Smillie et al., 2021). However, most prior studies employed reward-outcome paradigms which, as we show here, do not appear to afford exploration-oriented information seeking. Our results suggest a link between the exploration pathway and openness/intellect via curiosity (particularly joyous exploration): specifically, openness/intellect is related to exploration-motivated information seeking, but not safety-motivated information seeking. This aligns with the perspective that people higher in openness/intellect feel that uncertainty is enticing, and see many possibilities from engaging with the unknown (DeYoung, 2013).

Issues of Causality and our Model

By varying the experimental context, we observed changes in situation perceptions, emotions, and information seeking. Thus, our findings provide some initial evidence of the broader causal impact of the situation on motivations to seek non-instrumental information. More specifically, we proposed a conceptual model to begin to understand precisely how person and situation factors may relate to information seeking (Figure 1). This included a suggested causal direction whereby personality traits modulate the perceived situation, situation perceptions lead to state emotions, state emotions lead to goals for exploration and/or safety, these goals spur information seeking, and receipt of information induces post-information emotions. From this model we derived several specific hypotheses, many of which were supported by study results. This provides evidence that is consistent with our model. However,

unlike evidence for our broad proposal, our studies cannot provide direct evidence for many of the specific directional paths described in our conceptual model, including proposed mediations (Bullock et al., 2010). Indeed, although we think our model is useful, like all models, it is likely to be wrong (Box, 1976). For example, there may be strong bidirectional and circular pathways between situation perceptions and emotions, whereby feeling a certain emotion (e.g., fear) makes it more likely to perceive the situation in certain ways (e.g., interpret someone's comment as aggressive), which may induce further negative emotions (Lewis, 2005). It may also be challenging to separate reported emotions from reported situation perceptions, given their substantial conceptual overlap (Horstmann et al., 2020; Horstmann & Ziegler, 2019). Furthermore, there are doubtless other important variables to add to the model, such as alternative motivations (e.g., savoring, discussed earlier) or different elements of the perceived situation or different emotions (described in the Limitations section following). Accordingly, we think of our model less as a rigid set of laws and more as a helpful tool to frame our initial hypotheses, to think more clearly about various possible causal pathways, and to guide future research.[11]

Limitations and Future Directions

Considerations of participant fatigue and budget limitations influenced the number of trials we could include in our paradigms: for example, Study 1 included 20 trials per stimulus set, 10 of which included a choice to seek information. Although reliability was high in each stimulus set, indicating consistent preferences over trials, longer experiments would provide more stable estimates of mean effects and changes over time. Further, the Trivia and Reward-Outcome stimulus sets varied across a number of dimensions, and these differences could provide alternative explanations for differences in choice preference. However, to account for the limitations in experimental control, we developed two variations of the Trivia paradigm—the Bonus and Character stimulus sets—the latter of which was embedded within the Coin-Flip game alongside the Reward-Outcome stimuli. This provides greater assurance that peripheral elements are not the central drivers of observed differences between stimulus sets. Despite this, future research would benefit from comparing a range of paradigms with only small changes between them and observing whether differences in emotions, perceptions, and personality trait correlates of information seeking emerge across paradigms.

[11] We thank an anonymous reviewer for bringing our attention to these issues of causality and our conceptual model.

It was difficult to gauge how well states of joyous exploration and anxiety related to information seeking because the items chosen to represent these states were intercorrelated to such an extent that independent effects could not be effectively disentangled. The post-information emotions were challenging to distinguish for the same reason, forestalling detailed investigation of how information was received across the stimulus sets. This suggests that words to describe state emotions may not have been chosen optimally, and/or participants may not be willing or able to make fine-grained distinctions between specific emotions. This has implications for the choice of emotion words in studies, especially when they are measured with single items. It also demonstrates the value of including trait measures, which have typically been through many stages of validation and can provide more fine-grained insight into the different motivators. In the future, investigations of emotions and information seeking should improve assessment of state emotions, perhaps by creating latent measures across several different emotion items. Doing so might allow for more targeted tests of different parts of our conceptual model. For example, a study could assess how the connections between pre-information emotions, information seeking, and post-information emotions shift over the course of an experiment, and how this may be moderated by personality traits. This would be particularly effective with an increased number of trials per stimulus set.

Study 1 and 2 were different in ways which could suggest alternative explanations for effects. In Study 1, the Trivia paradigm was completed before the Coin Flip paradigm, whereas in Study 2, the Coin Flip paradigm was completed before the Trivia paradigm. This could have induced unforeseen order effects that might partially account for differences in results. Some concern can be ameliorated by observing that in Study 1, patterns of effects for the Trivia and Bonus stimuli were similar to patterns of effects for the Character stimuli, which was conceptually related to the exploration path but occurred at the opposite end of the survey. But counterbalancing the occurrence of different stimulus sets would be valuable for future research, and it may also help to disentangle one open question in particular: whether the low rate of information seeking for the Character condition reflected a stimulus-specific effect (e.g., decontextualized information about a language one has no knowledge of is less interesting) or an experiment-level effect (e.g., fatigue following completing the prior elements of the study). Similarly, although personality items were randomized within a block, they occurred at a similar point in the survey for each participant (in Study 1, between the Trivia and Coin Flip paradigm;

in Study 2, following both paradigms). Counterbalancing the appearance of personality surveys could forestall concerns that taking part in an experimental paradigm could have flow-on effects to survey ratings. Lastly, Study 1 assessed participants from the general population drawn from the online platform *Prolific Academic,* whereas Study 2 assessed university students participating for course credit. These cohorts differ in age, country of residence, and likely other factors (e.g., intelligence). Some confidence in the consistency between the two samples can be seen in the similar patterns of correlations (e.g., compare Figure 4 and Figure 7). Further, in terms of differences in intelligence, the minimal relation to information seeking in Study 1 suggests that any differences would not impact key Study 2 results. However, it would be preferable to recruit similar cohorts to have assurance that results are not impacted by differences in characteristics of the samples.

Finally, the current studies examined the roles that both the person and the situation play in behaviors such as information seeking and, via our conceptual model, provided a starting point for future investigations of these elements. We assessed choice preference across four stimulus sets and multiple personality traits, emotions, and situational affordances theorized to influence particular motivations. Importantly, this represents a small snapshot of possible situations: different paradigms might afford new motivations and relate to other personality traits, in line with the perspective that any element providing affective or cognitive value could motivate non-instrumental information seeking (Sharot & Sunstein, 2020). Future research can draw from our framework to propose and investigate these.

Conclusion

This research provides a proof of concept that people display context-dependent patterns of preferences for non-instrumental information and demonstrates how these preferences meaningfully map to particular personality traits. We found evidence consistent with an exploration pathway linked to curiosity, and some tentative evidence consistent with a safety pathway linked to uncertainty intolerance. We have demonstrated the value in jointly considering person and situation factors to understand the internal processes driving choice behavior, and thus, our results speak to the possibilities of interdisciplinary synthesis in understanding complex cognitive-emotional processes that motivate information-seeking.

Part 2

Chapter 5

Decoding Personality Trait Measures from Resting EEG: An Exploratory Report (Study 6)

5.1 Overview to Studies 6 and 7

Part 2 comprises a pair of studies (Study 6 and 7) that investigate whether Big 5 personality traits can be predicted from EEG-derived spectral power using MVPA. These provide an additional and complementary approach to interdisciplinary dialogue between personality psychology and cognitive neuroscience compared to the studies included in Part 1. Specifically, whereas Part 1 assessed how theory from personality psychology might be used to address current questions in cognitive neuroscience, the two studies that form Part 2 demonstrate how methods from cognitive neuroscience can be applied to investigate possible neural bases of personality. Together, the two parts demonstrate the rich and diverse ways that these fields can be integrated to yield knowledge that may not have been discovered in either field alone.

Study 6 was published as an Exploratory Report, a journal format which emphasises the value of openly exploratory research for hypothesis generation and data exploration/visualisation (McIntosh, 2017). In line with the principles of this research format, no particular hypotheses were presented concerning which personality traits might be predicted, and we reported effect sizes rather than statistical significance values. Results suggested that agreeableness and neuroticism could be consistently decoded across four testing conditions in particular frequencies of spectral power. The study concluded with an in-depth discussion of what it might mean for personality-relevant information to be present in neural indices, followed by suggestions for future research and future uses of the dataset.

Study 7 presented a pre-registered close replication of Study 6. The aim of Study 7 was to assess whether agreeableness and neuroticism would be consistently predicted by MVPA in an entirely new sample, which might indicate that effects were sufficiently robust to propose new theories of the biological bases of personality. However, study results did not replicate in the full testing sample. Importantly, due to restrictions on in-person data collection related to the COVID-19 pandemic, we collaborated with another research team in Germany to obtain a study sample that exceeded our minimum prespecified size. When subsequent MVPA analyses stratified by country were conducted, agreeableness could be decoded in participants from Australia and neuroticism from participants from Germany. However, given the smaller sample size of these

individual groups, it is likely far too early to be confident in prior findings despite these intriguing differences in effects. The chapter ends with several explanations for the lack of replication, including an explanation of important methodological factors to consider for robust machine learning analyses.

5.2 Empirical Study 6

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Exploratory Report

Decoding personality trait measures from resting EEG: An exploratory report

Hayley K. Jach[*], *Daniel Feuerriegel and Luke D. Smillie*

Melbourne School of Psychological Sciences, The University of Melbourne, Australia

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ABSTRACT

Can personality be predicted from oscillatory patterns produced by the brain at rest? To date, relatively few studies using electroencephalography (EEG) have yielded consistent relations between personality trait measures and spectral power. Thus, new exploratory research may help develop targeted hypotheses about how neural processes associated with EEG activity may relate to personality differences. We used multivariate pattern analysis to decode personality scores (i.e., Big Five traits) from resting EEG frequency power spectra. Up to 8 minutes of EEG data was recorded per participant prior to completing an unrelated task ($N = 168$, $M_{age} = 23.51$, 57% female) and, in a subset of participants, after task completion ($N = 96$, $M_{age} = 23.22$, 52% female). In each recording, participants alternated between open and closed eyes. Linear support vector regression with 10-fold cross validation was performed using the power from 62 scalp electrodes within 1 Hz frequency bins from 1 to 30 Hz. One Big Five trait, agreeableness, could be decoded from EEG power ranging from 8 to 19 Hz, and this was consistent across all four recording periods. Neuroticism was decodable using data within the 3–6 Hz range, albeit less consistently. Posterior alpha power negatively correlated with agreeableness, whereas parietal beta power positively correlated with agreeableness. We suggest methods to draw from our results and develop targeted future hypotheses, such as linking to individual alpha frequency and incorporating self-reported emotional states. Our open dataset can be harnessed to reproduce results or investigate new research questions concerning the biological basis of personality.

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1. Introduction

Personality traits describe enduring patterns of emotions, thoughts, and behavior. Personality traits are heritable (Bleidorn, Kandler, & Caspi, 2014), relatively stable across the lifespan (Bleidorn, Hopwood, & Lucas, 2018; Specht, Egloff, & Schmukle, 2011), and predict important life outcomes such as romantic satisfaction, occupational success, financial security, substance abuse, and criminal behavior (Ozer & Benet-

* *Corresponding author*. Melbourne School of Psychological Sciences, Redmond Barry Building, Melbourne University, 3010, Australia.
E-mail address: hayleyjach@gmail.com (H.K. Jach).
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Martinez, 2006; Soto, 2019). Researchers have dedicated almost a century to describing and refining the structure of personality traits (Allport, 1937; Digman, 1990), resulting in the dominant Big 5 model of personality (John, Naumann, & Soto, 2008). The Big 5 model decomposes trait variance into five core dimensions: *agreeableness* (pro-sociality, compassion, and politeness), *neuroticism* (anxiety, depression, and emotional volatility), *conscientiousness* (organization and action regulation in goal-directed behavior), *extraversion* (sociability, enthusiasm, and assertiveness), and *openness/intellect* (imagination, curiosity, and aesthetic sensitivity).

The growing literature of *personality neuroscience* investigates how personality traits relate to various neurobiological indices, with an ultimate goal to understand the mechanistic underpinnings of personality (Allen & DeYoung, 2017; DeYoung & Gray, 2009). In this area, researchers have correlated measures of neural activity—using methods such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI)—with personality trait measures. These measurements are often taken when participants are at rest and are not engaged in a predefined task. As personality traits are theorized to reflect relatively stable and sustained cognitive and emotive processes, we might expect patterns of neural activity reflecting or facilitating these processes to be detectable in such resting-state recordings. For example, individuals scoring higher in openness/intellect are more likely to imagine and daydream, as measured by retrospective self-report and experience sampling (Kane et al., 2017; Zhiyan & Singer, 1997), and increased daydreaming seems likely to occur at rest. There have, in turn, been several studies observing that openness/intellect relates to increased connectivity within the *default network* (Beaty et al., 2016, 2018), a collection of cortical regions implicated in a variety of self-reflective processes, including imagination. Relations between personality traits and resting-state activity have been found for each of the Big 5 personality traits (see Allen & DeYoung, 2017 for a review).

The majority of studies investigating personality correlates of resting-state activity have used fMRI connectivity metrics, which are valuable for identifying covariation in activity across brain regions that are active over the resting period. An alternative and complementary approach is to measure the brain's rhythmic oscillatory patterns: that is, dynamic patterns of energy in given frequency bands (alpha, beta, theta, etc.; Buzsáki, 2006). For this task, EEG—which has much higher temporal precision than fMRI—is the method of choice. Researchers have extensively documented typical oscillatory behaviors related to behavior and cognition at rest and in response to task demands (for a review, see Knyazev, 2007) and there is a growing interest in exploring individual differences in oscillatory activity, providing insights into how sensory stimulation is integrated into percepts over time (Cecere, Rees, & Romei, 2015), and differences in cognitive abilities (e.g., Grandy et al., 2013; Klimesch, Doppelmayr, Schimke, & Pachinger, 1996) or clinical populations (e.g., Schizophrenia and Attention Deficit Disorder, Başar & Güntekin, 2013; Autism Spectrum Disorders, Cornew, Roberts, Blaskey, & Edgar, 2012).

Investigations of the personality correlates of resting-state EEG activity have so far failed to yield robust and replicable findings. The largest collection of studies has concerned frontal alpha asymmetry (i.e., alpha power over right relative to left frontal cortical areas), which is thought to index processes associated with extraversion and neuroticism (Harmon-Jones, 2003; Wacker & Smillie, 2015). However, in a recent meta-analytic study combining all published studies (and a number of unpublished studies), Kuper, Käckenmester, and Wacker (2019) reported negligible effects, with less than .4% of the variance in extraversion and neuroticism explained by frontal alpha asymmetry. This is concerning for researchers working to integrate empirical results into overarching mechanistic theories in personality neuroscience (e.g., Kennis, Rademaker, & Geuze, 2013). If the evidence base drawn upon to develop theories in personality neuroscience is not robust, then the resultant theories will not be useful.

These knowledge gaps within the resting-state EEG literature present a challenge to personality neuroscience, but also signal an opportunity for new research to thoroughly explore how personality traits relate to EEG indices. One powerful tool for data-driven research is Multivariate Pattern Analysis (MVPA). Many techniques that fall under the umbrella of MVPA consider the joint contributions of multiple features of data simultaneously, whether they be multiple voxels when using fMRI or signals from multiple electrodes in the EEG (Grootswagers, Wardle, & Carlson, 2017). A key advantage of MVPA is that it can efficiently explore a large feature space to identify signals that can predict the outcome of interest in a data-driven fashion. MVPA has been extensively applied to fMRI data (see Tong & Pratte, 2012, for a review), and its usage in EEG has grown over the past decade. To date, researchers have used MVPA to decode a range of neural correlates of perceptual and cognitive processes, including sensory representations (Hogendoorn, Verstraten, & Cavanagh, 2015), face detection (Cauchoix, Barragan-Jason, Serre, & Barbeau, 2014), perceptual decisions (Bode et al., 2012), and evaluations of the subjective relevance of everyday objects (Turner, Johnston, de Boer, Morawetz, & Bode, 2017).

To our knowledge, only one study (Korjus et al., 2015) has used MVPA—specifically support vector machine classification—to assess whether personality can be predicted from resting EEG frequency power data. They used a median split to categorize those low or high on a given trait and attempted to discriminate between low/high personality trait groups using frequency band power estimates across 32 scalp channels. Although the models used could classify extraversion and openness/intellect at above chance levels, this was not statistically significant after corrections for multiple comparisons. Despite the strengths of this study, including a large sample ($N = 289$) and sophisticated analyses, there are several reasons why further research of this kind is required in order to be confident in its somewhat pessimistic conclusions. First, most participants provided only short periods of resting data (1 or 2 min, compared to 8–10 min in other studies; Wacker, Chavanon, & Stemmler, 2010), which may yield a relatively low signal to noise ratio when obtaining frequency domain power estimates. The authors also did not report the internal consistency of their personality measures, making it unclear how reliable the personality scales were. Poor reliability indicates that the same participants are responding inconsistently to survey items within a single Big 5 trait scale,

suggesting that the scale did not successfully tap a latent construct (Cronbach, 1951). Trying to predict something that was not measured precisely would clearly reduce model performance. Additionally, transforming Likert-scale responses to binary high-low categories is well-known to lower statistical power and potentially produce misleading results (MacCallum, Zhang, Preacher, & Rucker, 2002). As there were approximately Gaussian distributions of personality trait scores across their sample, this also meant that many participants on each side of the median split would have provided very similar personality trait scores. In addition, the authors used binomial tests to determine statistical significance, which requires a threshold level of classifier performance (here a ~57% correct classification rate) to reach statistical significance. If the factors mentioned above did hinder classifier performance, then even in the presence of real patterns that distinguish participants with low and high trait scores, the classifiers may not have met these cutoffs. Korjus et al. (2015) did conduct additional analyses using continuous trait measures using LASSO regression; however, they explored a very large feature space for optimizing the model in their analyses, including selection of task conditions (eyes open/closed), frequencies, electrode sets, and model fitting parameters. With such a large feature space relative to the number of observations, it is possible that their sparse regression approach may not have selected the most informative features in their data.

Given the dearth of research in this area, we attempted to predict Big 5 personality trait scores from resting state EEG data using a multivariate analysis technique well-suited to continuous outcome variables. As our study was entirely exploratory, we did not propose any hypotheses. However, our analyses were designed to provide comprehensive results that minimized inferences from noise. Full details of our approach are detailed in the Method, but we highlight key contributions here. First, we assessed the performance of models trained using power in particular frequency bands in separate analyses, rather than assessing all of the EEG data at once. This allowed us to ascertain which spectral bands may be most relevant to personality trait measures. Second, we assessed consistency across multiple testing conditions by collecting resting data at two time points: before and after completing a task that was unrelated to the current study. At each of these time points, we further assessed consistency across alternating periods of eyes-open versus eyes-closed recordings. This would account for effects that may be linked to the specifics of the testing session (e.g., the effect of having one's eyes open or closed; the effect of collecting data before or after the unrelated task). And third, we decided *a priori* to only make inferences from results where decoding performance was close to $r = .20$ in all four conditions, at approximately the same frequency bands for each condition, according to the following rationale. First, $r = .20$ is the average effect size in personality psychology (Giznac & Szorroli, 2016), and given that we are conducting a purely exploratory study, it seemed appropriate to anchor our predictions to the average effect size in the field. Second, $r = .20$ is the effect size that we have approximately 80% power to detect given our sample size using traditional methods, suggesting it would be unwise to trust inferences less than $r = .20$. And third, we would expect any true correlation between a neurobiological measure and a personality scale to be relatively small (Pickering & Pesola, 2014). Specifically, there are many possible causes for responses to any item on a personality scale, and there are also many possible causes for the recorded EEG signal. If there is a true relationship between oscillatory patterns and personality, then this suggests that some of the causes from the EEG signal overlap with some of the causes from the items that make up a personality measure. However, because the shared causes could only represent a small subset of the causes that contribute shared variance to a personality trait, any observable correlation between a personality trait and a neurobiological measure would not be expected to be higher than, at an optimistic estimate, the average effect size in personality research. Thus, assessing the traits that are consistently predicted across conditions at r~.20 is a further guard against over-interpreting spurious findings.

2. Method

2.1. Open science practices

Our materials, data, and analysis code are available so that others may view the data, reproduce our analyses, and conduct additional analyses (accessible from https://osf.io/3mnt7). As the study is exploratory, no part of the study procedures or analyses was pre-registered prior to the research being conducted. In accordance with Transparency and Openness Promotion guidelines, we report below how we determined our sample size, all data exclusions, all inclusion/exclusion criteria, whether inclusion/exclusion criteria were established prior to data analysis, all manipulations, and all measures in the study.

2.2. Participants and experimental procedure

Data were provided by 210 participants ($M_{age} = 23.85$, $SD_{age} = 5.48$, 59% female) who took part in a variety of EEG experiments in our lab (e.g., Hughes, Yates, Morton, & Smillie, 2015; Smillie et al., 2019) and provided personality trait ratings on a 5-point Likert scale via the Big 5 Aspects Scale (BFAS; DeYoung, Quilty, & Peterson, 2007). As we used existing data, sample size was determined by the number of participants that had previously been collected.

There was no manipulation in this study. Before completing tasks unrelated to the current study, participants were asked to sit at rest, alternating between open and closed eyes every 60 sec when prompted by the experimenter. This resulted in approximately eight minutes of data per participant, comprising four minutes eyes closed, and four minutes eyes open. We collected pre-task resting data for 205 participants.[1] For a subset of 102 participants, post-task resting data was also obtained approximately 60 min after the first resting state recording, in the same manner as the pre-task data.

[1] Five participants provided survey data but did not take part in the EEG experiment.

Following EEG data pre-processing (Section 2.3) we retained 168 participants in the pre-task conditions ($M_{age} = 23.51$, $SD_{age} = 5.32$, range = 18–41, 57% female), hereafter labeled pre-task eyes open and pre-task eyes closed; and retained 96 participants in the post-task conditions ($M_{age} = 23.22$, $SD_{age} = 4.77$, range = 18–37, 52% female), labeled post-task eyes open and post-task eyes closed. Note that 78 individuals provided only pre-task data, 6 individuals provided only post-task data, and 90 participants provided both pre-and post-task data. This brings the total number of personality survey responses to $N = 174$, and this is the sample that is used for internal consistency estimates and descriptive statistics (calculated using the Psych package, as implemented in R; Revelle, 2018).

2.3. EEG acquisition and pre-processing

We recorded EEG from 64 active scalp electrodes using a Biosemi Active Two system (Biosemi, the Netherlands). Recordings were grounded using common mode sense and driven right leg electrodes (http://www.biosemi.com/faq/cms&drl.htm). To this montage we added two electrodes located 1 cm from the outer canthi of each eye, and two electrodes above and below the right eye. EEG was sampled at 512 Hz (DC-coupled with an anti-aliasing filter, −3 dB at 102 Hz). We attempted to keep electrode offsets within ±40 μV, although this wasn't always possible (see below for description of removed channels).

All pre-processing was conducted in Brain Vision Analyzer Version 2.1.2 (Brain Products GmbH, 2017). To aid reproducibility, the full EEG processing pipeline used for this analysis can be found in our data documentation. EEG data were filtered with IIR zero-phase Butterworth filters (.5hz high-pass with time constant .318 and order 2; 30hz low-pass with order 2; 50hz notch) and an initial manual check for flat-lined or artefact-ridden channels was conducted; if found, these were excluded from subsequent processing steps (re-referencing, manual artefact removal and ocular artefact removal), and later interpolated (i.e., estimated from surrounding channels) as noted below. We made an *a priori* decision to remove a dataset if more than four channels appeared to be artefact-ridden or flat-lined. This resulted in the removal of 37 datasets in the pre-task condition, and 6 datasets in the post-task condition.[2] Our full data processing records are included with the open data and code.

We initially referenced the data to channel Cz (or, for 12 datasets where Cz appeared to be dead/artefact ridden, to CPz). Sections of data with muscle artefacts or skin potentials were identified by visual inspection and removed. Data were segmented into 1-min epochs time-locked to the onset of "eyes open" and "eyes closed" cues, and an Independent Components Analysis (ICA) was performed using an infomax (gradient) restricted algorithm, classic PCA sphering (such that all components are treated equally), a convergence bound of 1E-07, and a maximum of 512 iterations. Components corresponding to eye blinks and saccades were removed. Following ICA, we interpolated any excluded channels using spherical splines (4th order) and subsequently re-referenced to the average of all scalp channels. Next, data were segmented into 2-sec epochs with a 1-sec overlap. Segments were tapered using a Hamming window. Segments 200 msec before and after artefacts were excluded from analyses using an automated rejection algorithm (where artefacts were considered to be any of the following: greater than 50 uV difference in voltage per millisecond; greater than 200 uV difference in a 200 msec interval; less than .5 uV difference between the maximum and minimum voltage in a 100 msec interval). Segments of EEG data were converted into frequency domain representations using fast Fourier transforms (.5 Hz frequency resolution), and the average amplitudes in each frequency bin across segments were computed for each eyes open and eyes closed condition. Power in frequency bins ranging from .5 to 30 Hz were used for MVPA.

2.4. Multivariate pattern analyses of EEG power spectra

The Decision Decoding Toolbox (DDTBox; Bode, Feuerriegel, Bennett, & Alday, 2019) was used to perform support vector regression (SVR). Plots of decoding performance (Figs. 1 and 2) were computed in R version 3.6.1 (R Core Team, 2018) using ggplot2 (Wickham, 2016).

The feature space used across different analyses consisted of frequency spectra including 30 frequency bins ranging from .5 to 30 Hz at 62 scalp channels.[3] Sets of .5 Hz frequency bins were averaged to create the 30 frequency bins used for MVPA. For example, the 1 Hz frequency bin used for MVPA consisted of data from the .5 Hz and 1 Hz frequency bins produced by the FFTs.

Participants' scores for a given personality trait (e.g., neuroticism) were used as the values to be predicted in the regression models. We performed separate regression analyses for each condition (pre eyes open, pre eyes closed, post eyes open, post eyes closed), and each personality trait (neuroticism, openness/intellect, extraversion, agreeableness, and conscientiousness), resulting in 20 separate conditions. For each condition, we used SVR with a linear kernel, as implemented in LIBSVM (Chang & Lin, 2011), to predict personality trait scores from the joint patterns of spectral power over all 62 channels within a given frequency bin (e.g., 1 Hz). The analysis was then repeated for each of the remaining frequency bins from 2 to 30 Hz.

With this number of individual regressions and conditions—and given that our sample size is smaller than the number at which correlations of around $r = .20$ typically stabilize ($n \sim 250$; Schönbrodt & Perugini, 2013)—it is possible that some frequency bins may show high decoding performance

[2] Much of the data was originally collected to assess frontal activity (e.g., Hughes et al., 2015), and faulty or poorly connected channels in the parietal/occipital areas were frequently tolerated to expedite data collection. As a result, many more participants were removed here than might be expected.

[3] We analyzed the data without Cz and CPz, as these had been used as reference electrodes during data processing. As a robustness check, we assessed decoding performance both with and without these electrodes included, and results were highly similar. The linked data repository includes these electrodes such that researchers are able to replicate results with the full 64 channels.

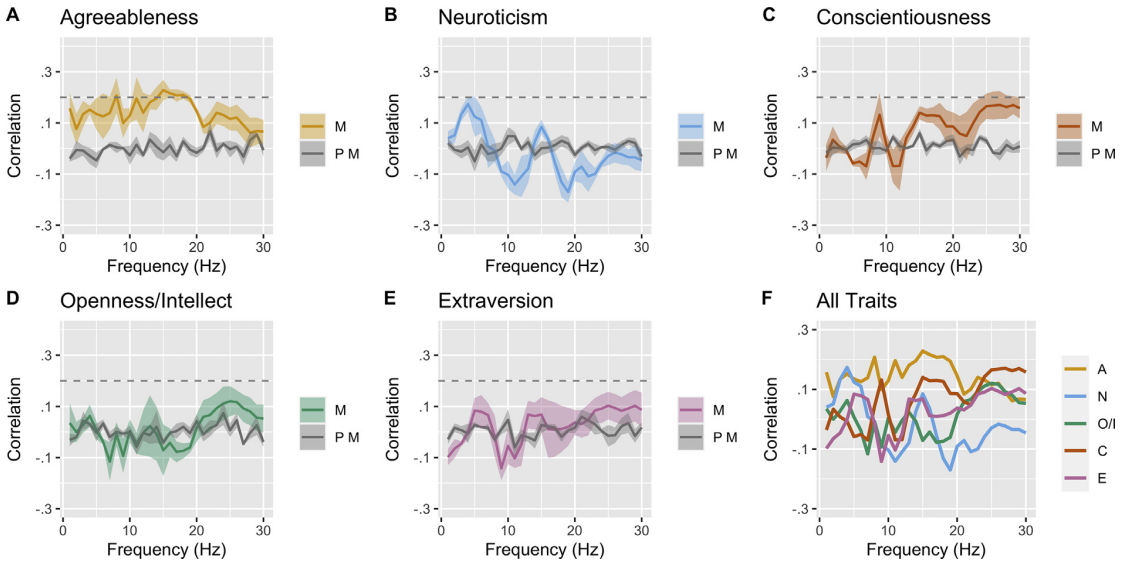

Fig. 1 – Mean decoding performance for each personality trait (A through E) and all traits combined (F). Colored lines depict decoding performance for real personality survey responses, and gray lines depict decoding performance of models trained using permuted labels. A dotted horizontal line at $r = .20$ is included to compare decoding performance to this threshold. Agreeableness is consistently decoded at approximately $r = .20$ across 8–19 Hz frequency bins, whereas neuroticism is consistently decoded close to $r = .20$ from 3 to 6hz. For A-E, error bars depict the standard error of correlation coefficients across the four conditions (pre eyes-open, pre eyes-closed, post eyes-open, and post eyes-closed). M = Mean Correlation Coefficient, PM = Permuted-Labels Analysis Mean Correlation Coefficient.

by chance. However, we implemented several steps to guard against making inferences from potentially spurious high values. First, to reduce the influence of random variation in decoding performance, we used 10-fold cross-validation procedures for all analyses. Cross-validation is the recommended practice to avoid data overfitting and to increase the stability of estimates (Arlot & Celisse, 2010). For each SVR analysis, the dataset was split into ten subsets; the model was trained on nine of the subsets and tested on the remaining subset. This process was repeated nine times with a different subset allocated as the test data each time. To minimize any drawing biases from the particular subset of data, we repeated this entire cross-validation procedure 10 times (5 times for permuted labels). Following this procedure, we averaged decoding performance measures over analysis repetitions (following Turner, Johnston, et al., 2017). In other words, we

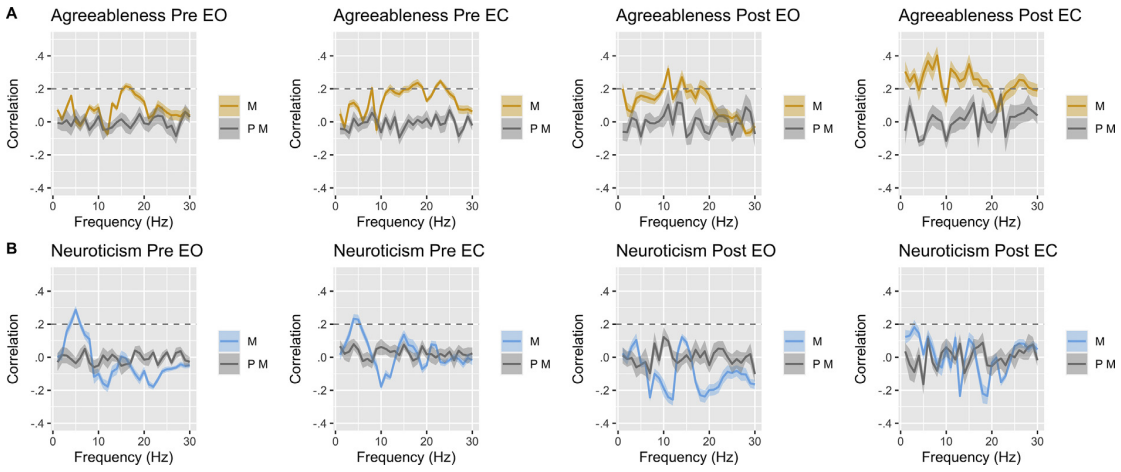

Fig. 2 – (A) Decoding performance for each condition of agreeableness, all four conditions. (B) Decoding performance for neuroticism, all four conditions. Error bars depict the standard error of the 10 repetitions of 10-fold cross-validation. EO = Eyes open, EC = Eyes closed, M = Mean Correlation Coefficient, PM = Permuted-Labels Analysis Mean Correlation Coefficient.

obtained the average of 100 regression coefficients per frequency bin, which should reduce the impact of outliers in decoding performance.

To provide a further safeguard against over-interpretation, we assessed consistency in model performance for each personality trait in four conditions (pre eyes open, pre eyes closed, post eyes open, post eyes closed) via the Fisher-transformed correlation coefficients between predicted and actual labels. As previously mentioned in Section 1, we decided *a priori* to only make inferences from results where decoding performance was close to $r = .20$ in all four conditions, at approximately the same frequency bands for each condition.

Finally, in addition to our SVR analyses predicting personality trait scores, we also randomized which personality scores were assigned to each participant dataset and performed SVR on this resulting EEG data with permuted labels. Permuted-labels decoding allowed us to empirically estimate the chance level of decoding performance, which is often a more stringent control than comparisons against theoretical chance level (Combrisson & Jerbi, 2015). We then compared decoding performance in the permuted labels analyses with that of the original analyses across different frequency bands. Although it is possible to compute a *p*-value by comparing actual decoding performance to a null distribution of e.g., 1,000 iterations of permuted labels decoding, we did not calculate *p*-values here so as not to incorrectly imply that our analyses were confirmatory. This aligns with recommendations for exploratory studies to focus on estimation of effect sizes and their uncertainty, rather than on significance testing (Szucs & Ioannidis, 2017).

2.5. Post-hoc spectral power correlations

Although above-chance decoding can indicate that information related to personality traits is present in the resting EEG data, this does not inform us as to the direction of such relations between neural and personality measures. Thus, for any above-chance decoding for a given personality trait that was consistent across the four conditions in any frequency band, we conducted post-hoc Spearman correlations (de Winter, Gosling, & Potter, 2016) between scores for that trait and measures of power within each frequency bin at each channel. This permitted assessment of any clear monotonic relations between spectral power and personality trait scores. Given the number of correlations computed for this analysis, there is likely to be some imprecision around the estimates. However, again, we focus on results that are highly similar across the four conditions (pre-task eyes open, pre-task eyes closed, post-task eyes open, post-task eyes closed).

3. Results

3.1. Descriptive statistics for personality traits and EEG measures

Means, standard deviations, reliability (omega total), and correlations between personality traits are presented in Table 1. All traits displayed strong internal consistency. Medium-to-large correlations could be observed between several personality traits: for example, agreeableness, extraversion, and openness/intellect. These patterns of intercorrelations are commonly observed in the literature (e.g., DeYoung, 2006) and support the assumption that our data are representative of typical personality survey scores. Supplementary Figure S1 compares the distributions of trait scores in the pre- ($N = 168$) and post- ($N = 96$) conditions, including correlations between traits in each of these conditions. These were very similar, suggesting that any differences in model decoding across pre- and post-conditions would not be due to differences in personality trait distributions.

Supplementary Figure S2 displays spectral power patterns at different frequency bands averaged across participants. EEG data were representative of what is typically observed in the literature (Buzsáki, 2006) suggesting that decoding results may also be representative of what is found in the wider population of individuals.

3.2. MVPA of frequency band power estimates

Fig. 1 displays the mean decoding performance over cross-validation folds, analysis repetitions, and pre/post eyes-open/eyes-closed conditions for each of the Big 5 traits, with Panel F providing a summary of the results for all traits. The supplementary information includes exact correlations obtained at each frequency bin.

For two of the five traits (agreeableness and neuroticism), scores could be predicted from the EEG data across multiple conditions. Of these, agreeableness (Fig. 1, Panel A) emerged as the trait that was most consistently predicted across the largest number of frequencies. The correlation between model-predicted agreeableness scores and survey scores was around $r = .20$ between approximately 8 and 19 Hz.

Table 1 – Means, standard deviations, internal consistency, and correlations between personality traits.

Variable	M	SD	ω	1	2	3	4
1. Agreeableness	3.91	.45	.87				
2. Conscientiousness	3.35	.52	.87	.11			
3. Extraversion	3.42	.54	.90	***.32***	***.30***		
4. Neuroticism	2.86	.65	.92	−.08	***−.35***	***−.26***	
5. Openness/Intellect	3.77	.46	.78	***.25***	.15	***.28***	−.05

Note. *M* and *SD* represent mean and standard deviation, respectively. ω = omega total (internal consistency; roughly equivalent but superior to Cronbach's alpha). Italic font indicates $p < .05$. Bold font indicates $p < .01$.

Assessing agreeableness results from each eyes open/closed and pre/post task conditions (Fig. 2, Panel A), there was higher variability in decoding performance when compared to the condition-averaged plots. Despite this, it is striking how consistently the model predicts agreeableness, particularly in the range of 12–18 Hz (the lower beta band).

Neuroticism also appeared to be consistently predicted by the model at levels above chance, in this instance between approximately 3 to 6 Hz (i.e., the theta band). For pre-task eyes open and pre-task eyes closed conditions (Fig. 2B, first and second plot), correlations hovered around $r = .20$ in this frequency band. For the two post-task conditions (Fig. 2B, third and fourth plot), the same pattern emerged, but the correlations were smaller (post-task eyes open $r \sim .10$; post-task eyes closed $r \sim .16$). Between 10 and 12 Hz there were somewhat consistent negative correlations between the model-predicted and actual neuroticism scores across conditions, which can also be seen in the condition-averaged plots for extraversion, openness/intellect, and conscientiousness. It is difficult to interpret decoding performance that is worse than chance level; however, this may hint at subgroups of participants that show different relations between neuroticism scores and EEG activity, or nonlinear relationships between EEG power and personality trait scores. Models trained predominantly on one subset, and tested on those from a different subset, could produce below-chance performance as seen here. For example, co-occurring differences in the individual alpha peak frequency and alpha band amplitude (e.g., Klimesch, Doppelmayr, Schwaiger, Auinger, & Winkler, 1999) might produce such nonlinear relationships.

Conscientiousness also appeared to be predicted by the model, specifically in the upper beta band (23–30 hz). However, the mean result shown in Fig. 1 appears to have been driven by very high decoding performance in one condition: post-task eyes closed (see Figure S3, Panel C). Here, correlations around $r = .30$ were observed for all of these frequency bins. Other conditions did show some evidence of decodable information, but effect sizes were very small: the post- and pre-task eyes closed conditions were around $r = .14$, and the pre eyes open condition produced a correlation between survey-personality and model-predicted personality of $r = .08$. We suggest that given this variability, results are not as convincing as those for the other two traits, particularly agreeableness.

Scores for openness/intellect and extraversion could not be reliably decoded across conditions (Supplementary Figures S4 and S5).

3.3. *Post-hoc correlation analyses*

As agreeableness and neuroticism were consistently decoded at above-chance levels across pre- and post-task conditions, we assessed the patterns of correlations between personality trait scores and power at each channel and frequency bin. Fig. 3 displays Spearman correlation coefficients describing strength of association between spectral power and personality trait scores across all 62 channels, either for every frequency bin (square plots) or averaged across the frequency bins that MVPA could decode (scalp maps). For agreeableness, relations were strikingly consistent across the four conditions. Specifically, activity in the upper alpha band at posterior electrodes correlated negatively with agreeableness scores, whereas activity in the beta band was positively correlated with agreeableness scores. This was distributed mainly over parietal areas in eyes open conditions, and across both parietal and frontal electrodes in eyes closed conditions. We did not observe any obvious pattern of correlations for neuroticism.

4. Discussion

In the current study we used MVPA to examine whether scores on any of the Big 5 personality traits could be predicted from spectral power of resting-state EEG. We found that agreeableness scores could be predicted based on EEG power in the alpha and lower beta bands (between 8 and 19 Hz), and that neuroticism scores could be predicted using EEG power in the lower theta band (between 3 and 6 Hz). Further analyses revealed that alpha power at posterior channels was negatively correlated with agreeableness, and parietal beta power was positively correlated with scores for this trait. These findings contribute new insights into the neural correlates of personality, particularly for agreeableness which, to our knowledge, has never before been linked to power in the beta band. If robust, the associations reported here will help to inform and constrain theory and research in personality neuroscience.

4.1. *Neural correlates of personality trait measures*

The primary motivation for conducting an exploratory study was the fledgling state of the literature concerning personality traits and resting state EEG. There is minimal direct prior research concerning the relation between oscillatory patterns and either agreeableness or neuroticism, either at rest or during a task, and the few studies that exist are considerably underpowered for analyzing individual differences (e.g., $N < 60$, see Mar, Spreng, & DeYoung, 2013 for discussion of this problem). It therefore did not make sense to formulate hypotheses about which traits would relate to which frequencies or brain regions. Rather, the lack of prior research made it appropriate to utilize data-driven methods that are inclusive of a wide range of oscillatory frequencies and brain regions. However, the lack of direct prior research to cross-reference also places obvious constraints on generating decisive explanations for the present observations. Until future research confirms our results with straightforward MVPA replications or targeted analyses relating a trait to a neural marker, we hold any inferences delicately. This does not detract from the value of our study for deriving tentative hypotheses to be tested in future work; indeed, observations such as we have made here are foundational

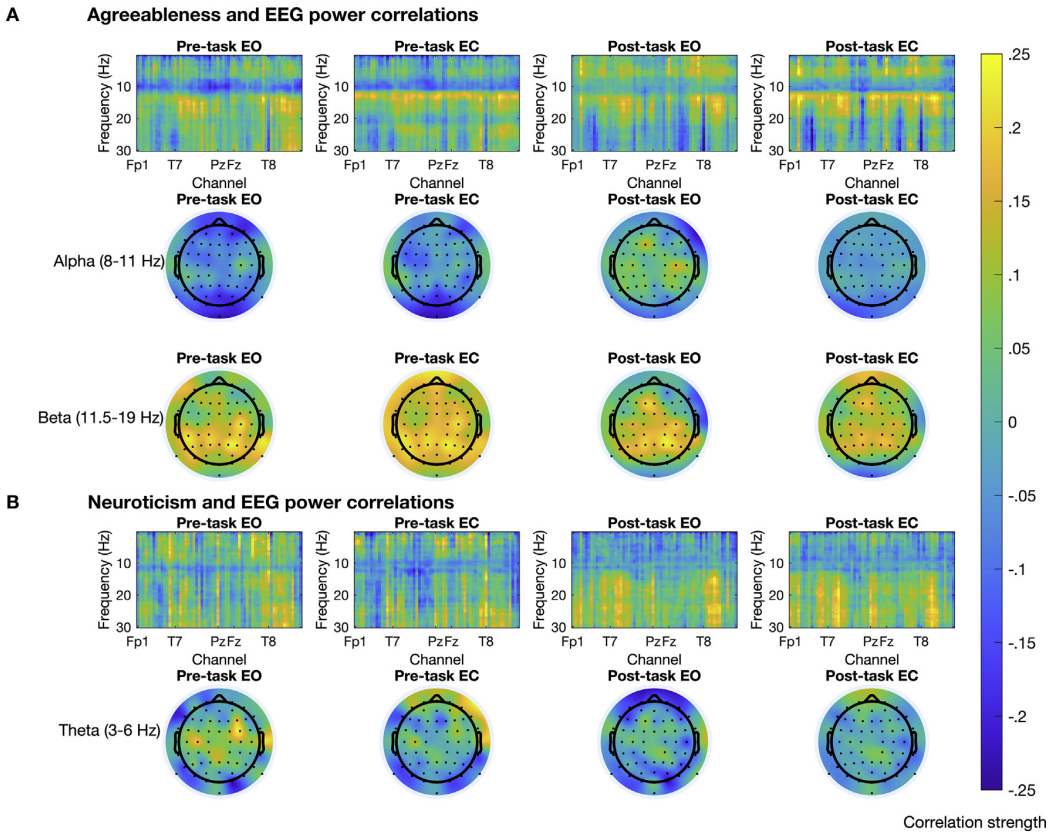

Fig. 3 – Correlations between spectral power at each electrode and frequency bin and personality trait scores for A) agreeableness and B) neuroticism. Scalp maps display Spearman correlation coefficients averaged across selected frequency bands. EO = Eyes open, EC = Eyes Closed.

and necessary before these hypotheses could be developed. With this caveat in mind, we now turn to potential explanations for our results, drawing on personality theory and prior research relating oscillatory patterns to relevant frequencies.

4.1.1. *How and why are personality traits linked to neural data?*

Personality neuroscience recognizes that all individual differences in behavior, cognition, and emotion must be represented by corresponding differences in brain activity (Allen & DeYoung, 2017). However, this provides little insight into *how* or *why* traits might be represented by neural data. Thoroughly parsing our results (and indeed, any data concerning neural correlates of personality) first requires consideration of what kinds of processes might, in principle, drive these observations.

Any relation between a neural measure and a personality trait can likely be explained in one of two ways. First, there could be behaviors, cognitions, or emotions occurring at the time that data is collected—that is, *state* processes—that individuals scoring higher on a personality trait are more likely to display. This possibility (that our neural measure is capturing one or more state processes) is in line with evidence that personality traits correspond well to density distributions of psychological states (Fleeson, 2001; Fleeson & Gallagher, 2009). This explanation would suggest that the neural measure reflects aspects of momentary cognition or emotion to which individuals higher on the personality trait are susceptible.

Second, there could be some more enduring or stable differences in neural activity between those higher or lower on the trait that is captured by the neural measure. This possibility is more of an essentialist perspective aligning with classic theories concerning the biological bases of personality (e.g., Depue, 1995; Eysenck, 1967). This explanation suggests that the neural measure reflects a modulatory process that is present to a greater or lesser degree in those higher in the personality trait, that might influence momentary emotion, behavior, or cognition, but is not itself a reflection of these processes.

Of course, these two kinds of explanations are not mutually exclusive: enduring differences in neural activity may influence phasic responding, and neural plasticity allows for state processes to influence brain structure, connectivity, and

general functioning (see Harmelech & Malach, 2013, for an outline of this process as a possible explanation for variance in the resting state).[4] Nevertheless, the distinction between momentary state and more sustained or chronic processes is important if the ultimate aim is to derive a mechanistic understanding of the biological basis of personality (Allen & DeYoung, 2017). We gain different insights from learning that we are measuring a momentary process versus a sustained modulatory factor that drives action tendencies. For example, chronic processes should be measurable during any situation, whereas state processes should only manifest in contexts that generate the relevant behavior, emotion, or cognition. Any proposed model of the links between the neural measure and behavior would thus be different when representing either of these explanations.

Both explanations are potentially congruent with the results obtained in the current study, and at present it is difficult to identify evidence that distinguishes between the two perspectives. As we measured participants at rest rather than performing a task, it might seem more likely that we detected a sustained process related to agreeableness and neuroticism. However, no testing situation is truly neutral, and there may be elements of the resting state that trigger specific emotions, behaviors, and cognitions. For example, as trait agreeableness describes differences in prosocial tendencies (Graziano, Habashi, Sheese, & Tobin, 2007; Habashi, Graziano, & Hoover, 2016), it is possible that during data collection more agreeable individuals experience positive thoughts and emotions about donating their time towards advancing scientific knowledge. Conversely, disagreeable individuals may experience apathy or even resentment at the time spent sitting in a dark room with nothing to do. Likewise for neuroticism, which describes differences in negative emotionality, anxiety, and volatility (Widiger, 2009), it is possible that more neurotic individuals experience anxious thoughts and feelings whilst in an unfamiliar testing environment, and these more negative states are reflected in the patterns of neural activity being assessed. However, it is crucial to note that when assessing potential support for these possibilities we confront a many-to-one problem in both the personality and the EEG literatures. That is to say, there are many personality trait-relevant states that could be experienced by participants at any point in time (e.g., high-neuroticism participants in the resting state might feel low mood and disengagement instead of anxiety; highly agreeable participants might tend to feel polite and compliant instead of prosocial) and there is simultaneously a vast literature concerning theories of frequency band processes (for reviews see Başar, Başar-Eroğlu, Karakaş, & Schürmann, 1999; Knyazev, 2007; Ward, 2003), many of which are relevant to personality traits and states.

If we were to assess the correspondence between prior EEG research and personality traits, we would invariably encounter this many-to-one problem. For example, Ertl, Hildebrandt, Ourina, Leicht, and Mulert (2013) found that frontal theta power was correlated with successful emotional regulation when watching aversive pictures. As individuals higher in neuroticism consistently demonstrate poorer emotion regulation strategies (John & Gross, 2007; Kokkonen & Pulkkinen, 2001; Yoon, Maltby, & Joormann, 2013), this could support the possibility that we are decoding the relative ease or difficulty in regulating one's anxiety during the resting state scan. However, theta has been associated with a vast range of processes including cognitive control (Cavanagh & Frank, 2014), memory retrieval and decision-making (Jacobs, Hwang, Curran, & Kahana, 2006), memory encoding (Kirov, Weiss, Siebner, Born, & Marshall, 2009), conscious awareness (Klimesch et al., 2001), and conflict between approach and avoidance (Shadli, Glue, McIntosh, & McNaughton, 2015). Any of these phenomena could be framed, more or less directly, as being of relevance to neuroticism. Likewise, concerning agreeableness and the beta band, beta has been linked with processes such as motor function and motor imagery (Feingold, Gibson, DePasquale, & Graybiel, 2015; Jenkinson & Brown, 2011; Nakagawa et al., 2011), emotion (Güntekin & Başar, 2010; Senkowski, Kautz, Hauck, Zimmermann, & Engel, 2011), and attention (Gao et al., 2017; Gola, Magnuski, Szumska, & Wróbel, 2013), any of which could be have some relevance to agreeableness (for example, trying to remain still so as not to compromise the recording would be a process consistent with higher-agreeableness individuals, as would higher positive affect and higher attention). Thus, although we cannot rule out state responses simply because participants are providing data at rest, it would be premature to nominate the most likely momentary process that could be driving an effect and consequently develop targeted hypotheses from our results. The sections below address this issue by identifying several promising methods that could be used to gain greater clarity on these issues.

4.2. *Hypothesis generation for future research*

4.2.1. *Leveraging existing EEG individual differences research*

EEG researchers increasingly acknowledge the impact of individual differences on EEG signals and processes. One particularly fruitful example of this is research concerning individual alpha peak frequency (Klimesch, 1997; 1999), which has been found to covary with measures of cognitive processing speed (Klimesch, 1999; but see; Ouyang, Hildebrandt, Schmitz, & Herrmann, 2020), fMRI measures of white matter architecture that may underlie patterns of functional connectivity (Valdés-Hernández et al., 2010), and even perceptual processes, such as perceptual stability in binocular rivalry tasks (Katyal, He, He, & Engel, 2019). The patterns of correlations between alpha and beta band power and agreeableness in our study might even be explained by shifts in alpha peak frequency. If higher alpha peak frequencies were present in individuals with high agreeableness, then we would expect to

[4] Finally, there is an additional artefactual explanation: it is possible that MVPA is detecting some increased motor movement not entirely removed by pre-processing (e.g., eye-blinks) that could meaningfully relate to the trait: for example, individuals higher in neuroticism looking around the room more due to nervousness. However, if eye blinks did contribute in the current study, we would be more likely to see correlations solely at frontal channels and decoding performance across a broad set of frequency bins, which was not the case. Future studies may wish to guard against this possibility by tracking eye movement and closely monitoring movement in the testing environment.

see larger power in the beta band and less power in the lower alpha band in those with high agreeableness scores, as we observed here. Future work could investigate the covariation between alpha power, alpha peak frequency, and personality traits. This avenue may be especially promising to investigate given that alpha power measures are thought to capture a fundamental aspect of how neural activity is coordinated across the brain (Klimesch, 2012; Mierau, Klimesch, & Lefebvre, 2017). Such analyses should ideally be performed after accounting for individual differences in the 1/f power spectrum, which can exert a large influence on alpha power measures (Ouyang et al., 2020).

4.2.2. *Experimental approaches*

An experimental approach may additionally help to identify the possible states that could drive above-chance decoding performance. First, researchers could assess emotions and other psychological states at intervals between resting-state data collection, and then use MVPA to predict those states in addition to personality traits. If the particular state (e.g., negative affect) is the reason why we are observing decoding performance for a given personality trait (e.g., neuroticism correlates with negative affect) then we would expect to observe stronger decoding performance for the state rather than the trait. If we do observe states that appear to be candidate processes underlying decoding accuracy, then subsequent studies could include a task designed to elicit a particular trait-relevant process alongside the resting state. If EEG differences are evoked by processes present in the moment, then we would expect that they would be induced to an even greater degree in a task designed to elicit them (e.g., for neuroticism, a fear induction paradigm).

4.2.3. *Decoding lower-order personality facets and nuances*

The current study assessed decoding performance for global personality traits. However, each trait can be decomposed into lower-order facets: for example, in the scale used for the current study, agreeableness can be divided into *politeness* and *compassion;* and neuroticism can be divided into *volatility* and *withdrawal* (DeYoung et al., 2007). Given that we did not have prespecified hypotheses for which traits could be decoded, we did not aim to assess the impact of individual facets. This also would have required us to conduct many more statistical tests, increasing the risk of spurious findings. However, future research can attempt to assess if specific facets within these traits are driving decoding performance. Given that facets within a trait are highly correlated with each other (as they must be, to form a general factor), these analyses should be conducted controlling for the other facet/s in the global trait. This approach could help to disentangle the tricky question of finding out whether it is a state response or trait regulatory process that we are detecting with MVPA: if one observed that only one facet in the global trait was driving decoding performance, then we would have some evidence against the regulatory process possibility (as some sort of regulatory process would be expected to affect shared variance across the facets). This could be taken even further by analyzing individual items in a scale (aka *nuances;* Mõttus, Kandler, Bleidorn, Riemann, & McCrae, 2017), although this would come at the cost of increased measurement error.

4.2.4. *Computational approaches*

The final method is to build mathematical models that test the correspondence between the model's predictions and future data. There are many different ways that formal models can incorporate neural measures and processes (see Turner, Forstmann, Love, Palmeri, & Van Maanen, 2017, for a review). Formal models are advantageous because researchers must specify all components of the model, including which neural level they wish to model (e.g., modeling state or phasic responses *vs* tonic or baseline responses—or the interconnections between these). Although these types of models are not frequently used in personality psychology, they have been effectively employed to investigate a theory linking extraversion with dopamine function (Wacker & Smillie, 2015), by simulating the firing of dopamine neurons in the basal ganglia in response to reward signals (Pickering & Pesola, 2014). For the current study, models could be built following results derived from investigations of individual alpha frequency or targeted state theories. Highly constrained hypotheses of how agreeableness or neuroticism relates to brain regions, frequencies, or emotional states would be a valuable way to build from the initial empirical findings of the current research and future research.

4.3. *Future uses of the open dataset*

Our data and analysis scripts are available online, providing the opportunity for them to be used to address new research questions, or to top-up with additional data and investigate whether results are consistent with a larger sample. Note that although we did not perform inferential analyses on the data, we did thoroughly explore the data, making null hypothesis significance testing with our data plus a top-up sample inappropriate (Banks et al., 2019) unless the research question was very different from our own. However, given that there is current uncertainty over how many data points are required for machine learning decoding performance to stabilize, it could be highly valuable to re-run MVPA results with progressively different numbers of participants and observe consistency of estimates. It is possible that with larger samples, consistent effects will be observed for additional personality traits.

Additionally, because we computed MVPA analyses separately for each frequency bin, it was not possible to assess the dynamic coupling between different frequencies. This has been suggested as a source of individual differences in personality traits (Knyazev et al., 2003; Knyazev, Schutter, & van Honk, 2006; Knyazev & Slobodskaya, 2003). For example, Miskovic et al. (2010) found that slow- and fast-wave coupling in the resting state related to social anxiety (which relates to neuroticism; Kashdan, 2002). Future researchers could use similar methods to explore the present data, perhaps specifically focusing on neuroticism.

Finally, our analysis scripts can assist with replications of the current findings. If researchers have collected EEG resting data and personality measures across large samples, then it would be straightforward to adapt the analysis scripts that we have provided to assess whether findings related to agreeableness and neuroticism are consistent in an entirely new sample.

5. Conclusion

The current study is one of the first to use multivariate pattern analysis to decode personality traits from EEG power spectra. We found that agreeableness and neuroticism could be decoded across multiple testing conditions, with post-hoc analyses demonstrating consistent associations between agreeableness and the alpha/beta band. These initial results are foundational before future confirmatory investigations could be proposed, several of which we discussed in Section 4.2 above. We hope that this study provides clues for future research to understand how neurobiological factors drive individual differences in emotion, cognition, and behavior—that is, personality.

Author credit statement

Hayley Jach: Conceptualization; data curation; formal analysis; investigation; methodology; project administration; visualization; writing — original draft; writing — review & editing.

Daniel Feuerriegel: Conceptualization; formal analysis; resources; software; supervision; writing — review & editing.

Luke Smillie: Conceptualization; data curation; resources; supervision; writing — review & editing.

Open practices

The study in this article earned Open Materials and Open Data badges for transparent practices. Materials and data for the study are available at https://osf.io/3mnt7/.

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Supplementary data

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Chapter 6

Personality in the Power Spectrum: A Replication MVPA EEG Study (Study 7)

Hayley K Jach[1*]
Daniel Feuerriegel[1]
Alan Pickering[2]
Luiza Bonfim[1]
Van Ngoc Duong[1]
Elizabeth Robinson[1]
Jan Wacker[3]
Luke D. Smillie[1]

* To whom all correspondence should be addressed: hayleyjach@gmail.com

[1]Melbourne School of Psychological Sciences, Redmond Barry Building, Melbourne University, 3010, Australia

[2]Department of Psychology, Goldsmiths, University of London, New Cross, London SE14 6NW, United Kingdom

[3]Faculty of Psychology and Human Movement Science, University of Hamburg, Von-Melle-Park 5, 20146, Germany

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Abstract

This study presents a pre-registered close replication of an Exploratory Report which assessed whether multivariate pattern analysis (MVPA) could be used to decode personality traits via spectral power derived from resting-state electroencephalography (Jach et al., 2020). The original study found that traits agreeableness and neuroticism could be consistently predicted across four conditions. The current study assessed a total sample of 197 participants including 77 participants from Australia (57% female, M_{age} = 19.7) and 120 participants from Germany (64% female, M_{age} = 24.75). Participants provided up to 5 minutes of eyes-open resting data, and support vector regression with ten repetitions of 10-fold cross validation was performed to predict reported personality traits from the power of 64 electrodes across 1-Hz frequency bins from 1 Hz to 30 Hz. In contrast to original findings, we did not decode agreeableness or neuroticism above our prescribed threshold in predicted frequency bins. However, when each country was assessed individually, agreeableness could be decoded in the Australian sample and neuroticism could be decoded in the German sample. We consider the evidence for possible reasons for lack of successful decoding including contextual effects or false positives for the original study. Possible future directions include large-scale collaborations between different research teams and novel analysis strategies distinguishing between oscillatory activity and broadband noise. We suggest that original study results are not sufficiently robust to inform theories of the biological basis of personality, but that open documentation of this complexity can assist the generation of more nuanced hypotheses, improved research practices, and methodological advances.

Introduction

Personality neuroscience seeks to understand the biological basis of relatively stable patterns of emotion, cognition, motivation, and behaviour—in other words, personality traits (Wilt & Revelle, 2015). Many links between personality traits and various neurobiological indices have been proposed, drawn from a broad swathe of methods including functional magnetic resonance imaging (fMRI), electroencephalography (EEG), drug manipulations, and genetic studies (see Allen & DeYoung, 2017, for a review). However, given the vast complexity of the brain and mind, it is reasonable to assume that we have only scratched the surface of possible neurobiological indices that may inform our understanding of personality. Exploratory research may reveal new candidate relations between neural and personality factors and thereby help to identify new targets for research funding and spur the development of novel theories and investigations. However, confirmation of exploratory findings via close replication studies are required to be confident that results generalise beyond a particular sample. The current study provides such a replication of a recent analysis that used multivariate pattern analysis to predict self-reported personality dimensions from resting-state EEG (Jach et al., 2020).

Multivariate pattern analysis (MVPA) is an umbrella term representing a cluster of related supervised machine learning methods (e.g., support vector machine classification or support vector regression) that are used to predict behaviour, outcomes, and/or neural indices. MVPA is a powerful technique for exploratory research as it can, in a completely data-driven fashion, efficiently and comprehensively map a large feature space to detect signals related to the variable of interest. As the term *multivariate* may suggest, these methods share an emphasis on the simultaneous use of multiple features within a dataset, such as multiple voxels in fMRI or channels in EEG. MVPA has been used extensively in fMRI research (Tong & Pratte, 2011), and is an emerging research method in EEG that has been used to predict error responses (Bode & Stahl, 2014), the perceived relevance of objects (Turner et al., 2017), predictions of visual stimuli (Blom et al., 2020), emotion (Grootswagers et al., 2017), and emotion regulation (Schubert et al., 2020).

The majority of studies using MVPA for EEG have decoded their outcome of choice from time-varying neural activity (i.e., signal amplitude of multiple channels across time). This approach is appropriate when stimuli or behaviour are time-locked and/or the time-course of cognitive processing is relevant. Alternatively, when EEG is recorded in participants as they spend several minutes sitting at rest with no particular task involved (i.e., the *resting state*), the entire

testing period is of interest and there are no specific time-locked behaviours to assess. In this context, it is valuable to transform the signal from the time domain to the frequency domain via spectrum analyses such as the Fourier transform; this procedure summarises the energy contained within different frequencies across the course of the testing period. Data in the frequency domain are likely to contain signals representing the brain's true rhythmic oscillations (e.g., alpha waves, oscillating ~8-12 Hz; theta waves, oscillating ~3-8 Hz; Buzsáki, 2006) in addition to broadband, aperiodic activity that forms a classic 1/*f*-like pattern in the power spectrum (He, 2014; Wen & Liu, 2016). Periodic and aperiodic signals are thought to have different generating mechanisms (Buzsáki & Draguhn, 2004; He et al., 2010), but both appear to have functional relevance for cognition and emotion, including individual differences (Başar et al., 1999; Dave et al., 2018; Knyazev, 2007; Ouyang et al., 2020; Ward, 2003). As personality is conceptualised in terms of consistent patterns of emotion and cognition, it is plausible that such patterns may be detectable in resting state EEG. Further, as it is necessary to collect a relatively large sample to derive stable correlation estimates (Schönbrodt & Perugini, 2013), resting state data confers a practical advantage: the cost and time required to collect neural data makes such samples prohibitive for many research teams, but adding a short resting period to studies that may be designed for other purposes makes it possible to combine datasets across projects and labs (Mar et al., 2013).

Although there has been much interest in assessing EEG resting state correlates of personality, particularly of broad motivational tendencies (Harmon-Jones, 2003), meta-analyses suggest minimal-to-no evidence for associations between personality and commonly derived resting-state EEG indices (Kuper et al., 2019). This suggests that novel exploratory research is necessary to kick-start new lines of inquiry. Accordingly, Jach and colleagues (2020) used MVPA to predict personality traits from the frequency domain of resting-state EEG. They measured personality traits with the *Big 5* (John et al., 2008), a descriptive model of personality that parsimoniously partitions differences between people into five broad dimensions: *extraversion* (representing enthusiasm, sociability, and assertiveness), *neuroticism* (representing anxiety, depression, and negative emotionality) *agreeableness* (representing compassion, politeness, and altruism), *openness/intellect* (representing imagination, intellect, and aesthetic sensitivity), and *conscientiousness* (representing orderliness and achievement-striving). The authors found that the model could decode two personality traits—agreeableness and neuroticism—where the correlation between personality trait scores and model-predicted trait scores was near or above a predefined

threshold of $r \sim .20$ (i.e., the average effect size in individual differences research; Gignac & Szodorai, 2016). For agreeableness, the model could predict scores in the frequencies between 8 Hz and 19 Hz, and for neuroticism, between 3 and 6 Hz. These results were consistent across four testing conditions, including data obtained before and after completing an unrelated experiment and when the resting state was measured with open or closed eyes. Taken together, this suggested that there was consistent information at these frequencies (either periodic or aperiodic; classic spectrum analyses cannot separate the two) that could distinguish whether individuals were higher or lower on these traits. For agreeableness, follow-up analyses offered clues to the regional specificity of model decoding performance at particular frequencies: activity in the upper alpha band at posterior electrodes correlated negatively with agreeableness scores, whereas activity across a wide range of brain regions in the beta band was positively correlated with agreeableness scores.

These findings were novel (no prior study had predicted these traits with MVPA, and power in the alpha and beta bands had never previously been related to agreeableness) and could, in principle, spur new investigations to the neural basis of these personality traits. However, it is important to avoid getting ahead of ourselves: before proposing candidate bases for observed effects, it is crucial to establish that these effects can generalise to a new sample. Even though Jach et al. (2020) found consistent results across conditions, these conditions were tested at similar times across mostly the same participants. Establishing replicability beyond a single study provides reassurances that results were not due to the particular context, particular EEG acquisition procedure, particular participants, or a simple fluke.

This is the purpose of the current study: we provide a pre-registered close replication of Jach et al. (2020) to assess study generalisability. The study hypotheses are as follows:

H1. Broad Hypothesis: Using support vector regression, the model will be able to decode agreeableness and neuroticism consistently from resting state EEG.

H2. Survey agreeableness and model-predicted agreeableness (as derived from resting state EEG) will correlate at $r \geq .18$ (i.e., the approximate effect size observed by Jach et al., 2020) within any or multiple frequencies between 8 and 19 Hz.

H3. Survey neuroticism and model-predicted neuroticism (as derived from resting state EEG) will correlate at $r \geq .18$ within any or multiple frequencies between 3 and 6 Hz.

We are agnostic concerning replication of remaining personality traits, and make no hypotheses for what we would expect, but present results for these traits for completeness.

Method

Deviations from Pre-Registration

This study was pre-registered in 2019. The pre-registration specified a minimum sample size of 150 participants (https://osf.io/9fq5x/?view_only=af29f737e8894106a9550f6d1ef1c9e1). This target sample size was chosen as it provided 80% power to detect an effect size of $r = .20$ (one-tailed) with traditional analyses and is on par with the sample size collected by Jach et al. (2020), who were able to successfully predict agreeableness and neuroticism. At the time of the pre-registration we had collected 58 datasets, and we planned to test the remaining participants in 2020. However, due to campus lockdowns introduced to curb the spread of COVID-19, data collection was halted in March 2020, at which point only 87 participants had been recruited. Thus, we did not reach our pre-specified minimum sample size. Fortunately, collaborators provided an existing dataset[12] including resting data and Big 5 personality trait scores for 120 German participants. By combining this sample with our Australian sample, we were able to exceed our minimum target sample size. Note that because the German dataset included only Eyes Open data, we were not able to also assess the Eyes Closed data from the Australian dataset, and thus could not average over Eyes Open and Eyes Closed data to judge consistency of decoding performance as specified in the pre-registration. However, for the full manuscript arising from this research, we plan to collect the full 150 Australian participants throughout the remainder of 2021. Results will include data from the full Australian and German samples, and we will contrast Eyes Open and Eyes Closed data at that stage.

One further pre-registration deviation related to EEG pre-processing is specified in the Section *EEG acquisition and pre-processing*. Otherwise, we follow all specifications of the pre-registration.

Participants and Procedure

Sample 1 initially consisted of 87 undergraduate students from an Australian university completing the experiment for course credit. Before taking part in the EEG component of the

[12] This dataset has previously been used in research (Käckenmester et al., 2018) but EEG data collected for pre-task resting state was only used for reliability estimates and was not analysed for the authors' particular research question.

experiment, participants were directed to a *Qualtrics*™ survey where they provided demographic details and Big 5 personality trait scores via the Big Five Aspect Scales (DeYoung et al., 2007) on a 5-point Likert scale. For EEG testing, participants were asked to sit in a quiet, darkened testing booth for 10 minutes, alternating between open eyes (staring passively at a fixation cross on a computer screen) and closed eyes every 60 seconds, with the change in condition marked by a beep. The first 58 participants completed only this resting task and were then released from the testing booth. The remaining participants took part in an unrelated experiment lasting approximately 20 minutes after providing resting data. Participants were excluded for failing to provide personality trait data (N = 6) or for providing EEG data where 5 or more channels were bad or faulty (N = 4). Following exclusions, 77 participants were included for analyses (57% female, M_{age} = 19.7, SD_{age} = 2.5).

Sample 2 comprised 120 participants based in Germany (64% female, M_{age} = 24.75, SD_{age} = 4) who completed the study for course credit (if students; 90% of the sample) or 25 euros for remaining non-students. This sample has been used in prior research (Käckenmester et al., 2018), where the full experimental procedure has been detailed. Participants completed a version of the Big Five Aspect Scales that was translated into German by Marko Paelecke and Patrick Mussel. Before taking part in an experiment, participants provided five minutes of eyes-open resting state data where they were staring passively at a fixation cross. We extracted this section for the current study. Combining Sample 1 and 2 into a single dataset produced a total sample size of N = 197.

EEG Acquisition and Pre-processing

For both samples, EEG was recorded from 64 electrodes following the international 10-20 system (Klem et al.,1999), using BioSemi ActiveTwo (Amsterdam, NL.). Recordings were referenced online to common mode sense and driven right leg electrodes (http://www.biosemi.com/faq/cms&drl.htm). Sample 1 was sampled at 512 Hz (DC-coupled with an anti-aliasing filter, 3dB at 102 Hz), whereas Sample 2 was initially sampled at 2048 Hz and then down-sampled to 512 Hz (converted via cubic spline interpolation with 24dB/oct at 230.4Hz).

All data from both samples was pre-processed using BrainVision Analyser Version 2.2 (Brain Products GmbH, 2017). IIR zero-phase Butterworth filters (0.5 Hz highpass, 30 Hz lowpass, and 50 Hz notch) were initially applied, and faulty channels were identified and removed. Data was initially referenced to Cz and an initial manual data inspection was conducted to remove data indicating strong muscle activity or sweat artifacts. Sample 1 included both eyes-open and

eyes-closed sections and these were hence segmented into separate epochs; the remaining steps were executed on both samples. An independent components analysis was performed using a maximum of 512 iterations, an infomax-gradient restricted algorithm, classic PCA sphering (where all components are treated equally), and a convergence bound of 1E-07. Components reflecting ocular artifacts such as blinks or saccades were removed. Faulty channels and the original reference Cz were removed and subsequently interpolated, and data was re-referenced to the average of all 64 channels. Subsequently, data was segmented into epochs of 2 seconds with a 1-second overlap, tapered with a Hamming window, and an automatic artifact rejection procedure removed potential artifacts meeting prespecified criteria (namely, a difference in voltage of more than 50 uV per millisecond, a difference in voltage of more than 200 uV in a 200-millisecond interval, and a minimum/maximum voltage difference of less than 5 uV in a 100-millisecond interval). If an artifact was identified, it was marked as contaminated 200ms before and after the event. Finally, a fast Fourier transform with 0.5 Hz resolution converted data to power in the frequency domain, segments were averaged, and results were exported into separate .csv files for MVPA analyses.

Note that this pipeline is almost identical to that conducted by Jach et al. (2020) with the exception that the initial reference channel is excluded and then interpolated, rather than being removed entirely. This alteration was made in order to retain the full 64 channels for MVPA analyses, as in the prior pipeline, only 62 channels were able to be analysed.[13]

Multivariate Pattern Analysis

Support vector regression (SVR) analyses were implemented via LIBSVM (Chang & Lin, 2011) in the Decision Decoding Toolbox (Bode et al., 2019) within MATLAB Version R2020a (The MathWorks, Inc.). Analyses closely followed those undertaken by Jach et al. (2020).

The feature space used for all analyses included the power in frequency spectra from 0.5 to 30 Hz in 0.5 Hz bins across 64 channels. We averaged each two 0.5 Hz bins to form 1 Hz bins for the purpose of halving analyses required for decoding. Data to be predicted via supervised learning were mean-scored Big 5 personality traits (agreeableness, neuroticism, extraversion, openness/intellect, and neuroticism). For each trait, SVR with a linear kernel was performed separately for each frequency bin from the joint patterns of spectral power across all 64 EEG

[13] Results from Jach et al. (2020) were highly similar with 64 or 62 channels, so this is unlikely to influence any difference in decoding performance for the current study.

channels, producing 30 analyses revealing decoding performance for each bin (1 Hz, 2 Hz, 3 Hz, etc.). Cross-validation was used throughout to avoid overfitting and increase stability of estimates. Specifically, data was split into 10 subsets and the model was trained on the first nine subsets and tested on the tenth. This process was then repeated with a different subset as the test set. Ten repetitions of 10-fold cross-validation were performed with a different data-split per each repetition, and decoding performance was averaged across analysis repetitions.

For comparison purposes, we performed the same SVR analyses (with 5 repetitions of 10-fold cross-validation) in a condition where personality trait ratings had been randomly swapped amongst participants, meaning that there should be no signal contained within personality ratings. These permuted labels analyses allowed us to confirm that decoding results from the main analyses were not due to the unique structure of personality responses absent their connection to participants.

Because our analyses combined two datasets collected in different countries and time points, any differences between the two datasets may cause unforeseen effects in decoding. Thus, we describe the distributions and intercorrelations of the two survey datasets thoroughly to establish their consistency. Moreover, we perform analyses on each individual dataset in addition to the merged dataset and compare results across these.

Results

Descriptive Statistics and Correlations

Table 1 displays mean, standard deviation, skew, and kurtosis values across personality traits for the combined (Australian and German) sample, as well as each sample individually. Most variables had relatively similar summary statistics across datasets, and this was echoed by Figure 1, which displays similar overlapping histograms between countries.

Table 2 shows correlations between Big 5 traits for the combined sample and each sample separately. For the combined sample, correlations between personality traits are of a similar sign and magnitude to those from Jach and colleagues (2020), suggesting consistency between these datasets. Moreover, trait intercorrelations are similar between the Australian and German samples (e.g., the correlation between openness/intellect and extraversion is $r = .42$ in the Australian sample and $r = .36$ in the German sample; the correlation between agreeableness and neuroticism is non-significant and negative in both samples). The sole discrepancy in correlation sign between the two samples is between openness/intellect and conscientiousness, which is $r = .27$ ($p = .016$) in

the Australian sample and r = -.05 (p = .614) in the German sample. Overall, the two samples can be judged to be highly similar, which is promising for combining them for decoding.

However, one large disparity concerned skew and kurtosis values for agreeableness: the Australian sample had values within an acceptable range (< 1), but values for the German sample indicated non-normality, particularly for kurtosis. On inspection, this was due to one outlier in the German sample with a particularly low score on agreeableness compared to the remainder of the sample. To assess whether this outlying value has an undue influence on results, we present findings for agreeableness without the outlier in the Supplementary Materials as a robustness check.

Table 1.

Descriptive Statistics for Combined, Australian, and German Samples

	Mean			*SD*			Skew			Kurtosis		
	All	A	G	All	A	G	All	A	G	All	A	G
Openness/Intellect	3.67	3.70	3.64	0.48	0.52	0.46	-0.18	-0.21	-0.20	-0.06	-0.39	0.16
Conscientiousness	3.27	3.14	3.35	0.51	0.52	0.49	0.07	0.19	0.05	-0.43	-0.73	-0.19
Extraversion	3.50	3.48	3.51	0.49	0.53	0.47	-0.03	0.23	-0.26	-0.22	-0.60	0.09
Agreeableness	3.87	3.88	3.86	0.43	0.46	0.41	-0.73	-0.45	-0.98	1.25	-0.27	2.55
Neuroticism	2.85	2.94	2.79	0.65	0.62	0.65	-0.08	-0.41	0.13	-0.47	-0.32	-0.44

Note. All = Combined Australian and German sample, A = Australia, G = Germany, *SD* = Standard Deviation.

Table 2.

Zero-Order Correlation matrix for Combined, Australian, and German Samples

	Openness/Intellect			Conscientiousness			Extraversion			Agreeableness		
	All	A	G	All	A	G	All	A	G	All	A	G
Openness/Intellect	--	--	--									
Conscientiousness	.08	*.27*	-.05	--	--	--						
Extraversion	**.38**	**.42**	**.36**	**.21**	.13	**.26**	--	--	--			
Agreeableness	.14	.11	.16	.14	.18	.12	**.23**	**.33**	.15	--	--	--
Neuroticism	**-.20**	**-.30**	-.16	**-.28**	*-.23*	**-.28**	**-.31**	**-.43**	*-.23*	-.06	-.10	-.05

Note. Italics indicate $p < .05$. **Bold font** indicates $p < .01$.

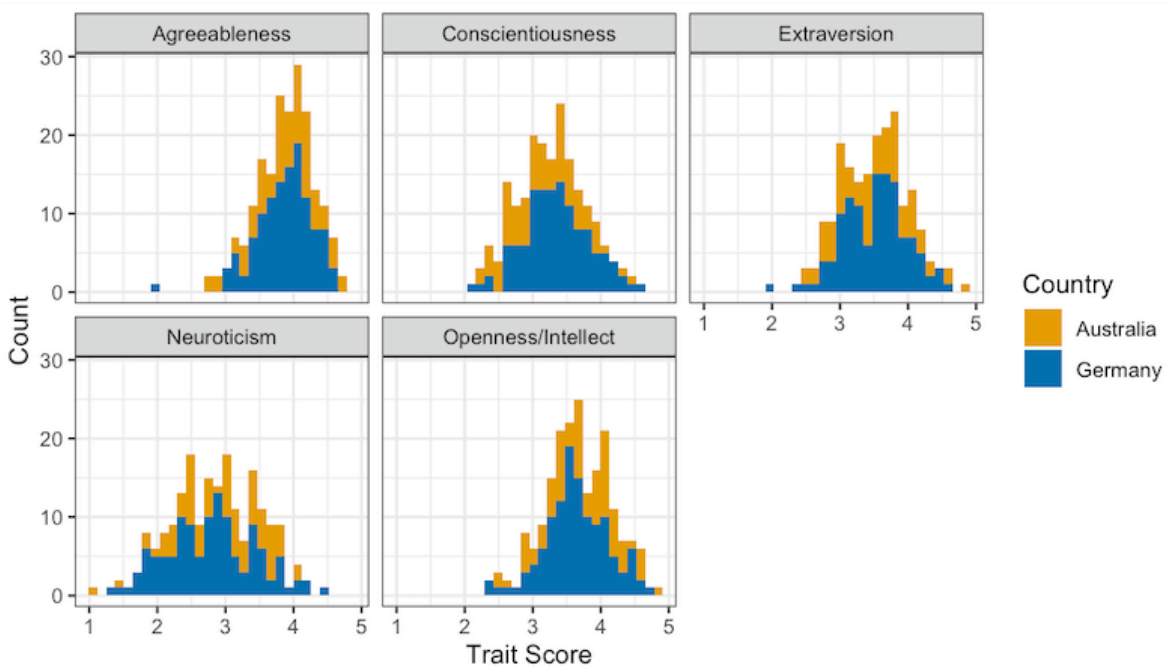

Figure 1. Histograms of personality traits across Australian and German samples.

MVPA-Derived Decoding Performance of Personality from Spectral Power

Figure 2 shows decoding performance across all personality traits and conditions (Australian sample, German sample, and combined sample). Considering the combined sample, neither agreeableness nor neuroticism reached our prespecified minimum correlation of $r = .18$ in the relevant frequency bins (see also Supplementary Table 1 for exact correlation values). Specifically, within our specified frequency windows, the correlation between model-derived personality scores and self-reported personality scores reached only as high as $r = .09$ (at 11-12 Hz) for agreeableness, and $r = .10$ (at 6 Hz) for neuroticism. However, when stratified by country, striking differences in decoding performance emerged. For the Australian sample, agreeableness could be predicted at a minimum of $r = .18$ across certain frequencies in the alpha band (at 8 Hz) and beta band (from 16-18 Hz), as predicted; but the correlation between model-predicted neuroticism and survey neuroticism failed to reach the prespecified threshold. Conversely, for the German sample, neuroticism could be predicted in the theta band (from 3-5 Hz), as predicted, but agreeableness was not predicted in any of the frequencies that we specified.

For remaining traits, the most consistently decoded across the German and Australian samples was extraversion, where frequency bins between 18 and 22 Hz were decoded at above the threshold for the Australian sample (*r*s between .19 and .33) and

near the threshold for the German sample (*r*s between .11 and .16). In the combined sample, extraversion was decoded above the threshold for most of these frequency bins.

Meanwhile, openness/intellect was decoded in the combined sample, but not in the same frequencies for either of the individual samples. Conscientiousness was decoded in the Australian sample in the higher frequencies, but this was not the case for the German sample, and decoding performance failed to reach our prespecified threshold in the combined sample.

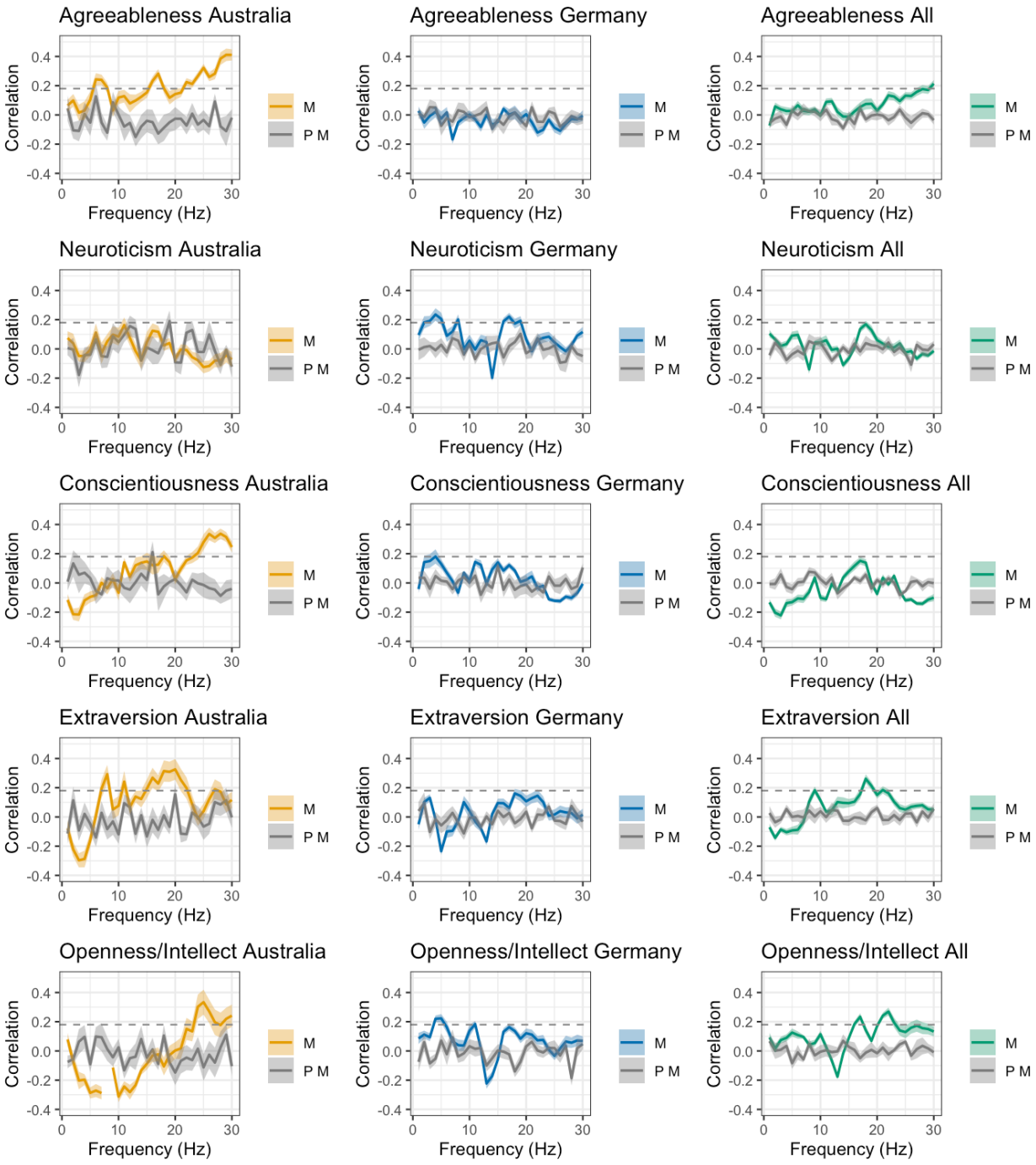

Figure 2. Decoding performance across frequency bins 1-30 Hz for all Big 5 traits, for the Australian sample, German sample, and combined sample. Plots show Spearman correlations between model-predicted personality traits and survey scores. M = Mean decoding performance, P M = A comparison permuted mean performance, where personality labels are randomly swapped prior to decoding. The dashed line represents a correlation value of .18, our prespecified threshold. Error bars depict standard error across repetitions of 10-fold cross-validation. Note that openness/intellect in the

Australian sample is missing a value at 8 Hz (r = -.51) due to this being outside the plotting area.

As the German agreeableness personality ratings included one outlying value that produced a non-normal distribution of scores, we repeated these analyses without this outlier in the German and combined datasets to assess its impact on model decoding performance. As shown in Figure S1, there was minimal change to decoding performance in the combined dataset. For the German dataset, decoding performance did increase around 18 Hz, but did not exceed the r = .18 threshold. Thus, we can infer that the outlying value was relatively uninfluential to scores, and likely not a central reason for agreeableness not to have been decoded in the German sample.

Spectral Power-Personality Trait Correlations

To assess whether the differential decoding performance by country could be visually identified in the power spectrum, we conducted Spearman correlation analyses between relevant personality traits (agreeableness and neuroticism) and power across channels and frequencies (full power spectrum Figure 3; averaged scalp maps across relevant frequencies depicted in Figure 4). These results should be interpreted with caution given that correlations have not been corrected for multiple comparisons.

For both traits, intriguing differences in correlation patterns emerge. In the Australian sample, positive correlations can be observed in the frequency windows 6-8 Hz and 16-18 Hz, where agreeableness had been successfully decoded. The topography of positive correlations was broad across channels (Figure 4) suggesting the contribution of multiple brain regions. However, in the German sample—where agreeableness was not decodable—the positive correlation is much weaker. Conversely, for neuroticism (which was decodable in the German but not Australian sample) a positive correlation between the frequencies 3-5 Hz can be seen in frontal and temporal channels that is absent from the Australian sample. These findings suggest a possible explanation for decoding being observed in only one country per trait.

Contrasting these results with the study we aimed to replicate, Jach and colleagues (2020) found consistent correlations results for agreeableness, whereby negative correlations emerged in the alpha band (averaging 8-11 Hz) and positive correlations emerged in the beta band (averaging 11.5 – 19 Hz). The current study replicated the positive correlations in the beta band, but unexpectedly, we found

positive (not negative) correlations for the alpha band. Note, however, that our alpha band averaged over slightly lower frequencies corresponding to where the trait was decoded in the current study (6 – 8 Hz) and includes frequencies that can be considered part of the canonical theta band. Jach et al. (2020) also observed positive correlations with agreeableness around the 6-8 Hz-mark across all conditions (see their Figure 3), indicating that we replicated this pattern of correlations. It is intriguing that these slightly lower frequencies were not successfully decoded in the original study, although we note in Figure 2 of that study that they do reach close to their threshold for successful decoding performance in three of the four conditions.

Two other features shown in Figure 3 are notable. First, in both traits within the Australian sample, and for neuroticism in the German sample, frequencies at around 10-11 Hz (the canonical alpha band) are negatively correlated with the trait across a wide range of channels. This was also consistent with correlations observed previously (Jach et al., 2020; see their Figure 3). Yet personality traits were not successfully decoded by MVPA in these frequencies in the current study. Second, for neuroticism, the German sample displays a heavy group of positive correlations across a wide range of channels in the upper beta band (~ 22 Hz–30 Hz) despite these frequencies not being decoded by MVPA. Thus, although correlation analyses may offer potential clues to decoding performance, it appears they do not neatly connect to model decoding results.

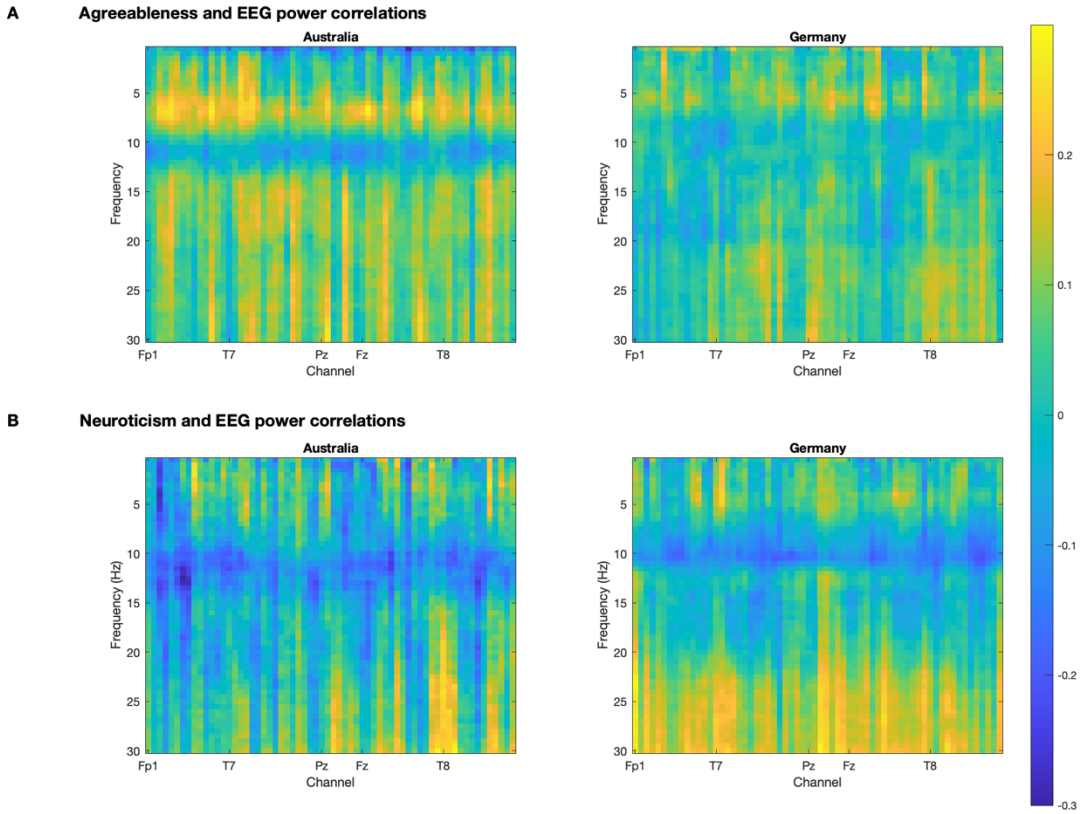

Figure 3. Spearman correlations between personality trait and EEG power across all channels and frequencies analysed (1-30 Hz), stratified by country.

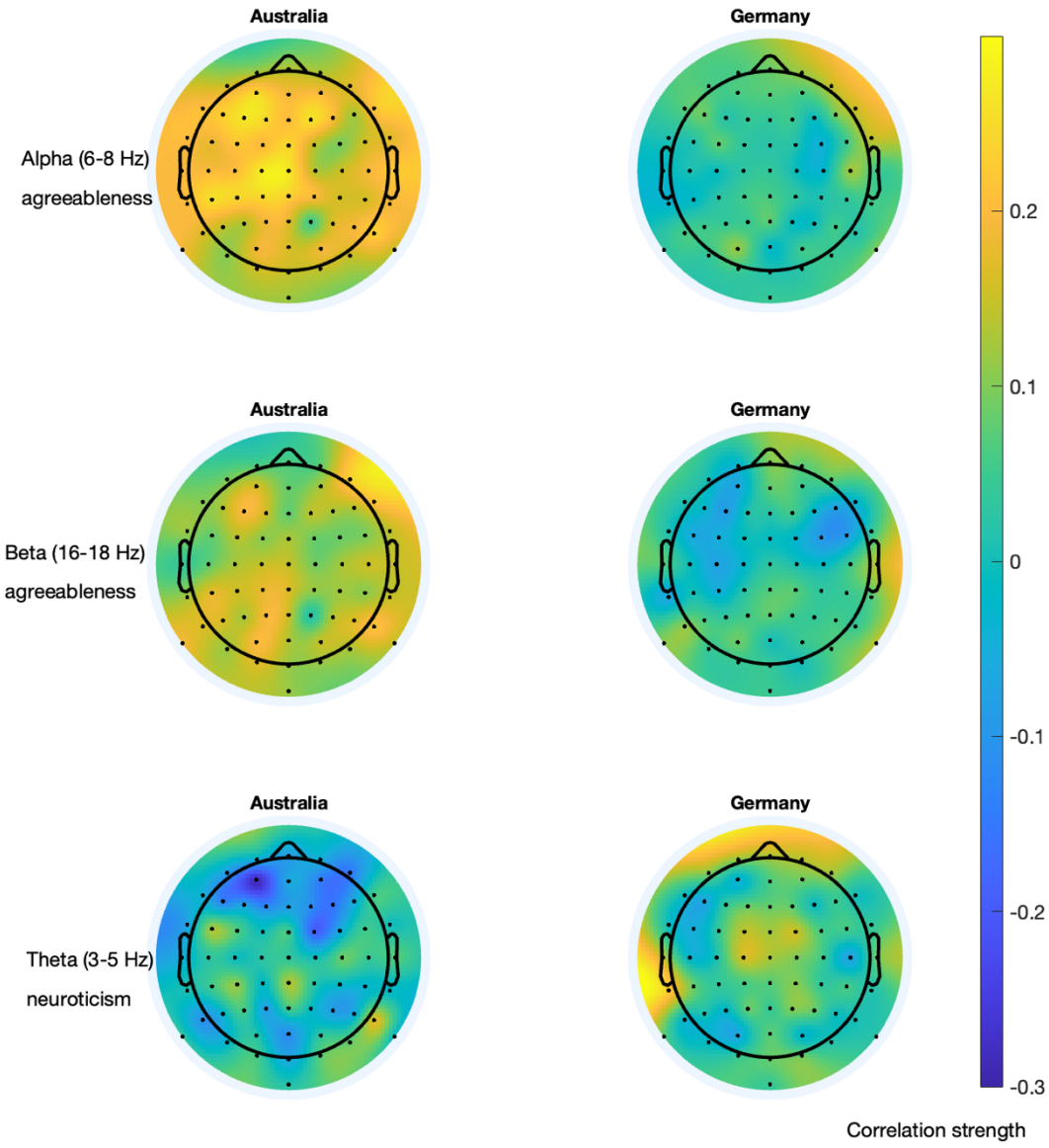

Figure 4. Scalp maps of Spearman correlations between personality trait and EEG power, averaged across relevant frequencies where traits could be decoded for given countries (as specified in the figure).

Discussion

The current study provided a close replication of prior research that decoded the Big 5 personality traits *agreeableness* and *neuroticism* with MVPA (Jach et al., 2020) in order to assess whether the originally reported effects are sufficiently robust to inform theories of the biological basis of personality. Despite using near-identical pre-processing procedures and analyses, we did not replicate study effects in the full sample, suggesting that it is too early to be confident in prior findings. However, when we stratified our analyses by country, we could decode agreeableness in participants from Australia, and neuroticism in participants from Germany. In both cases this decoding overlapped with the same frequency bins that were earlier decoded by Jach et al. (2020). In addition to decoding results, we performed follow-up correlation analyses between spectral power and agreeableness/neuroticism (Figures 3 and 4). When stratified by country, correlations in relevant frequencies were strikingly different between the Australian and German sample, with medium-sized correlations between spectral power and agreeableness observed across a wide range of channels for the Australian dataset (but not the German dataset), and medium-sized correlations between spectral power and neuroticism observed in frontal and occipital channels for the German dataset (but not the Australian dataset).

What explanations can be proposed for the lack of successful decoding in the combined sample, compared to individual country decoding? The German and Australian samples had similar distributions of trait scores (Table 1; Figure 1), suggesting cultural differences in self-reported personality traits is not a likely explanation[14] (and a large cross-cultural study has estimated such differences to be very small; Kajonius & Giolla, 2017). Alternatively, it is possible that differences in decoding between countries are due to contextual factors within each country's testing procedure, which could differentially elicit state emotions, motivations, and cognitions. For example, in the Australian sample, the testing session was relatively short: for 58 participants, resting state was the only EEG data collected; and for the remaining participants, the additional task lasted only 20 minutes. Conversely, in the German sample, resting data were acquired alongside experimental paradigms lasting 30 to 50

[14] Though we acknowledge that to be truly confident in this inference, it would be necessary to test for measurement invariance. However, the sample size required for this latent variable analysis exceeds what we have achieved. At present, we plan to test for measurement invariance when the full $N = 150$ Australian sample is recruited.

minutes, which may have increased anticipation of a longer testing sequence, thereby evoking greater momentary anxiety about the time and effort commitment for the study. Existing research finds that contextual variables can successfully alter EEG markers of approach motivation measured in the resting state (Wacker et al., 2013), suggesting some precedence for this interpretation.

Note that this explanation assumes that the information we are picking up by MVPA reflects momentary states that might aggregate to produce personality traits (Fleeson, 2001; Fleeson & Gallagher, 2009) which is aligned with the hypothesis that personality traits relate to neural data via their predisposition to feel differing strength and frequency of state emotions, cognitions, and motivations (Jach et al., 2020). This hypothesis is also supported by correlation results, which display very different patterns of relations between personality and spectral power by country and trait. If MVPA was instead detecting more enduring differences in neural processes—that is, context-free cues to the biological basis of personality—these patterns should not differ across situations and should also not differ by country (as it is highly implausible that participants from Australia and Germany would have different biological bases of personality traits).

Crucially, the accuracy of contextual factors as an explanation hinges on the country-level decoding performance reported above being accurate, and this may not be the case due to the size of each country's sample. When stratified by country, neither sample met our prespecified threshold of 150 participants (Australia $N = 77$; Germany $N = 120$), and consequently, inferences should be tentative until we have collected the full planned Australian sample of $N = 150$. Particularly for the Australian sample, the participant size is nowhere near sufficient to obtain stable correlation estimates (Schönbrodt & Perugini, 2013), and hence data may be unduly noisy and lead personality ratings to relate to neural features by chance, which would nonetheless be picked up by MVPA decoding and drive apparent performance.

An alternative explanation for why we did not successfully decode agreeableness or neuroticism in the combined sample is that the original study results were a false positive. When would false positives be likely within the context of machine learning? A recent study considered how various factors influence how frequently support vector machine (SVM; the categorical equivalent of SVR) overestimates classification accuracy in the context of relatively small samples (similar in size to the current research). They found that two key factors played a role in spurious

inference from machine learning. First, the higher the feature-to-sample ratio, the more likely the model was to overfit (i.e., output spuriously high classification accuracy). For example, when there were 840 features and only 42 participants, a model with no signal spuriously produced 100% accuracy; conversely, when there were twice or three times as many participants as features, then the model performed far more accurately (see Figure 6 from the paper; Vabalas et al., 2019). Jach and colleagues (2020) used 2.5 times as many participants as features for two conditions, and 1.5 for the other two conditions, suggesting that this issue would not be a problem for their study (particularly for the larger two conditions). The second factor was the form of cross-validation used in model decoding. It has been demonstrated that *k*-fold cross-validation is much more likely than nested cross-validation to overestimate classification accuracy (Powell et al., 2020; Vabalas et al., 2019). This is because if the data used for validation is also involved in parameter tuning and feature selection, then the models fit the noise in both training and validation data and performance is consequently inflated. In contrast, using nested cross-validation produced true chance performance regardless of sample size. In Jach et al. (2020), and in the current study, analyses indeed used *k*-fold rather than nested cross-validation. However, in the toolbox used for all analyses, most hyper-parameters are pre-set, and all channels are automatically used rather than selecting a subset (Bode et al., 2019). This suggests that problems related to parameter tuning and feature extraction/selection are not a problem for the current research, and that this would not have produced spuriously high classification accuracy in Jach et al. (2020) or in the current study.

Of course, we cannot ultimately know whether Jach et al. (2020) or the current study provided a false positive or false negative, respectively. This uncertainty is a feature of all research, but particularly relevant to new research programs, which are first concerned with establishing whether or not effects are present. Given this uncertainty, what are the next steps forward for this research? First, it is vital to collect the full 150 participants to reach our prespecified target sample for the Australian data; this will allow us to have more confidence that results observed in the original study were (or were not) replicated in the current study. Second, if results from this full sample continue to suggest a disparity in decoding personality traits between Australian and German samples, it would be next beneficial to reach beyond the particular samples we have accrued and collaborate with other research teams who have obtained relatively large resting-state EEG datasets including personality trait scores (Mar et al.,

2013). Ideally such datasets would be a minimum of 150 participants to ensure a sufficient feature-to-sample ratio and adequate statistical power to detect at least a correlation of $r = .18$. As part of this project, it would be wise to collect all documented contextual variables related to data acquisition, such as room light and temperature, other tasks performed within the same session, time taken for the test, and set-up time per participant. This may allow us to identify plausible contextual variables that could elicit differing motivations, cognitions, and emotions, and form the basis of new hypotheses for effects.

The current study assessed decoding for each frequency separately. Recently, one research team successfully predicted individual differences by assessing parameters related to the power spectrum distribution as a whole (Ouyang et al., 2020). In this instance, the researchers distinguished between putative oscillatory activity versus $1/f$ noise, finding differential prediction of individual differences for each of these. Although such an approach is outside the scope of the current study, it could be a valuable method to triangulate with current findings and hence observe whether the same traits can be decoded, or new traits can be predicted. Two traits that might be particularly relevant to explore are extraversion (given this trait's surprisingly successful decoding in the current study in both the combined and stratified samples) and openness/intellect (which is the feature of much resting state research in fMRI; Beaty et al., 2016, 2018).

Contrasting decoding with mass univariate correlation results, it is curious that correlations considered an average size in personality psychology ($r = |.20\text{-}.30|$; Gignac & Szodorai, 2016) were visible across many channels in frequencies where MVPA *could not* successfully decode agreeableness or neuroticism (Figure 3). One explanation could simply be that these relations would disappear after correction for multiple comparisons. However, given their breadth across a large number of EEG channels and consistency with correlation patterns observed by Jach et al. (2020), they are unlikely to all be spurious. Alternatively, it is possible that even if true correlations exist, the patterns of covariance do not feature in enough participants for this to be detected by MVPA when cross-validation is performed, because cross-validation splits the data into ten and tests its prediction on only a tenth of the sample (which, even for our largest dataset of $N = 197$, would only be 19 or 20 participants). One solution to this would be to use smaller folds, thereby including more participants in each test set, although this would come at the expense of participants from which to train the model. Alternatively,

employing an entirely new sample as the test dataset, rather than a new train/test set as per the current study, would maximise participants for assessment. Future research may also wish to tackle the disparity between correlation results and decoding results with the use of alternative analyses methods such as modelling the power spectrum (as described above).

Conclusion

Replication is a foundation of incremental science (Lindsay, 2015; Simons, 2014). In this study, we conducted a close replication of a study that used machine learning to predict the personality traits agreeableness and neuroticism from resting-state EEG (Jach et al., 2020). We did not cleanly replicate study results in our full sample, although observed intriguing differential prediction of traits when stratified by sample. Indeed, although neither of our focal traits were decoded in the combined sample, agreeableness was successfully decoded in the Australian sample whereas neuroticism was successfully in the German sample. Thus, although it is too early to consider the original findings robust, the interest sparked by those findings is sustained by the patterns that emerged in this replication attempt. To probe further, more research is needed, perhaps involving larger multi-site collaborations (Mar et al., 2013) or novel methods (e.g., Ouyang et al., 2020). Accepting uncertainty in our knowledge is crucial for the journey toward understanding the biological basis of personality, and open documentation of this complexity can assist the generation of more nuanced hypotheses, improved research practices, and methodological advances.

Chapter 7
General Discussion

7.1 Overview

Personality psychology and cognitive neuroscience both aim to understand emotion, behaviour, cognition, and motivation, via an emphasis on individual differences of these factors or their neural bases, respectively. Personality psychology has been dubbed "the last refuge of the generalist in psychology" (Revelle, 2008, p. 1), and cognitive neuroscience rests on the twin foundations of cognitive science and neuroscience, while also incorporating knowledge from diverse fields such as affective science and decision science. Thus, cross-disciplinary synthesis is at the heart of these disciplines, and the works within this thesis contribute to each of these research traditions.

Across seven studies, I investigated how theories and methods from personality psychology and cognitive neuroscience could be combined to provide new perspectives on existing research questions and to provide new observations that could spur novel research programs. Specifically, I examined how person and situation factors may relate to information seeking (Part 1, Studies 1-5) and used machine learning to explore, then try to confirm, relations between EEG-derived spectral power and personality (Part 2, Studies 6 and 7).

This final thesis chapter aims to review both the strengths and challenges of such an approach. Once again separating Part 1 and 2, this General Discussion begins with a summary of the key study findings, then considers the implications, strengths, and limitations of the current research, followed by key topics for future investigation.

7.2 Part 1 Discussion

7.2.1 Summary. Part 1 of this thesis investigated person and situation factors related to information seeking; a current topic of interest within cognitive neuroscience (Bennett et al., 2016, 2020; Bromberg-Martin & Hikosaka, 2009; Charpentier et al., 2018; Eliaz & Schotter, 2010; Vasconcelos et al., 2015; Wang & Hayden, 2019). One dominant explanation for information seeking is a desire to reduce uncertainty. However, individuals differ in how intolerant of uncertainty they are, which means that the desire to reduce uncertainty may not be a universal but depend on a person's personality. Uncertainty intolerance is a personality trait with a strong positive association with neuroticism and negative association with openness/intellect. The uncertainty-reduction explanation for information seeking conflicts with a theory from

personality psychology in which openness/intellect is proposed to be grounded in enhanced sensitivity to the reward value of information (DeYoung, 2013). To clarify the putative links between uncertainty intolerance and each of neuroticism and openness/intellect, Study 1 presented a pre-registered replication of these associations. Having confirmed these relations, Studies 2 and 3 then examined whether openness/intellect predicted information seeking using a paradigm designed to eliminate any uncertainty about an upcoming reward. Openness/intellect did not predict information seeking, but trait curiosity (joyous exploration) and uncertainty intolerance each revealed independent predictive effects. Given that joyous exploration is strongly positively correlated with openness/intellect and uncertainty intolerance is strongly negatively correlated with openness/intellect, I proposed that these dual effects may have combined to eliminate any direct effect of openness/intellect on information seeking; and that although we did not see clear evidence for the information-seeking theory of openness/intellect, some tentative evidence may be observed via curiosity. Finally, in Study 4 and 5 (Chapter 4) I drew on the knowledge gained from Studies 1-3 to propose a conceptual model of information seeking that comprised two main motivational pathways: one via a drive for exploration, and the other via a drive for safety. The degree to which either pathway would be activated was proposed to be a function of how much the perceived situation afforded positivity, negativity, and intellect, and also personality factors (see Chapter 4 for details), with the exploration pathway more likely to be experienced by people higher in trait curiosity (joyous exploration/deprivation sensitivity) and openness/intellect, and the safety pathway more likely to be experienced by people higher in intolerance of uncertainty and curiosity only as a feeling of deprivation. Across Study 4 and 5, I found consistent evidence for the exploration pathway, and encouraging but more tentative evidence for the safety pathway.

7.2.2 Research implications, strengths, and challenges. Incorporating knowledge and theory from personality psychology can bring a new perspective to the question of why people seek non-instrumental information. Prior information-seeking experiments have demonstrated individual differences in choice responses (Bennett et al., 2016; Brydevall et al., 2017; Kobayashi et al., 2019), and some theoretical papers explicitly recognise individual differences (Sharot & Sunstein, 2020). But an incorporation of personality psychology knowledge and theory goes beyond simply acknowledging the existence of individual differences. Rather, descriptive personality

models can provide a language to describe the main dimensions of differences between people (John & Srivastava, 1999), and to illuminate the psychological meaning or significance of individual differences in a given phenomenon. Drawing on the knowledge and frameworks from personality psychology allowed me to identify distinct personality dimensions (i.e., curiosity, uncertainty intolerance, neuroticism, and openness/intellect) that might characterise individual differences in information seeking. Furthermore, understanding the nomological network of personality traits (i.e., the particular mapping of how traits relate to one another; Cronbach & Meehl, 1955) allowed me to identify which of these perspectives were incompatible or in some degree of conflict with one another (e.g., how the information-seeking theory of openness/intellect conflicted with uncertainty-reduction explanations for information seeking). Assessing how personality trait scores differentially predicted the behavioural outcome of interest enabled me to adjudicate between these distinct perspectives. This ultimately led to a suggestion to refine the information-seeking theory of openness/intellect to be specific for curiosity-driven information seeking (Chapter 3). This particular use of individual differences (to disconfirm and/or refine particular psychological theories) is why personality psychology has been called a "crucible in theory construction" (Underwood, 1975, manuscript title).

Moreover, this knowledge of personality nomological networks was integrated with more recent theories of the relations between psychological states and traits (Fleeson & Gallagher, 2009) and of the interactions between persons and situations (Rauthmann & Sherman, 2020) to develop a conceptual model of information seeking that specified the contexts under which I would expect different traits to drive decisions, and the putative affective processes involved (Chapter 4). The studies presented in Chapter 4 did not support every element of this theory of information seeking. However, results clearly demonstrated that the person, the perceived situation, and affective states each related to one's proclivity to seek information. These findings demonstrate the value of including measures from personality psychology in concert with cognitive neuroscience paradigms, and thus, one key implication of Part 1 of the thesis is the usefulness of such measures for future information-seeking studies.

Relatedly, study results have demonstrated that experimental paradigms used to study non-instrumental information seeking are not necessarily perceived equally by participants, even if they all feature a choice for information that does not increase the likelihood of explicit extrinsic rewards. This suggests the need to use multiple

experimental tasks, or at least be aware of the constraints on generalizability imposed by only a single experimental context.

Of course, the incorporation of concepts from personality psychology presents some challenges for researchers in cognitive neuroscience. First, it requires more time and money to run these studies, given a requirement for a sample size sufficient to have stable estimates of correlations ($N \sim 250$; Schönbrodt & Perugini, 2013) to be confident that observed patterns of relations are not due to chance alone. Studies in cognitive neuroscience typically have much smaller sample sizes (Button et al., 2013), and the costs of larger samples may become prohibitive when neural measures are collected, because testing each participant is labour-intensive and it is costly to run equipment (e.g., an fMRI scanner). In addition, although it is relatively easy to administer and score a personality questionnaire, it would be far less trivial for a cognitive neuroscientist to gain a deep understanding of personality frameworks, models, theories, and methods. The overall time and effort required may lead cognitive neuroscientists to default to smaller sample sizes and limit inferences to within-subject effects. While acknowledging the practical limitations of incorporating personality psychology into cognitive neuroscience, I nevertheless suggest that the extra effort may be worthwhile given the value to theory construction as outlined above (Underwood, 1975). Personality neuroscientists have suggested that cross-laboratory collaborations could be valuable for aggregating neural and personality data to address questions pertinent to individual differences (Mar et al., 2013); an example of this collaboration can be seen in Study 7 (Chapter 6). Alternatively, studies using experimental paradigms without accompanying neural data, such as the studies within Part 1 of this thesis, can assess behaviour and require minimal extra resources than studies on smaller groups (particularly if data is collected online). Finally, if researchers do not have the resources to collect a sample size sufficient to measure individual differences, insights could also be built by including multiple experimental paradigms measuring situation perceptions for each of these paradigms, thereby accounting for contextual differences in mean information-seeking preference. The key is to advance from assuming that all people will demonstrate the same behaviours (e.g., information seeking) in all contexts, to understanding that people can demonstrate diverse behaviours across the same and different contexts. This added nuance brings complexity, but also the potential for greater understanding.

7.2.3 Future directions.

7.2.3.1. Disentangle uncertainty reduction from information gain. As mentioned at the beginning of this thesis, information is defined for current purposes as data that causes a transition from prior to posterior belief (Lawrence, 1999). In all current information-seeking paradigms I am aware of, information gain results in uncertainty reduction. This means that it is impossible to experimentally isolate a decision to seek information from a decision to become more certain. But in real-world contexts, information gain is sometimes accompanied by *increased* uncertainty. For example, imagine that you are a detective trying to deduce the culprit in a murder case. You may strongly suspect one person, but then obtain new information that causes you doubt (i.e., become more uncertain about) your previous belief. Furthermore, uncertainty can immediately follow information gain when it leads you to be aware of greater mysteries. This is also true in any scholarly endeavour, where the more one learns about a topic, the more they realize how little they really know. These subtleties in the dynamics of information-seeking are missing from current lab-based paradigms—including all paradigms used within this thesis—which permit information-gain only of a kind that reduces uncertainty.

I noted the need for future research to attempt to disentangle uncertainty reduction from information gain in the manuscript within Chapter 3. However, it bears repeating because it can address any claims that the uncertainty-reduction theory of information seeking was fully supported by Study 4 and 5 purely because we observed preferences for information in scenarios where information gain was mapped to uncertainty reduction. This is a challenging argument to discredit with evidence from personality and situation perception correlates alone. People who find uncertainty aversive would logically want to reduce uncertainty, but people who seek information to reduce uncertainty may do this for reasons other than finding uncertainty aversive (e.g., it could be an automatic imperative that is not accompanied by a particular emotional valence, or could be accompanied by more apparently positive emotions such as curiosity; Gottlieb et al., 2013; Schwartenbeck et al., 2019). By developing a paradigm where all elements of the task are the same except for information that increases or decreases uncertainty, this question can be clarified. Given that people higher in joyous exploration and openness/intellect are more tolerant of uncertainty, these individuals may be more willing to engage in temporary increases in uncertainty (i.e., exploring the unknown to "increase the experience of uncertainty to an interesting

level"; DeYoung, 2013, p. 8). Conversely, people who are more intolerant of uncertainty may only be willing to seek information that reduces uncertainty. In line with this aim, one idea could be to randomise participants into two groups who receive progressive amounts of information that differ only in respect to uncertainty (increasing or decreasing). Following this, participants could be given the choice to seek further information. An alternative paradigm could contrast information sampling in a high-variance (i.e., high uncertainty) or low-variance (low uncertainty) environment, and then provide a "free choice" period where participants can either continue to seek information in these same conditions or take part in a control task which is equated for task boredom and complexity. We might expect uncertainty intolerance to negatively predict seeking information in conditions where uncertainty increases, and positively predict seeking information where uncertainty decreases. Meanwhile, given that individuals higher in openness/intellect and joyous exploration are more tolerant of uncertainty, their decisions may be unrelated to the uncertainty in the environment, or may even show the opposite effect to uncertainty intolerance.

Paradigms such as those described above would provide further benefits to inferences and theory specification. Specifically, the information-seeking stimulus sets used in Study 4 or 5 contained many peripheral differences between these tasks, such as the amount of information gained, visual details, variety of stimuli, and so on; and equating conditions would eliminate these factors as possible counter-explanations for study findings. Further, a paradigm where uncertainty can be specified mathematically (as it could be via information theory; Shannon, 1948; Wibral et al., 2014) would make it possible to simulate predictions for behaviour, including how information and uncertainty may relate to personality traits. This means that at least part of the conceptual theory could be instantiated in a formal process model. Such formal models are valuable to force the researcher to specify precisely how and to what degree parts of the model connect to one another, and provide objective quantification of how closely predictions matched data (Fried, 2020; Guest & Martin, 2020). A possible starting point for such models could be earlier models of choice preference proposed for reward-outcome paradigms (Bennett et al., 2016, 2020; Iigaya et al., 2016).

7.2.3.2. Understanding the emotional-motivational core of curiosity and where curiosity is located in relation to Big 5 traits. Curiosity has accrued various and sometimes conflicting definitions in its long research history: for example, it has been described as a feeling of deprivation arising from awareness of a gap in one's

knowledge (Loewenstein, 1994); a desire to reduce the internal conflict aroused by middling levels of strangeness or complexity (Berlyne, 1954); a drive-state for information (Kidd & Hayden, 2015); the desire to know and understand (Gottlieb et al., 2013; Litman, 2005); and a positive emotional-motivational system related to the detection and search for what is new and challenging (Kashdan et al., 2004). Measures of trait curiosity reflect these diverse definitions. One initial study found evidence of two factors of curiosity, one representing *depth of interest* and the second *breadth of interest* (Ainley, 1987). More recently, Litman (2008) proposed two different factors of curiosity represent both "wanting" information (curiosity-as-deprivation) and "liking" information (curiosity-as-interest). Kashdan and colleagues proposed yet another two-factor model of curiosity that included curiosity-as-interest and a factor closely related to uncertainty tolerance, described as being willing to accept complexity in daily life (Kashdan et al., 2009). More recently, Kashdan (Kashdan et al., 2018; 2019) presented a new structural model comprising five factors, which included curiosity-as-interest (i.e., joyous exploration), curiosity-as-deprivation (i.e., deprivation sensitivity), and uncertainty tolerance (i.e., stress tolerance) in addition to thrill seeking (similar to Ainley's *breadth of interest*) and social curiosity factors.

The multi-faceted nature of curiosity means that any explanation that information seeking is "curiosity-driven" (as I proposed in the manuscript within Chapter 3) is potentially vague and confusing. In Chapter 4 I attempted to clarify this proposal by specifying how different facets of curiosity would relate to information seeking in different situations. But the links between different facets of curiosity and tendencies toward emotions and behaviours have not been robustly established. Although Litman (2005) linked curiosity-as-interest to opioid-mediated "liking" of information and curiosity-as-deprivation to a dopamine-mediated "wanting" of information, there is no direct evidence supporting a link between these facets and specific neurotransmitters or related motivational states. I proposed that rather than representing information-wanting, deprivation sensitivity might be an interstitial facet comprising both positive emotions representing interest for information and negative emotions representing the aversive nature of not knowing. In support of this view, I observed positive correlations between deprivation sensitivity and each of joyous exploration/uncertainty intolerance. However, more direct evidence would be to link facet scores to reports of momentary emotions that might be expected to relate to interest or deprivation, respectively. When I did so in Study 4, results were inconclusive

due to multicollinearity between state measures, suggesting that further work is necessary to understand the different emotional-motivational processes being tapped by different curiosity facets.

Some additional insight might be gleaned by investigating where facets of curiosity are located within the Big 5 framework. I have proposed throughout this set of studies (see Chapter 4 and 5) that curiosity, particularly joyous exploration, could be considered a facet of openness/intellect. Kashdan and colleagues (Kashdan et al., 2018, 2020) have also observed strong relations between joyous exploration and openness/intellect, supporting this perspective. However, assessing correlations does not account for measurement error or unique variance accounted for by Big 5 traits. In one recent study, a large collection of standalone scales (including measures of curiosity) was examined, in terms of their overlap with the Big 5, to determine whether this overlap was comparable to Big 5 facet scales (Bainbridge et al., Accepted). Curiosity was one of the scales to overlap with the Big 5 to such a degree that it could be considered a Big 5 facet (reinforcing arguments by Christensen & Silvia, 2020, and Woo et al., 2014). Further, the authors found that curiosity strongly loaded on openness/intellect, with minimal loadings on other Big 5 traits, suggesting it could be "located" within openness/intellect. However, this study used an earlier measure of curiosity that did not distinguish between joyous exploration and deprivation sensitivity (Kashdan et al., 2004). Thus, future research employing the same method with recent scales (Kashdan et al., 2020; Litman, 2008) would provide important insights as to whether some or all facets can be located within the Big 5, and the degree to which facets are interstitial. This could facilitate further theories concerning which motivational or emotional processes are at the heart of different facets of curiosity.

7.2.3.3. Further investigation of the information-seeking theory of openness/intellect. When proposing the information-seeking theory of openness/intellect, DeYoung (2013) connected information seeking to exploration, which he defined as behaviour motivated by the reward value of uncertainty. However, DeYoung did not explicitly contrast this exploratory motivation with other motivations to seek information, which left it ambiguous as to whether openness/intellect was theorised to predict information seeking in any context. This studies within this thesis uncovered particular conditions under which openness/intellect predicted information seeking: Study 4 and 5 demonstrated that openness/intellect predicted information seeking for the Trivia, Bonus, and Character stimulus sets, but not the Reward-Outcome

stimulus set; and statistical mediation models presented in Study 4 are consistent with the relation between openness/intellect and information seeking being driven by feelings of curiosity, as we originally hypothesised in Study 2/3. Thus, I proposed that openness/intellect was related to exploration-oriented information seeking (via feelings of interest and positivity) but not safety-oriented information seeking (via uncertainty intolerance).

Where do we go from here to assess this theory? If exploration-oriented information seeking is a motivational core of openness/intellect and one reason why we observe covariation between items that form measures of openness/intellect, and joyous exploration reflects a tendency toward exploration-oriented information-seeking, then joyous exploration should correlate with multiple openness/intellect scale items/facets, not just the average or latent average. Thus, one possible next future research direction would be to assess patterns of correlations between joyous exploration and openness/intellect at lower levels of the trait hierarchy, such as the individual items or "nuances" that form openness/intellect (Mõttus et al., 2017).

Further, similar to existing theories that propose dopamine is the mechanism linking extraversion to an increased sensitivity to reward (Wacker & Smillie, 2015), DeYoung (2013) proposed that dopamine is the neural mechanism linking openness/intellect to increased sensitivity to information. This connection to dopamine could therefore explain the shared variance between extraversion and openness/intellect. Thus far, the only investigation of how dopamine might relate to openness/intellect in the context of information gain was conducted by Smillie and colleagues (Under Review). Participants completed a reward-outcome paradigm after having taken either a placebo or the dopaminergic drug *sulpiride*. This therefore provided a direct test of how dopamine may influence the link between information seeking and openness/intellect. Sulpiride modestly increased information seeking in this study—potentially confirming a role of dopamine in information-reward valuation—however, no positive relation between openness/intellect and information seeking was found in either the placebo condition or under sulpiride. As those authors noted, it is possible that the paradigm used in this study did not capture the form of information seeking to which individuals high in openness/intellect are disposed. Indeed, these findings partly informed the decision to compare between the reward-outcome paradigm and the trivia paradigm in Chapter 4 of this thesis, which confirmed that openness/intellect is associated with information seeking in the latter but not the

former paradigm. Future researchers might design a dopaminergic manipulation alongside a trivia paradigm to assess further evidence for the impact of dopamine on information seeking.

Finally, EEG studies have previously linked extraversion to dopamine function via the size of the *reward positivity,* an event-related potential reflecting a reward-prediction-error signal (Sambrook & Goslin, 2015) that is putatively driven by phasic dopamine firing (Hauser et al., 2014; Holroyd & Coles, 2002). These studies contrasted unexpected rewards with unexpected non-rewards, finding that the size of the difference waves between conditions correlated with extraversion (Cooper et al., 2014; Smillie et al., 2011, 2019). A similar paradigm could possibly be constructed comparing instances of unexpected information gain or non-gain, which has been successfully accomplished with a reward-outcome paradigm (Brydevall et al., 2017). For future research, stimuli from the Character information-seeking measure from Study 4 may be appropriate, given that information seeking for this stimulus set was related to joyous exploration and openness/intellect, and the stimuli are simple and consistent between trials.

7.2.4 Part 1 conclusion. I first established the nomological network linking Big 5 traits to uncertainty attitudes (Study 1), the results of which suggested that the uncertainty-reduction theory of information seeking conflicted with personality theories linking openness/intellect to information seeking. This led to a series of studies finding that people display context-dependent patterns of preferences for non-instrumental information that meaningfully map to particular individual differences (Studies 2-5). Thus, I demonstrate how personality psychology can be a valuable lens through which to view and tackle research questions from cognitive neuroscience.

7.3 Part 2 Discussion

7.3.1 Summary. Part 2 of the thesis (Chapters 5 and 6) employed cognitive neuroscience methods to generate novel observations that could form the basis for new theories of the biological basis of personality. Specifically, I used the data-driven analysis method MVPA to predict Big 5 personality traits from resting-state EEG data. In Study 6 I found that the traits agreeableness and neuroticism could be consistently identified from patterns of spectral power across four testing conditions. Study 7 presented a pre-registered replication of Study 6. I failed to replicate study results in a combined Australian and German sample but observed successful decoding for agreeableness in the Australian sample and neuroticism in the German sample.

7.3.2 Research interpretation: accounting for uncertainty. New techniques and processes hold great possibility to discover effects that could not be detected with traditional methods. For example, the findings presented in relation to agreeableness in Study 6 had never before been documented. Further, the very similar patterns of Spearman correlations between spectral power and personality traits across studies and samples (see Chapter 6, Figure 3, and Chapter 7, Figure 3) has not, to my knowledge, been previously recognised. Specific to agreeableness, patterns of positive correlations in the beta band across a wide range of brain regions was replicated in the Australian sample (where this trait was successfully decoded). Finally, by sharing Study 6 data online accompanied by extensive code and documentation, I aimed to make it straightforward for future researchers to implement similar methods with their own individual differences data.

However, findings from Study 6 were not directly replicated in the combined sample of Study 7. It is crucial to account for this failed replication, but this is challenging when new techniques are applied, because it is much harder to assess whether there were methodological issues (e.g., too small a sample) or substantive issues (e.g., context-dependent differences in state expression of personality traits, as described in Study 7) that were more likely to have caused the failure to replicate. MVPA is not a new technique in cognitive neuroscience, but the conditions and purpose of its use in the current study are new. The typical use of MVPA is to predict neural representations related to behaviour that can be directly quantified, such as visual features of a scene or errors in a trial (Bode & Stahl, 2014; Tong & Pratte, 2011). Only recently has the method been used to predict subjective reported responses. Even here, the focus is on predicting trial-level subjective responses per participant from EEG in the time domain (e.g., Schubert et al., 2020; Turner et al., 2017). In contrast, the current studies aimed to predict group-level differences in subjective reported personality traits from EEG in the frequency domain. The novel use of MVPA means that we cannot refer to established norms in analysis strategy or sample size planning when assessing the failure to replicate. However, there are several possibilities for why decoding personality trait scores may be more difficult than traditional target outcomes. For example, there is likely more noise involved when trying to predict cross-sectional averaged-trait scores from neural data than there would be in predicting multiple ratings from the same person. Some of this noise could be ameliorated by forming latent variable trait scores rather than simple averaged scores, which would be a valuable

approach for future studies to take if the sample size is sufficient to construct latent measures (which it was not for the current studies). However, latent measures of personality would not account for the added noise in the EEG measures. Although trial-level noise is reduced in the frequency domain due to averaging across many short epochs within the testing period, by comparing spectral power across participants rather than between trials for each participant, idiosyncratic participant-level noise that is irrelevant for the purposes of personality ratings might appear. In within-subject analyses, this would be inherently controlled as it would be consistent across trials. However, for between-participant analyses, these large differences could make it more difficult to uncover personality-relevant effects.

Further, we should expect small correlations between personality scales and any neurobiological measure, given that r = .20 is the average effect size in personality psychology (Gignac & Szodorai, 2016) and given that we would expect any personality trait to be multiply determined. For example, Ahadi and Diener (1989) found that when two outcomes were entirely determined by only four variables, two of which overlapped, the correlation between any variable and its outcome did not exceed r = .45. The effects that we are investigating are likely due to many more small accumulating factors, suggesting effect sizes are likely to be far smaller than this upper bound (Pickering & Pesola, 2014; Strube, 1991; see also our explanation in Study 6). Small effect sizes are important and meaningful for predicting behaviour (Funder & Ozer, 2019) but they require large samples to reliably detect, which presents a logistical challenge for labour-intensive collection of EEG or fMRI data.

Taken together, the substantial advantages of pursuing new methods to understand the neural bases of personality are counterbalanced by a need to accept some measure of uncertainty and confusion in our inferences and interpretation of results. Of course, this should not be mistaken for a limitation of the current method. Instead, uncertainty is the nature of the beast when exploring new methods or asking new questions in science. Ultimately, when it comes to uniting personality and neural measures, we are combining one known (i.e., distributions of personality trait scores and their intercorrelations, which have been consistently documented over literally thousands of studies; Gignac & Szodorai, 2016) with an unknown (i.e., how these personality factors are represented in the brain). So long as the challenges are openly documented and confusing results are not squirreled away in the file drawer, such

complexity can spur novel insights to answer substantive research questions and associated methodological research questions.

7.3.3 Future Directions. Specific topics for future directions were provided in the individual studies comprising Part 2, and their reiteration here would be redundant. Instead, I provide some general guidelines on future strategies for this form of research.

Given the confusion in interpreting results described in Section 7.3.2 above, there is a clear need for future research to conduct simulation studies assessing how frequently noise is erroneously decoded or signal is correctly decoded. The closest existing study fulfilling this aim assessed how often support vector machine—a categorical analogue of support vector regression—falsely decoded noise (Vabalas et al., 2019). This study found that if there were at least 2 or 3 times as many participants compared to features, this should produce relatively accurate decoding. We met this participant-to-feature criterion in Study 6 and in the combined and German sample in Study 7. However, sufficient sample sizes for support vector regression may be higher than what is required for support vector machine, and issues such as measurement error could inflate the problem. Thus, a simulation study targeted to typical data in personality neuroscience would be a valuable methodological addition to these concerns.

Second, open science practices (including sharing data, methodology and analysis scripts) are imperative for research where the presence or absence of effects still need to be established. Allowing other teams to easily reproduce analyses can assure the research community that inconsistent results are not due to methodological errors or differences in analysis strategy. Open data allows researchers to conduct their own follow-up sensitivity analyses to assess how robust results are under different specifications of the data or analyses (Weston et al., 2019). Providing analysis script templates and clear README files also provides a service to other researchers who are curious to try these new methods but unsure where to begin.

Third, as I mentioned in the Discussion of Part 1, multi-site collaborations are also highly valuable in order to gain a sufficient sample size to address neural data. However, as the current study demonstrates, there can also be challenges in combining datasets across sites, where differences between results could reflect differences in testing protocol, equipment used, pre-processing strategy, or participant features such as culture or age (e.g., university students versus general population). Thus, future research that collaborates across research teams should ideally remain as similar as

possible in relation to the above features, at least in an early stage in testing when the aim is to provide a straightforward replication of the data in similar conditions.

7.3.4 Part 2 Conclusion. I used MVPA, an emerging method from cognitive neuroscience, to explore whether personality trait-relevant information was contained in the resting state as measured by EEG. Study 6 found that agreeableness and neuroticism could be consistently decoded. However, Study 7 failed to replicate these findings in the full sample. Despite this increased uncertainty, results demonstrate that it is possible to employ this new method with personality data, suggesting it is a promising approach to provide clues to the biological bases of personality. I have suggested several future approaches within Study 6 and in Chapter 7 above to work toward transfiguring current uncertainty into insight. More broadly, cognitive neuroscience can be a valuable lens through which to view and tackle research questions from personality psychology.

7.4 Concluding Remarks

In this thesis, I presented seven new empirical studies situated at the intersection of personality psychology and cognitive neuroscience. The chapters that formed this thesis were divided into two parts: Part 1 (Studies 1-5) comprised an investigation of motivations related to information seeking, and Part 2 (Studies 6 and 7) used machine learning to investigate relations between personality traits and EEG-derived neural indices. Though each section is distinct, both are connected by an explicit appreciation for the value of interdisciplinary dialogue. Neither section could have existed without drawing methods, theories, and knowledge from both fields.

The thesis does not shy away from the challenges of interdisciplinary attempts at knowledge building (e.g., Section 7.3). Nevertheless, as a whole, the studies I have presented here demonstrate core strengths of an interdisciplinary approach. Embracing both the personality and cognitive neuroscience literatures led me to combine person and situation assessment methods from personality psychology with experimental paradigms from cognitive neuroscience (Part 1) and, conversely, to integrate methods from cognitive neuroscience to explore the biological basis of personality (Part 2). Further, understanding the correlates of personality traits allowed me to propose constraints on different theories of information seeking (Studies 3-5), ultimately leading to the development of a new theory of motivations for information seeking. Overall, the seven studies presented here demonstrate the diverse and multifaceted ways that personality psychology and cognitive neuroscience can enrich one another.

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Appendices

Appendix A

Supplementary Materials for Chapter 2 (Jach & Smillie, 2019)

S.1 Regressions Using Latent Variables, Companion to Section 3.3

Our regression analyses in Section 3.3 employed several measures that were computed with mean scores rather than latent variables. As incremental validity claims can be misleading when using observed variables (Westfall & Yarkoni, 2016), we also present the analyses from Section 3.3.1 with latent variables. The *lavaan* package (Rosseel, 2012) was used for all analyses.

For personality traits, latent variables were specified as second-order factors comprised of subscales, which in turn were comprised of items (e.g., extraversion was measured as a second-order latent factor made up of the three subscales *assertiveness, energy levels,* and *sociability,* where each subscale was indicated by four items). As we had two measures of openness to experience, we used aspects from the BFAS and facets from the BFI-2 to compute a second-order factor comprised of five sub-factors (openness, intellect, aesthetic appreciation, curiosity, and creativity). For ambiguity tolerance, a single variable was computed across the 25 items in the two scales (TfA and MSTAT).

Findings from the main text were replicated with latent variables and were of a similar magnitude. Specifically, openness to experience significantly predicted ambiguity tolerance, $\beta = 0.62$, 95% CI [0.54, 0.70], and continued to predict ambiguity tolerance even controlling for intelligence, $\beta = 0.62$, 95% CI [0.53, 0.70]. Intelligence did not significantly predict ambiguity tolerance in this model; $\beta = 0.02$, 95% CI [-0.09, 0.13].

Extraversion also positively predicted ambiguity tolerance, $\beta = 0.43$, 95% CI [0.32, 0.54], and this relation held when including openness to experience, $\beta = 0.23$, 95% CI [0.11, 0.34], although openness remained the stronger predictor, $\beta = 0.52$, 95% CI [0.42, 0.62]. We also found that openness to experience strongly negatively predicted uncertainty intolerance, controlling for intelligence, $\beta = -.46$, 95% CI [-0.56, -0.36], and when neuroticism was added to this model, it was the stronger predictor (neuroticism positively predicting uncertainty intolerance, $\beta = 0.67$, 95% CI [0.59, 0.74]; versus openness to experience negatively predicting uncertainty intolerance $\beta =$

-.24, 95% CI [-0.33, -0.14]. Using a chi-square test to assess nested model comparisons, the model with added neuroticism was a significantly better fit than the simpler model with only openness to experience and intelligence, $\chi^2(768) = 1472.41$, $p < .001$.

S.2 Behavioral Ambiguity Tolerance Results

As mentioned in section 3.3.2 of the main manuscript, we planned to test the effect of personality traits on behavioral ambiguity tolerance by computing a behavioral ambiguity tolerance index, combining all five behavioral tasks. However, given the very poor internal consistency of our behavioral ambiguity tolerance measure, it was not appropriate to compute a combined index. Instead, we include below the results of several different logistic regressions predicting each behavioral ambiguity tolerance measure from openness to experience, extraversion, neuroticism, and plasticity (computed as a latent variable from BFI-2 Extraversion and Open-Mindedness). Table S1 summarizes these analyses. None of the hypothesized personality variables predicted any of the five behavioral ambiguity tolerance tasks.

Finally, we also explored whether modelling behavioral ambiguity tolerance as a latent variable would better account for measurement error. However, similar to our analyses in Table S1, none of the latent variable measures (openness to experience, extraversion, neuroticism and plasticity—measured as a third-order latent variable combining extraversion and openness to experience) predicted behavioral ambiguity tolerance. Model fits were also mostly poor for these analyses. Table S2 includes the regression coefficients and model fit indices for each structural equation model.

Table S1

Regressions Predicting Behavioral Ambiguity Tolerance from Personality Traits

	BAT1	BAT2	BAT3	BAT4	BAT5
Openness to Experience	b = 0.13, p = .28	b = 0.14, p = .26	b =-0.11, p = .42	b = 0.02, p= .90	b = -0.08, p = .50
Extraversion	b = 0.05, p =.72	b = 0.15, p= .23	b = 0.16, p = .35	b = -0.002, p=.99	b = 0.002, p = .99
Plasticity	b = 0.15, p = .22	b = 0.18, p = .15	b = 0.05, p = .72	b = 0.03, p = .83	b =-0.08, p = .55
Negative Emotionality	b = -0.14, p = .26	b = 0.08, p = .51	b = -0.28, p = .07	b = 0.16, p = .22	b = 0.014, p = .91

Note. BAT = Behavioral ambiguity tolerance.

Table S2

Latent Variable Regressions and Model Fits Predicting Behavioral Ambiguity Tolerance from Personality Traits

Model predicting ambiguity tolerance	β	95% CI	RMSEA	SRMR	CFI
Openness to Experience	0.09	[-0.06, 0.25]	.09	.10	.710
Negative Emotionality	-0.06	[-0.22, 0.09]	.08	.06	.91
Extraversion	0.06	[-0.11, 0.23]	.09	.07	.83
Plasticity	0.11	[-0.13, 0.35]	.09	.11	.69

Note. ~ = is predicted by, β = Standardized beta weight, 95% CI = 95% Confidence interval for standardized beta weight, RMSEA = Root Mean Square Error of Approximation, SRMR = Standardized Root Mean Residual, CFI = Comparative Fit Index.

S.3 Network Analysis, Companion to Sections 2.4.2 and 3.4

The following section includes supplementary details for analyses used to compute a network analysis in Section 3.4 of the main paper. We used the *R* package *bootnet* (Epskamp, Borsboom, & Fried, 2018) for all analyses. First, for Big 5 personality traits, we averaged over participant responses to obtain scores for each of the three aspects contained within a given trait (for example, the facets *energy, sociability,* and *assertiveness* were used to describe extraversion). As we also measured openness to experience with the Openness/Intellect scale from the BFAS, we additionally included the aspects *openness* and *intellect* in our network.

For measures of ambiguity tolerance, we compared the factor structure from the initial papers introducing the scales (McLain, 2009; Herman et al., 2010; Carleton et al., 2007) to the factor structure in our sample derived by an exploratory graph analysis[15]. For intolerance of uncertainty, the two-factor structure found by Carleton et al. (2007) was reproduced in our sample, and the items loaded heavily onto their expected factor. For MSTAT, McLain (2009) found evidence for three factors, which was also the case for the exploratory graph analysis. Finally, for TfA, the original study suggested four factors (Herman et al., 2010). However, we found that the exploratory graph analysis suggested three factors. As we had converging results, we also assessed results predicted by a factor analysis. The parallel analysis suggested four factors, but the MAP test only suggested three factors. Assessing the item content loading on the different factors, it was also difficult so see a clear pattern across items within individual components for TfA. Due to this confusion surrounding subcomponents of TfA, we decided not to include this measure in our network analysis. (Note that an analysis checking the network model with TfA was conducted, and the structure of the network was highly similar, and conclusions related to traits were identical).

Table S3 and Table S4 list the three MSTAT dimensions and two Intolerance of Uncertainty dimensions, respectively, derived by the exploratory graph analysis. As

[15] As exploratory graph analysis is a new analysis procedure, we also conducted exploratory factor analyses (using the *psych* package; Revelle, 2017) on the same data to see if results converged. For intolerance of uncertainty, the same results were found across both methods. For MSTAT, the MAP and parallel analysis suggested that two factors were sufficient—however, this contrasted with both the original author finding from the study, and from our exploratory graph analysis results, so we retained three dimensions.

outlined in the main paper, when assessing the item content in each dimension we observed that MSTAT had one factor related to ambiguity *avoidant* items (M1) second dimension related to ambiguity *tolerant* items (M2), and a third dimension that seemed to involve problem solving with complexity (M3). For intolerance of uncertainty, the suggested factors were the same as defined in the original scale by Carleton et al. (2007): prospective anxiety (IoU1) and inhibitory anxiety (IoU2).

Table S3.
MSTAT Tolerance for Ambiguity EGA Dimensions

Item number	Item	Dimension
1	I don't tolerate ambiguous situations well. (R)	M1
3	I try to avoid situations that are ambiguous. (R)	M1
11	I dislike ambiguous situations. (R)	M1
12	I find it hard to make a choice when the outcome is uncertain. (R)	M1
4	I prefer familiar situations to new ones. (R)	M2
7	I am tolerant of ambiguous situations.	M2
8	I enjoy tackling problems that are complex enough to be ambiguous.	M2
10	I generally prefer novelty over familiarity.	M2
13	I prefer a situation in which there is some ambiguity.	M2
2	I would rather avoid solving a problem that must be viewed from several different perspectives. (R)	M3
5	Problems that cannot be considered from just one point of view are a little threatening. (R)	M3
6	I avoid situations that are too complicated for me to easily understand. (R)	M3
9	I try to avoid problems that don't seem to have only one "best" solution. (R)	M3

Note. (R)= Reverse scored.

Table S4.
Intolerance of Uncertainty EGA Dimensions

Item number	Item	Dimension
1	Unforeseen events upset me greatly.	IoU1
2	It frustrates me not having all the information I need.	IoU1
3	One should always look ahead so as to avoid surprises.	IoU1
4	A small, unforeseen event can spoil everything, even with the best of planning.	IoU1
5	I always want to know what the future has in store for me.	IoU1
6	I can't stand being taken by surprise.	IoU1
7	I should be able to organize everything in advance.	IoU 1

8	Uncertainty keeps me from living a full life.	IoU 2
9	When it's time to act, uncertainty paralyses me.	IoU 2
10	When I am uncertain I can't function very well.	IoU 2
11	The smallest doubt can stop me from acting.	IoU 2
12	I must get away from all uncertain situations.	IoU 2

Table S5 displays the partial correlation matrix with 95% bootstrapped confidence intervals that corresponds to Figure 1 in the main document. Edges are ordered from the absolute largest to smallest correlation value. Edges between personality trait dimensions and ambiguity tolerance have been highlighted for ease of interpretability: ambiguity and openness to experience correlations have been highlighted orange; ambiguity and extraversion correlations have been highlighted green; and ambiguity and neuroticism correlations have been highlighted blue.

Table S5
Partial Correlations for Network Model (Section 3.4)

Node 1	Node 2	CI lower	CI upper	Correlation
OAes	Open	.52	.69	.61
ExSoc	ExAssert	.27	.50	.39
M1	IoU1	-.46	-0.30	-.38
NegDep	NegAnx	.29	.47	.38
NegVol	NegAnx	.29	.48	.38
OCur	Intel	.27	.46	.37
ExSoc	ExEnergy	.22	.42	.32
M1	M2	.24	.41	.32
M1	M3	.23	.39	.31
NegDep	ExEnergy	-.35	-.20	-.28
NegDep	NegVol	.13	.34	.24
OCur	Open	.14	.33	.24
M3	Intel	.13	.33	.23
M1	IoU2	-.31	-.13	-.22
OCre	OCur	.11	.32	.22
M3	IoU2	-.30	-.11	-.21
NegDep	IoU2	.12	.29	.21
OAes	OCre	.06	.28	.17
M2	IoU1	-.25	-.07	-.16
OCre	Intel	.05	.25	.15
OCre	Open	.06	.24	.15
OCur	M3	.07	.24	.15
ExAssert	M2	.05	.23	.14
IoU1	IoU2	.05	.22	.14

NegVol	Intel	-.20	-.03	-.11
OCre	ExAssert	.01	.20	.10
NegVol	IoU2	.00	.18	.09
ExEnergy	M2	-.01	.16	.08
ExAssert	ExEnergy	-.02	.19	.08
NegDep	ExAssert	-.14	.00	-.07
NegAnx	IoU2	-.01	.15	.07
IoU2	Intel	-.13	.01	-.06
ExAssert	Intel	-.02	.15	.06
ExEnergy	Open	-.02	.15	.06
OCre	ExEnergy	-.03	.12	.05
OAes	NegDep	-.01	.11	.05
NegAnx	ExEnergy	-.11	.03	-.04
OCre	IoU2	-.10	.02	-.04
NegVol	M2	-.05	.13	.04
OAes	OCur	-.04	.12	.04
NegAnx	Open	-.01	.10	.04
NegAnx	M1	-.08	.02	-.03
NegAnx	M2	-.11	.06	-.03
NegAnx	IoU1	-.03	.10	.03
IoU1	Open	-.03	.09	.03
NegDep	M3	-.04	.11	.03
OAes	ExEnergy	-.03	.10	.03
IoU1	Intel	-.07	.10	.02
OAes	M2	-.03	.07	.02
OCre	M1	-.02	.06	.02
M1	Intel	-.04	.09	.02
ExAssert	Open	-.09	.07	-.01
NegDep	ExSoc	-.07	.05	-.01
ExSoc	M3	-.05	.03	-.01
ExAssert	IoU2	-.06	.05	-.01
NegAnx	ExAssert	-.05	.04	-.01
NegDep	Open	-.04	.05	.01
OAes	NegVol	-.04	.06	.01
OCur	IoU1	-.04	.07	.01
OCre	M3	-.05	.08	.01

Finally, in Figure 1 in the main paper, we measured openness to experience with two scales: the BFI-2 and the BFAS. As it was possible that the intercorrelations between similar measures of aesthetic appreciation (*openness* and *aesthetic sensitivity*) could be high enough to obscure any meaningful associations with other measures, we

also conducted network analyses where openness to experience was measured with either BFI-2 Open-Mindedness or BFAS Openness-Intellect, respectively. Figures S1 and S2 display these networks. Results were similar to the network depicted in Figure 1, and interpretations regarding our central findings (intellect and M3; assertiveness and M2; depression and IoU2) the same. The one difference is an association between the *openness* aspect and M3 (r = .09, 95% CI [.01, .17]), but this effect was far smaller than that linking intellect and M3, and included CIs that almost encompassed zero.

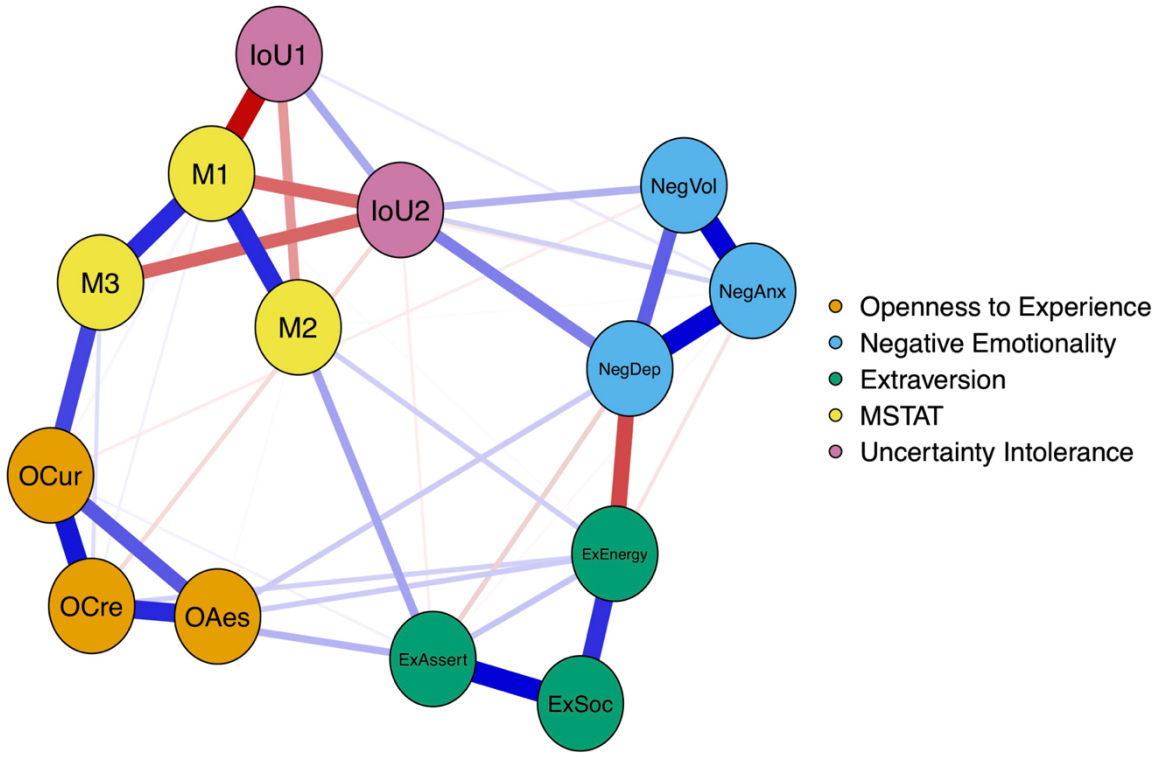

Figure S1. Network model with Openness to Experience measured with only BFI-2 Open Mindedness. Interpretation of the graph is as per Figure 1 in the main text.

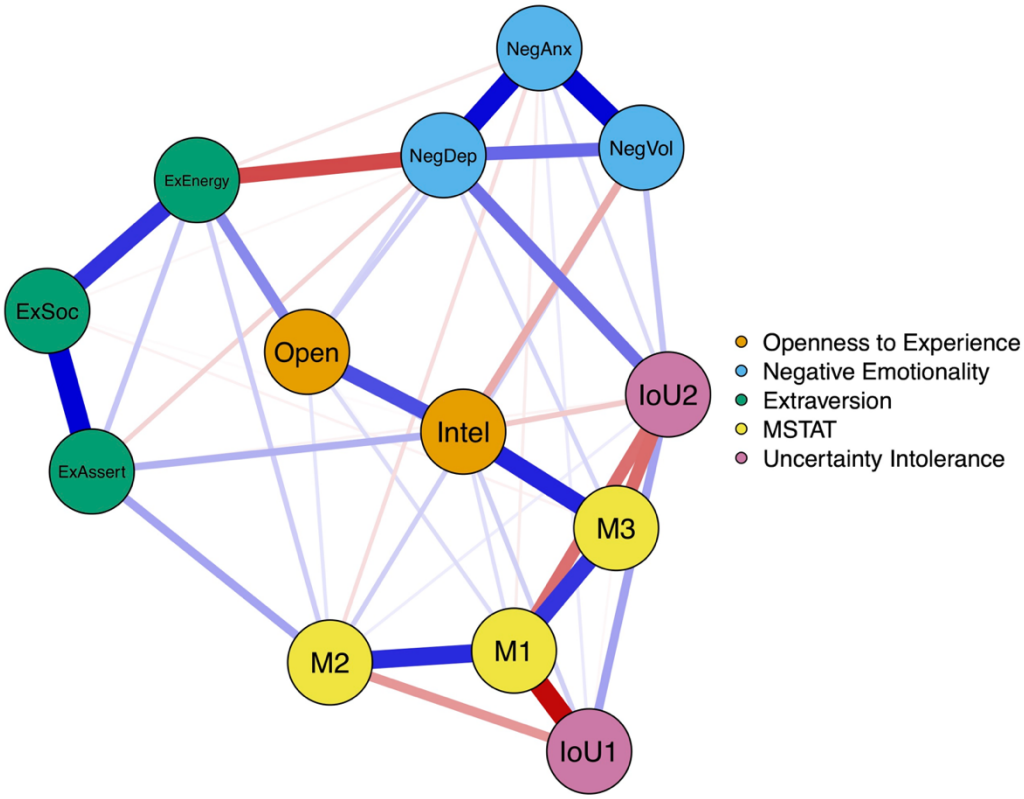

Figure S2. Network model with Openness to Experience measured with only BFAS Openness/Intellect. Interpretation of the graph is as per Figure 1 in the main text.

Table S6.
Networks With Single Measures of Openness to Experience.

Network with BFAS Openness/Intellect					Network with BFI-2 Open Mindedness				
Node 1	Node 2	CI lower	CI upper	Correlation	Node 1	Node 2	CI lower	CI upper	Correlation
ExSoc	ExAssert	.28	.51	.40	NegDep	NegAnx	.29	.47	.38
M1	IoU1	-.47	-.30	-.39	ExSoc	ExAssert	.27	.49	.38
NegDep	NegAnx	.30	.47	.39	NegVol	NegAnx	.29	.48	.38
NegVol	NegAnx	.30	.49	.39	M1	IoU1	-.45	-.29	-.37
M3	Intel	.24	.45	.35	OCre	OCur	.25	.46	.35
M1	M2	.25	.42	.33	M1	M3	.24	.40	.32
M1	M3	.23	.40	.32	M1	M2	.24	.41	.32
ExSoc	ExEnergy	.22	.43	.32	OAes	OCre	.21	.44	.32
NegDep	ExEnergy	-.37	-.20	-.28	ExSoc	ExEnergy	.21	.42	.31
Open	Intel	.17	.39	.28	OCur	M3	.19	.37	.28
NegDep	NegVol	.13	.34	.24	NegDep	ExEnergy	-.35	-.19	-.27
M3	IoU2	-.34	-.13	-.23	OAes	OCur	.15	.35	.25
M1	IoU2	-.31	-.13	-.22	NegDep	NegVol	.14	.34	.24
NegDep	IoU2	.14	.31	.22	M3	IoU2	-.32	-.14	-.23
ExEnergy	Open	.06	.31	.18	M1	IoU2	-.32	-.14	-.23
M2	IoU1	-.26	-.07	-.16	NegDep	IoU2	.10	.28	.19
ExAssert	M2	.04	.24	.14	M2	IoU1	-.25	-.06	-.16
IoU1	IoU2	.05	.24	.14	ExAssert	M2	.04	.23	.14
NegVol	Intel	-.23	-.03	-.13	IoU1	IoU2	.04	.22	.13
ExAssert	Intel	.02	.22	.12	NegVol	IoU2	.02	.21	.12
ExAssert	ExEnergy	-.02	.20	.09	OCre	ExAssert	.02	.20	.11
M3	Open	.01	.17	.09	ExAssert	ExEnergy	-.02	.19	.09
NegVol	IoU2	.00	.19	.09	OAes	ExEnergy	-.03	.18	.08
IoU2	Intel	-.16	.00	-.08	OAes	NegDep	-.01	.16	.08

NegAnx	Open	-.02	.17	.08
ExEnergy	M2	-.01	.17	.08
NegDep	ExAssert	-.14	.01	-.07
NegDep	Open	-.03	.17	.07
IoU1	Intel	-.05	.19	.07
NegVol	M2	-.03	.17	.07
NegAnx	IoU2	-.02	.14	.06
NegDep	M3	-.03	.15	.06
NegAnx	M2	-.15	.04	-.05
M1	Intel	-.03	.13	.05
IoU1	Open	-.05	.15	.05

NegDep	ExAssert	-.14	.01	-.07
OCre	ExEnergy	-.02	.15	.07
NegAnx	IoU2	-.01	.15	.07
ExEnergy	M2	-.01	.16	.07
OCre	IoU2	-.13	.02	-.06
OCre	M3	-.04	.13	.05

Appendix B

Supplementary Materials for Chapter 3 (Jach & Smillie, 2021)

Jach, H. K., & Smillie, L. D. (2021), Testing the information-seeking theory of Openness/Intellect. *European Journal of Personality,* 35(1), 103-119.

S1. Pre-registration compliance

Pre-registration link: osf.io/fsx5e

Section	Part	Followed exactly?	Details as necessary
Study information and hypotheses	All	Yes	We stated that variables would *correlate* and *predict* outcomes. As we were only using univariate predictors, the result from a correlation and regression would be identical, so we only report one in the manuscript body. Additionally, the final two hypotheses are reported in the supplementary materials (Section S4) rather than the main manuscript body, as they were tangential to the main aims of this paper.
Design plan	All	Yes	
Sampling plan	All	1 person above sample plan.	Our target sample was N = 300. We assumed that some participants would fail attention and comprehension checks, and so slightly oversampled (N = 316), which, after removing these participants, produced a final sample of N = 301.
Variables	Measured variables	Yes	We analyzed the Ellsberg paradigm decisions in the supplementary information (Section 4)
Variables	Indices	Yes	We reported latent variables analyses in the supplementary information (Section 2 and 3). We reported the network analysis and behavioral ambiguity tolerance (i.e., Ellsberg paradigm) in Section 4 of the supplementary information.
Analysis plan	All	Yes	Again, latent variables were reported in supplementary Section 2 and 3; and the network analysis is reported in supplementary Section 4. In addition to our pre-registered analyses, the supplementary information also includes Poisson regressions for all analyses as a robustness check (as some variables were not normally distributed).

S2. Study 1

Table S2.1 Full Descriptive Statistics

Table S2.1
Study 1 Descriptive Statistics.

	mean	sd	median	range	skew	kurtosis
Information seeking	0.63	0.36	0.67	1.00	-0.34	-1.50
Openness/Intellect	3.65	0.49	3.65	2.30	-0.17	-0.75
Openness	3.44	0.44	3.40	2.00	-0.23	-0.50
Intellect	3.85	0.75	4.00	3.40	-0.44	-0.39
Agreeableness	3.83	0.64	3.90	2.65	-0.25	-0.88
Conscientiousness	3.58	0.67	3.50	3.30	-0.22	-0.14
Neuroticism	2.63	0.93	2.75	3.50	0.05	-0.93
Extraversion	3.22	0.76	3.15	3.65	-0.02	-0.09
Curiosity	3.37	0.51	3.36	3.28	-0.22	0.91
Joyous exploration	3.87	0.77	4.00	3.80	-0.75	0.93
Deprivation sensitivity	3.57	0.79	3.60	4.00	-0.47	0.08
Stress tolerance	3.10	1.07	3.00	4.00	0.08	-0.80
Social curiosity	3.59	0.82	3.60	3.80	-0.50	-0.34
Thrill seeking	2.70	0.96	2.80	4.00	0.20	-0.83
Intolerance of uncertainty	3.10	0.87	3.08	3.92	-0.12	-0.72
Ambiguity tolerance	3.06	0.75	3.00	3.54	0.13	-0.23

Note. $N = 151$.

Figure S2.1 Figure displaying information seeking choices

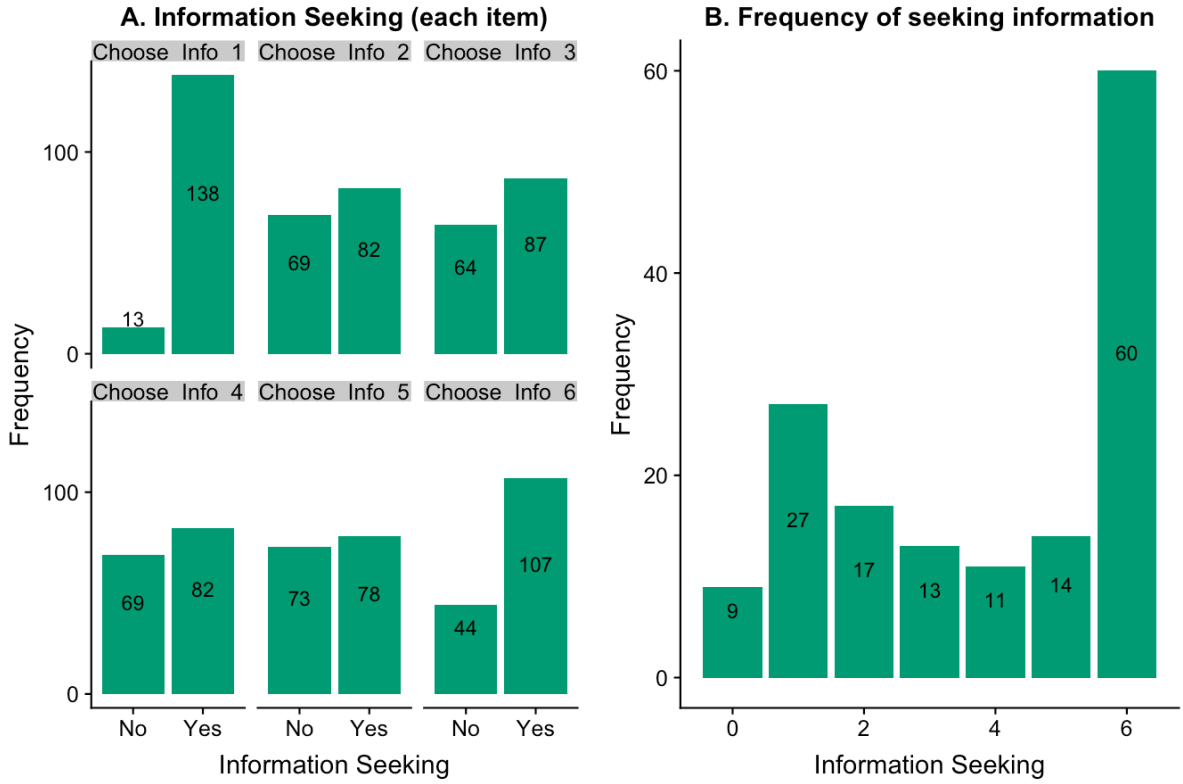

Figure S2.2 Study 1, information seeking responses to each individual item. *A.* Summarizing responses to each information seeking item. Participants are overwhelmingly likely to choose information for the first item, but are also consistently likely to choose information throughout all the games. *B.* Counting the number of times that participants chose information. More than a third of individuals always chose information.

S2.2 Poisson Regressions, Study 1

As non-normal dependent variables can cause biased estimates of standard errors and significance tests (Coxe, West, & Aiken, 2009), we here include a parallel version of Section 2.2.2 in the main manuscript where information seeking is recomputed as a count variable from which Poisson regressions are conducted. A key assumption of Poisson regression is that the mean is equal to the variance (Coxe et al., 2009), but we observed that information seeking was over-dispersed, with a larger variance than mean ($Z = 2.32$, $p = .010$). Thus, the following regressions use quasi-Poisson regression, which includes an additional scaling parameter that accounts for the degree of over-dispersion (Chambers & Hastie, 1992). All findings converge with those in the main manuscript body. Specifically, deprivation sensitivity predicted information seeking, ($b = 0.14$, $t(149) = 2.23$, $p = .027$). Meanwhile, openness/intellect and joyous exploration did not predict information seeking as independent predictors

(openness/intellect b = -.11, $t(149)$ = -1.19, p = .238; joyous exploration b = .09, $t(149)$ = 1.39, p = .167). We also found that ambiguity tolerance, uncertainty intolerance, and stress tolerance did not predict information seeking, either measured together (ambiguity tolerance b = -.05, p = .466 ; intolerance of uncertainty b = .05, p = .332; stress tolerance b = .002, p = .956) or as a multivariate regression (bs = -0.01, 0.19, and 0.14, respectively; ps all >.05).

S3. Study 2
Parallel Regressions: With Latent Variables, Tetrachoric Factor Scores and with Poisson Regression

Table S3.1
Variables Predicting Information Seeking (6 Item Measure)

Predictor/s	Latent Variables	Information seeking = tetrachoric factor scores	Quasi-Poisson regression
Openness/Intellect	β = -0.11, (95% CI [-0.23, 0.02]), SE = 0.06, Z = -1.70, p = .089	β = -0.05, t(299) = -0.82, p = .412	b = -0.07, t(299) = -0.85, p = .398
Curiosity	β = 0.19, (95% CI [0.07, 0.31]), SE = 0.06, Z = 3.13, p = .002	β = 0.09, t(299) = 1.59, p = .113	b = 0.12, t(299) = 1.58, p = .116
Deprivation sensitivity	β = 0.20, (95% CI [0.07, 0.32]), SE = 0.06, Z = 3.09, p = .002	β = 0.19, t(299) = 3.34, p < .001	b = 0.17, t(299) = 3.51, p < .001
Joyous exploration	β = 0.16, (95% CI [0.03, 0.28]), SE = 0.06, Z = 2.46, p = .014	β = 0.15, t(299) = 2.58, p = .010	b = 0.15, t(299) = 2.67, p = .008
Ambiguity tolerance	β = 0.24, (95% CI [0.12, 0.36]), SE = 0.06, Z = 3.91, p < .001	β = -0.15, t(299) = -2.62, p = .009.	b = -0.14, t(299) = -2.63, p = .009
Intolerance of Uncertainty	β = 0.27, (95% CI [0.16, 0.39]), SE = 0.06, Z = 4.61, p < .001	β = 0.26, t(299) = 4.74, p < .001.	b = -0.22, t(299) = 4.67, p < .001
Neuroticism	β = 0.19, (95% CI [0.07, 0.31]), SE = 0.06, Z = 3.16, p = .002	β = 0.13, t(299) = 2.23, p = .026.	b = 0.11, t(299) = 2.28, p = .023
Joyous exploration + intolerance of uncertainty	Joyous exploration β = 0.22, (95% CI [0.10, 0.33]), SE = 0.06, Z = 3.64, p < .001; intolerance of uncertainty β = 0.31, (95% CI [0.20, 0.42]), SE = 0.06, Z = 5.41, p < .001	Joyous exploration β = .18, t(298) = 3.34, p < .001; intolerance of uncertainty β = .29, t(298) = 5.20, p < .001	Joyous exploration b = .18, t(298) = 3.28, p = .001; intolerance of uncertainty b = .23, t(298) = 5.08, p < .001

Table S3.2
Latent Variables Analysis Predicting Information Seeking (Single Item)

Predictor/s	Latent Variables
Openness/Intellect	β = -0.20, (95% CI [-0.32, -0.08]), SE = 0.06, Z = -3.30, p = .001
Ambiguity tolerance	β = 0.23, (95% CI [0.11, 0.35]), SE = 0.06, Z = 3.75, p < .001
Intolerance of Uncertainty	β = 0.21, (95% CI [0.08, 0.32]), SE = 0.06, Z = 3.45, p = .001
Neuroticism	β = 0.19, (95% CI [0.07, 0.31]), SE = 0.06, Z = 3.22, p = .001

Table S3.3
Bayes Factor Comparisons of Linear Regression Models Predicting Information-Seeking as a 6- or 1-item index.

Predictor/s	M_{10} Bayes Factor, 6 item information seeking	M_{10} Bayes Factor, 1 item information seeking
Openness/Intellect (O/I)	0.18	5.90
Deprivation sensitivity (DS)	44.87	0.24
Joyous exploration (JE)	3.82	0.26
Ambiguity tolerance (AT)	3.46	1.21
Intolerance of Uncertainty (IoU)	4,898.79	16.07
O/I + DS	52.92	8.99
O/I + JE	106.42	1565.92
O/I + AT	0.71	1.56
O/I + IoU	1,057.25	15.20
DS + JE	12.13	0.06
DS + AT	176.09	0.40
DS + IoU	7,348.64	2.87
JE + AT	2,299.17	2.93
JE + IoU	**208,067.21**	10.82
AT + IoU	2,691.08	3.16
O/I + DS + JE	282.44	330.92
O/I + DS+ JE	48.47	2.15
O/I + DS+ IoU	1,457.07	6.01
O/I + JE + AT	3,231.07	915.17
O/I + JE + IoU	152,236.53	**1975.53**
O/I + AT+ IoU	539.39	7.24
DS + JE + AT	934.61	0.69
DS + JE + IoU	38,583.84	4.19
DS + AT + IoU	2,043.68	0.70
JE + AT + IoU	38,433.33	2.52
O/I + DS + JE + AT	1,745.99	210.24
O/I + DS + JE + IoU	33,881.38	547.15
O/I + DS + AT + IoU	508.33	2.51
O/I + JE + AT + IoU	32,489.06	445.25
DS + JE + AT + IoU	8,342.94	1.08
O/I + DS + JE + AT + IoU	8,098.13	138.47

Note. Bold text indicates the most supported model.

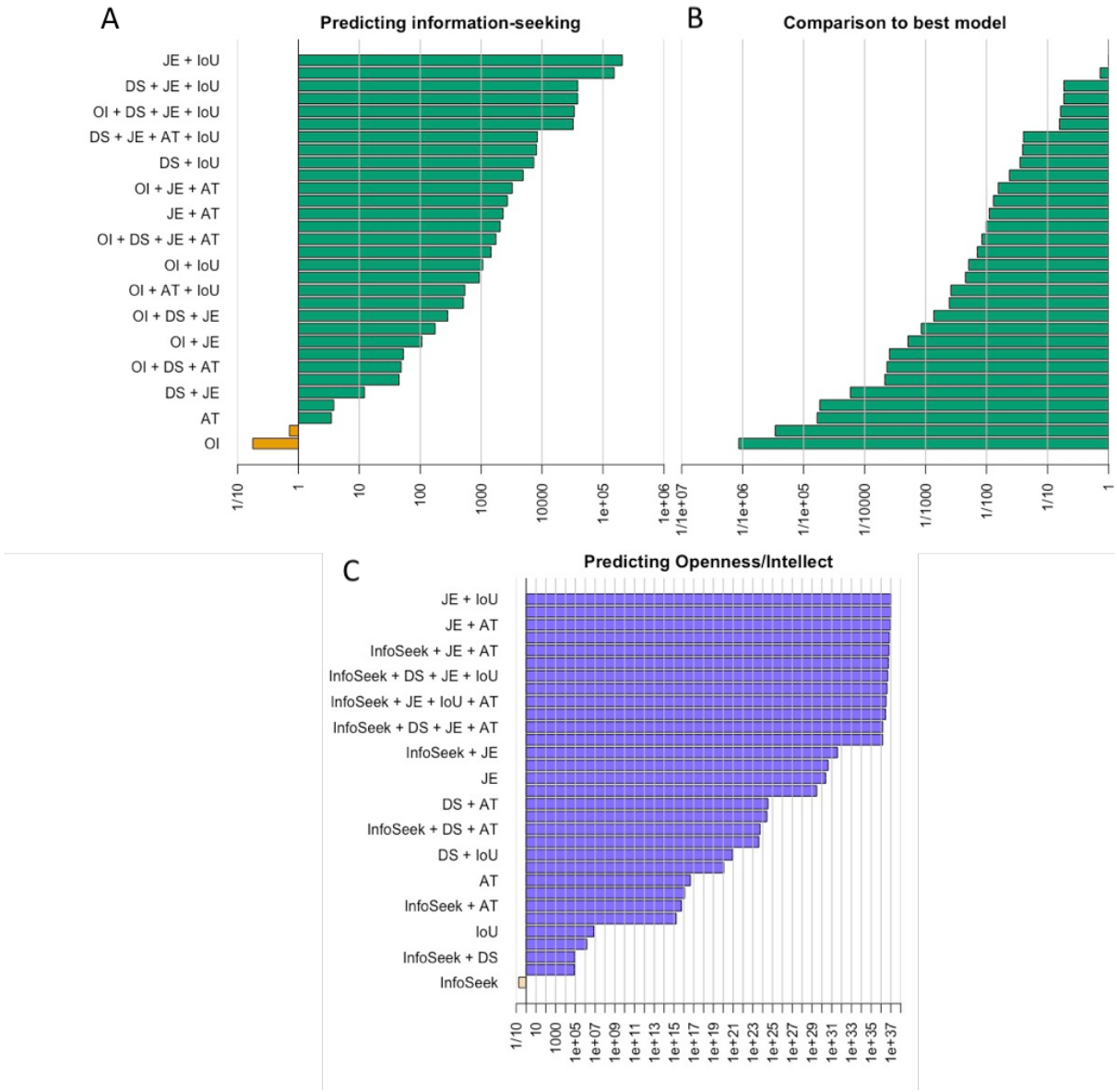

Figure S3.1. Bayes factor regression model comparisons. *A*. Predicting information-seeking. B. Comparing the best performing model predicting information-seeking (joyous exploration and intolerance of uncertainty) to all other models. *C*. Predicting openness/intellect. JE = Joyous exploration, DS = Deprivation sensitivity, IoU = Intolerance of uncertainty, OI = Openness/intellect, AT = Ambiguity tolerance.

S4 Additional Ambiguity Tolerance Replication Study

S4.1 Hypotheses

To assess the relation between ambiguity attitudes and personality traits, we conducted a replication of Jach and Smillie (2019). We hypothesized that the pattern of results concerning survey ambiguity tolerance found by these authors would be reproduced: specifically, openness/intellect and extraversion would predict survey ambiguity tolerance (and negatively predict intolerance of uncertainty); and neuroticism would negatively correlate with and predict survey ambiguity tolerance (and would positively correlate with and predict intolerance of uncertainty). We were also curious to observe if behavioral ambiguity tolerance has a higher reliability than in Jach and Smillie (2019). If internal consistency was > .50, we hypothesized that the pattern of results pertaining to survey ambiguity tolerance would also be reproduced in behavioral ambiguity tolerance (but with a smaller effect size).

We also attempted to replicate key elements of the regularized partial correlation network analysis conducted by Jach and Smillie (2019) with the BFAS scale. Specifically, we expected the BFAS Intellect measure to have a stronger connection to ambiguity tolerance than BFAS Openness, and that openness to experience would only be reliably connect to ambiguity tolerance (i.e., with CIs that do not include zero) via the intellect to ambiguity tolerance connection. We also predicted that extraversion would only be reliably connected to ambiguity tolerance via the assertiveness to ambiguity tolerance connection (i.e., not enthusiasm to ambiguity tolerance). Finally, we predicted that neuroticism would have a stronger relationship to intolerance of uncertainty than it does to ambiguity tolerance.

S4.2 Method

Almost all details regarding methods were identical to the main manuscript body, with the exception that the main manuscript does not describe our we also measure of behavioral ambiguity tolerance. We measured behavioral ambiguity tolerance with three variants of the Ellsberg paradigm (Ellsberg, 1961; described in Camer & Weber, 1992): specifically, the 2-color problem, the 2-color problem with second-order probabilities, and the 3-color problem, Act 1. In this tasks, participants choose between two options that have equal expected utility, but one option that is more ambiguous than the other. For example, participants can choose between a 50/50 chance of obtaining a reward, or an entirely unknown chance of obtaining a reward). Existing evidence suggests that this scale may not be reliable (Jach & Smillie, 2019) which we wanted to double-check.

S4.3 Results

S4.3.1 Ambiguity Attitudes and Personality Traits. As Table 1 demonstrates, the pattern of correlations reported by Jach & Smillie (2019) was replicated here. Specifically, openness/intellect correlated positively with ambiguity tolerance (r = .49) and negatively with intolerance of uncertainty (r = -.34); extraversion demonstrated the same pattern (ambiguity tolerance r = .49; uncertainty intolerance r = -.46) and neuroticism the opposite pattern (ambiguity tolerance r = -.48; uncertainty intolerance r = .68). As found in Jach and Smillie (2019), behavioral ambiguity tolerance demonstrated very poor reliability (ω_t = .28) and did not significantly correlate with any other variable.

Table S4.1

Means, standard deviations, and correlations with confidence intervals

Variable	*M*	*SD*	ω_t	1	2	3	4	5
1. Ambiguity tolerance	3.02	0.72	.91					
2. Intolerance of Uncertainty	3.23	0.85	.94	-.78** [-.82, -.73]				
3. ambiguity tolerance (behaviour)	0.47	0.32	.28	.04 [-.07, .16]	-.06 [-.17, .05]			
4. Openness/Intellect	3.59	0.48	.90	.49** [.40, .57]	-.34** [-.44, -.24]	.10 [-.01, .21]		
5. Extraversion	3.21	0.72	.93	.49** [.40, .57]	-.46** [-.55, -.37]	-.01 [-.13, .10]	.40** [.30, .49]	
6. Neuroticism	2.61	0.82	.95	-.48** [-.56, -.39]	.68** [.61, .74]	-.01 [-.12, .10]	-.35** [-.44, -.25]	-.50** [-.58, -.41]

Note. M, *SD,* and ω_t are used to represent mean, standard deviation, and omega total, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$.

Considering survey ambiguity tolerance, when entered together in a multivariate regression, openness/intellect and extraversion positively predicted ambiguity tolerance, and neuroticism negatively predicted ambiguity tolerance (openness/intellect β = 0.31, $t(297)$ = 6.17, p <.001; extraversion β = 0.24, $t(297)$ = 4.39, p <.001; neuroticism β = -0.25, $t(297)$ = -4.70, p <.001), together accounting for 39% of the variance in ambiguity tolerance. For intolerance of uncertainty, as we expected, neuroticism was a strong univariate predictor, β = 0.70, $t(299)$ = 16.00, p <.001, R^2 = .46. Openness/intellect and extraversion each separately, significantly negatively predicted this trait (openness/intellect β = -0.34, $t(299)$ = -6.28, p <.001, R^2 = .12; extraversion β = -0.46, $t(299)$ = -9.02, p <.001; R^2 = .21). As found by Jach and Smillie (2019), when openness/intellect and neuroticism were entered together in a regression predicting intolerance of uncertainty, both were significant predictors (openness/intellect β = -0.12, $t(298)$ = -2.65, p <.001; neuroticism β = 0.64, $t(298)$ = 14.22, p <.001; R^2 = .47) but the percentage of variance accounted for rose by 35% with the addition of neuroticism. We explored adding extraversion as a predictor to this regression, and found that in this instance, openness/intellect ceased to be a significant predictor of intolerance of uncertainty (β = -0.08, $t(297)$ = -1.84, p = .067). This is consistent with the view that intolerance of uncertainty, although conceptually equivalent to ambiguity tolerance, employs strongly emotive language that is more strongly endorsed by those higher in neuroticism (see, e.g., the very high correlation of r = .68 between neuroticism and intolerance of uncertainty). In sum, all predictions concerning survey variables were replicated in this study.

S4.3.2 Network analyses. We conducted a network analysis to assess the replicability of the network structure reported in Jach and Smillie (2019). We initially planned to attempt to repeat the network model with latent variables (Epskamp, Rhemtulla, & Borsboom 2017), but as the number of parameters exceeds the number of participants for this model, that was not possible.

We first performed an exploratory graph analysis to assess the dimensional structure of intolerance of uncertainty and ambiguity tolerance. Intolerance of uncertainty broke into two dimensions, with items identical to those found by Jach and Smillie (2019) and as found in the original paper (Carleton et al., 2007). For ambiguity tolerance, results suggested three dimensions: M1 measuring general ambiguity avoidance, M2 measuring ambiguity tolerance, and M3 measuring an appreciation of complexity of thoughts. The items forming these dimensions were identical to those obtained by Jach and Smillie (2019) with the exception of item number 4 (*I prefer familiar situations to new ones*) that fell under M2 in the original study, and under M1 in the current study. As the semantic content of the item appeared to be

conceptually closer to M1 (ambiguity avoidance) than M2 (ambiguity seeking) we included item 4 into the computation of M1.

We next computed a regularized partial correlation network analysis (Figure 1) using the R package bootnet, following the guidelines of Epskamp, Borsboom, and Fried (2018). Results from this analysis were mostly consistent with the network analysis reported in Jach and Smillie (2019). For openness/intellect, the strongest connection was between the intellect aspect and M3, representing appreciation of complex problem solving, r = .28, 95% CI [.18, .39]. Further, openness/intellect was only reliably connected to ambiguity tolerance via intellect (that is, all partial correlations between openness and ambiguity tolerance/uncertainty intolerance had confidence intervals that included zero). One point of difference from Jach and Smillie (2019) was that intellect maintained a robust positive correlation with the *prospective anxiety* facet of uncertainty intolerance (r = .20, 95% CI [.08, .33]) such that higher intellect related to higher *intolerance* of uncertainty. Intellect also maintained a weak negative relation with inhibitory anxiety and a weak positive relation with general ambiguity seeking, with the confidence intervals were close to zero in both instances.

Concerning extraversion, this was only reliably connected to ambiguity attitudes via assertiveness, not enthusiasm: all correlations between enthusiasm and ambiguity/uncertainty tolerance encompassed zero. Similarly to Jach and Smillie (2019), the assertiveness aspect related to general ambiguity seeking (r = .17, 95% CI [.06, .27]). Interestingly, assertiveness was also negatively related to M3 (ambiguity problem solving), r = -.14, 95% CI [-.26, -.05].

For neuroticism, both aspects were related to inhibitory anxiety facet of uncertainty intolerance (withdrawal r = .34, 95% CI [.25, .45]; volatility r = .19, 95% CI [.08, .29]), whereas there were no robust relations between neuroticism and prospective anxiety. Meanwhile, as predicted, the relation between neuroticism and ambiguity tolerance was weaker than that between neuroticism and uncertainty intolerance, with no relations present where the confidence intervals did not touch zero.

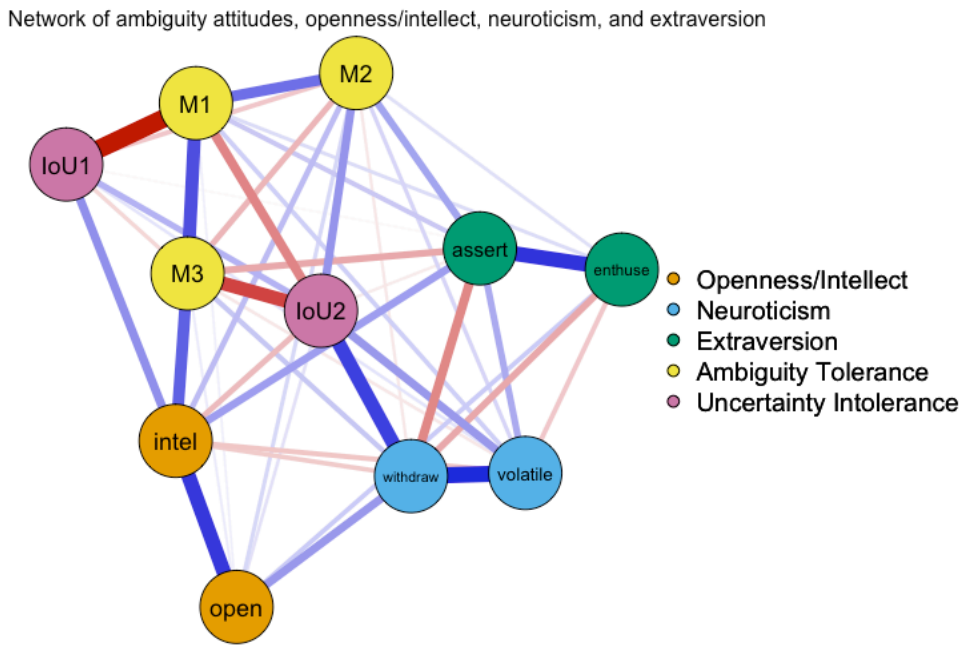

Figure S4.1. Partial correlation network analysis of personality aspects and ambiguity tolerance facets. Circles represent facets/aspects (i.e., *nodes*) and lines represent partial correlations between facets (i.e., *edges*). Any edge between two nodes is conditional on all other relations in the networks. Blue lines represent positive partial correlations, whereas red lines represent negative partial correlations.

Table S4.2.
Network Analysis Partial Correlation Results

Variable 1	Variable 2	Partial *r*	[95% CI]
M1 ambiguity avoid	IoU1 prospective	-.47	[-.55, .39]
Volatility	Withdrawal	.40	[.29, .50]
Enthusiasm	Assertiveness	.37	[.25, .50]
Openness	Intellect	.36	[.26, .47]
M3 problem-solve	IoU2 inhibitory	-.34	[-.45 -.24]
Withdrawal	**IoU2 inhibitory**	**.34**	**[.25, .45]**
M1 ambiguity avoid	M3 problem-solve	.32	[.22, .43]
Intellect	**M3 problem-solve**	**.28**	**[.19, .39]**
M1 ambiguity avoid	M2 ambiguity seek	.25	[.15, .37]
M1 ambiguity avoid	IoU2 inhibitory	-.22	[-.34, -.11]
Withdrawal	Assertiveness	-.22	[-.34, -.10]
Intellect	**IoU1 prospective**	**.20**	**[.08, .33]**
Volatility	**IoU2 inhibitory**	**.19**	**[.08, .29]**
Openness	Withdrawal	.19	[.09, .29]
M2 ambiguity seek	IoU2 inhibitory	.19	[.06, .33]
Assertiveness	**M2 ambiguity seek**	**.17**	**[.06, .27]**
Intellect	Assertiveness	.16	[.06, .30]

Assertiveness	**M3 problem-solve**	**-.14**	**[-.26, -.05]**
Withdrawal	Enthusiasm	-.14	[-.26, -.04]
Volatility	Assertiveness	.14	[.03, .28]
IoU1 prospective	IoU2 inhibitory	.13	[.02, .25]
M2 ambiguity seek	M3 problem-solve	-.12	[-0.25, .00]
Intellect	**IoU2 inhibitory**	**-.12**	**[-.22, -.02]**
Intellect	**M2 ambiguity seek**	**.11**	**[.01, .23]**

Note. Relations between personality traits and ambiguity attitudes that do not contain zero are displayed in bold font for ease of viewing. For the sake of parsimony, only robust relations (with confidence intervals not equaling zero) are included.

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Appendix C

Supplementary Materials for Chapter 4 (Jach, DeYoung, & Smillie, Under Review)

S1 Study 1, Hypothesis 1 Bayesian regressions with Observed Variables

Our pre-registration specified that we would assess evidence for the null using Bayesian regressions on observed variables with the *BayesFactor* R package (Rouder & Morey, 2012). However, we decided to instead compute Bayes Factors from the regression coefficients derived from structural equation models using the *bain* R package (Gu et al., 2020). We did this because it is a better approach: as the Bayes Factors are computed directly from parameter estimates that account for measurement error, they provide more accurate estimates of relative evidence for the null or alternative hypotheses than if they had been computed on observed variables. However, to be consistent with our preregistration, this section contains all analyses under the method originally planned.

The method used to compute Bayesian regressions via the BayesFactor package compares a null hypothesis in which regression slopes are zero to an alternative hypothesis where regression slopes are non-zero, using a default prior calculated from a version of the multivariate Cauchy distribution (Rouder & Morey, 2012). Bayes factors greater than 1 provide evidence for the alternative hypothesis, whereas Bayes factors less than 1 provide evidence for the null hypothesis. However, as it can be more difficult to intuit the degree of support for values less than 1 than values greater than 1, we have taken the reciprocal of values < 1 such that values for the null are also greater than one. We use the label M_{01} to indicate support for the null, consistent with Rouder and Morey (2012). We follow common practice in judging Bayes factors greater than 3 to be substantial evidence for the null/alternative hypothesis (Jeffreys, 1961).

In the first part of our predictions for Hypothesis 1, we predicted that openness/intellect, joyous exploration, and intelligence would not predict information seeking for the Reward-Outcome stimuli. Bayesian regressions suggested substantial evidence for the null from a multivariate regression predicting preferences for Reward-Outcome information by openness/intellect and joyous exploration (M_{01} = 10.96), and evidence for the null increased further when adding intelligence into the regression (M_{01} = 52.51). However, when considered as univariate predictors, openness/intellect and joyous exploration each suggested inconclusive evidence for the null (openness/intellect M_{01} = 2.53, joyous exploration M_{01} = 2.02) and only intelligence indicated strong evidence for the null (M_{01} = 8.70).

The second half of our predictions grouped under Hypothesis 1 concerned effects related to neuroticism and intolerance of uncertainty. We hypothesized that these traits would positively predict seeking information for Reward-Outcome stimuli. However, neither neuroticism nor intolerance of uncertainty significantly predicted seeking information, and Bayes factor regressions suggested substantial evidence for the null for neuroticism (M_{01} = 9.00) though only anecdotal evidence for intolerance of uncertainty (M_{01} = 1.97). Second, we hypothesized that neuroticism and intolerance of uncertainty would not positively predict seeking information in the remaining three stimulus sets. These predictions were somewhat supported, as no significant positive effects were observed (main manuscript, Table 3, Models 10 and 11). Indeed, for the Character stimuli, intolerance of uncertainty demonstrated substantial evidence of a null effect (M_{01} = 3.94) and neuroticism *negatively* predicted seeking information. For neuroticism for the Bonus stimuli, Bayes factor regressions found substantial evidence for a null effect (M_{01} = 7.53). However, only anecdotal evidence for the null was observed for neuroticism for the Trivia stimuli (M_{01} = 1.71), and for intolerance of uncertainty in the Trivia (M_{01} = 2.55) and Bonus (M_{01} = 1.49) stimulus sets.

S2 Hypothesis 2 Extra Information

Supplementary Table 1

P-values for Mean differences (non-parametric Wilcoxon test) between stimulus sets for situation ratings, pre-information ratings, and post-information ratings.

Rating	Stimuli 1	Stimuli 2	Adjusted *p*	Sig.
1. Intellect	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	RO	Char	<.001	****
2. pOsitivity	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	RO	Char	<.001	****
3. Negativity	Trivia	RO	.002	***
	Trivia	Char	.230	*
	RO	Char	<.001	****
4. Confidence	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	RO	Char	<.001	****
5. Curiosity	Trivia	RO	.001	****
	Trivia	Char	<.001	****
	RO	Char	<.001	****
6. Bothered	Trivia	RO	>.999	ns
	Trivia	Char	<.001	****

	RO	Char	<.001	****
7. Uncertain	Trivia	RO	>.999	ns
	Trivia	Char	<.001	****
	RO	Char	<.001	****
8. Need	Trivia	RO	>.999	ns
	Trivia	Char	<.001	****
	RO	Char	<.001	****
9. Surprised	Trivia	Bonus	<.001	****
	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	Bonus	RO	<.001	****
	Bonus	Char	<.001	****
	RO	Char	<.001	****
10. Relieved	Trivia	Bonus	<.001	****
	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	Bonus	RO	<.001	****
	Bonus	Char	.066	**
	RO	Char	<.001	****
11. Interested	Trivia	Bonus	.026	***
	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	Bonus	RO	<.001	****
	Bonus	Char	<.001	****
	RO	Char	.002	****
12. Amazed	Trivia	Bonus	<.001	****
	Trivia	RO	<.001	****
	Trivia	Char	<.001	****
	Bonus	RO	<.001	****
	Bonus	Char	<.001	****
	RO	Char	<.001	****
13. Pleased	Trivia	Bonus	<.001	****
	Trivia	RO	>.999	*
	Trivia	Char	<.001	****
	Bonus	RO	<.001	****
	Bonus	Char	<.001	****
	RO	Char	<.001	****

S3 Hypothesis 3

Hypothesis 3 (Supplementary Table 2) specified relations between state emotions and personality traits/situation ratings following the general principles of our theoretical model.

Note that there is no clear precedent in the literature for how to represent state emotions of joyous exploration, deprivation sensitivity, or anxiety on each trial in a way that effectively measures that construct, does not induce demand characteristics, and/or involve ethical issues (e.g., asking participants directly about their anxiety). Following reflection, we thought that people feeling more interest would be more likely to endorse being "curious"; that people feeling more deprivation would be more likely to endorse being more curious and "needing" the information; and that individuals feeling more anxiety about not knowing the information would be more likely to endorse needing the information and being more "bothered" by not knowing the information. Thus, these operationalizations were used for Hypothesis 3, while acknowledging that they may be imperfect representations of the constructs of interest.

As summarized in Supplementary Table 3, there was mixed support for these hypotheses. Hypotheses related to state curiosity, pleasure, and interest were fully supported: for example, trait curiosity correlated with state curiosity in the Trivia and Character stimulus sets. Hypotheses related to state need, surprise, confidence and feeling bothered were partially supported: for example, as predicted, being bothered correlated with negativity, deprivation sensitivity, and intellect, but, unexpectedly, being bothered did not significantly relate to neuroticism and related to intolerance of uncertainty for only the Reward-Outcome stimuli. Finally, hypotheses related to state uncertainty and relief were not supported: for example, neuroticism was not significantly positively correlated with uncertainty ratings for the Reward-Outcome stimuli, nor was this correlation weaker in the Trivia and Character stimulus sets than for the Reward-Outcome stimuli.

Supplementary Table 2

Hypothesis 3

Broad Hypothesis	Precise Hypotheses
3. Pre- and post-information state ratings will relate to trait epistemic emotions, situation ratings, and select Big 5 personality traits. (Section 3.2.3)	For the Trivia and Character stimuli, trait curiosity (joyous exploration and deprivation sensitivity) and openness/intellect will positively relate to state curiosity.
	For Trivia and Character stimuli, intolerance of uncertainty will not relate to state curiosity.
	Situation ratings of pOsitivity and Intellect will positively relate to state curiosity in the Trivia and Character stimulus sets.
	In all stimulus sets, state bothered will positively relate to neuroticism, intolerance of uncertainty, and deprivation sensitivity.

	It may also initially positively relate to joyous exploration but will not be significant after controlling for deprivation sensitivity.
	State *bothered* will positively relate to situation ratings of Negativity.
	State *need* will positively relate to deprivation sensitivity, neuroticism, and intolerance of uncertainty, and situation ratings of Negativity and Intellect.
	State *uncertainty* and *confidence* will relate to neuroticism (positively and negatively, respectively) for the Reward-Outcome stimuli.
	State uncertainty and confidence will relate to neuroticism in the Trivia, Bonus, and Character stimulus sets to a lesser extent than for Reward-Outcome stimuli.
	For post-information ratings, being pleased, interested, and surprised will positively relate to joyous exploration, openness/intellect, and pOsitivity ratings.
	For Trivia and Reward-Outcome stimulus sets, when participants are correct, state relief will positivity relate to neuroticism and intolerance of uncertainty.

To some extent, these results align with those of Hypothesis 1: we successfully predicted relations to state curiosity for the Trivia and Character stimuli, whereas predictions were less successful for negative emotions and related personality traits (intolerance of uncertainty, neuroticism) for the Reward-Outcome stimuli.

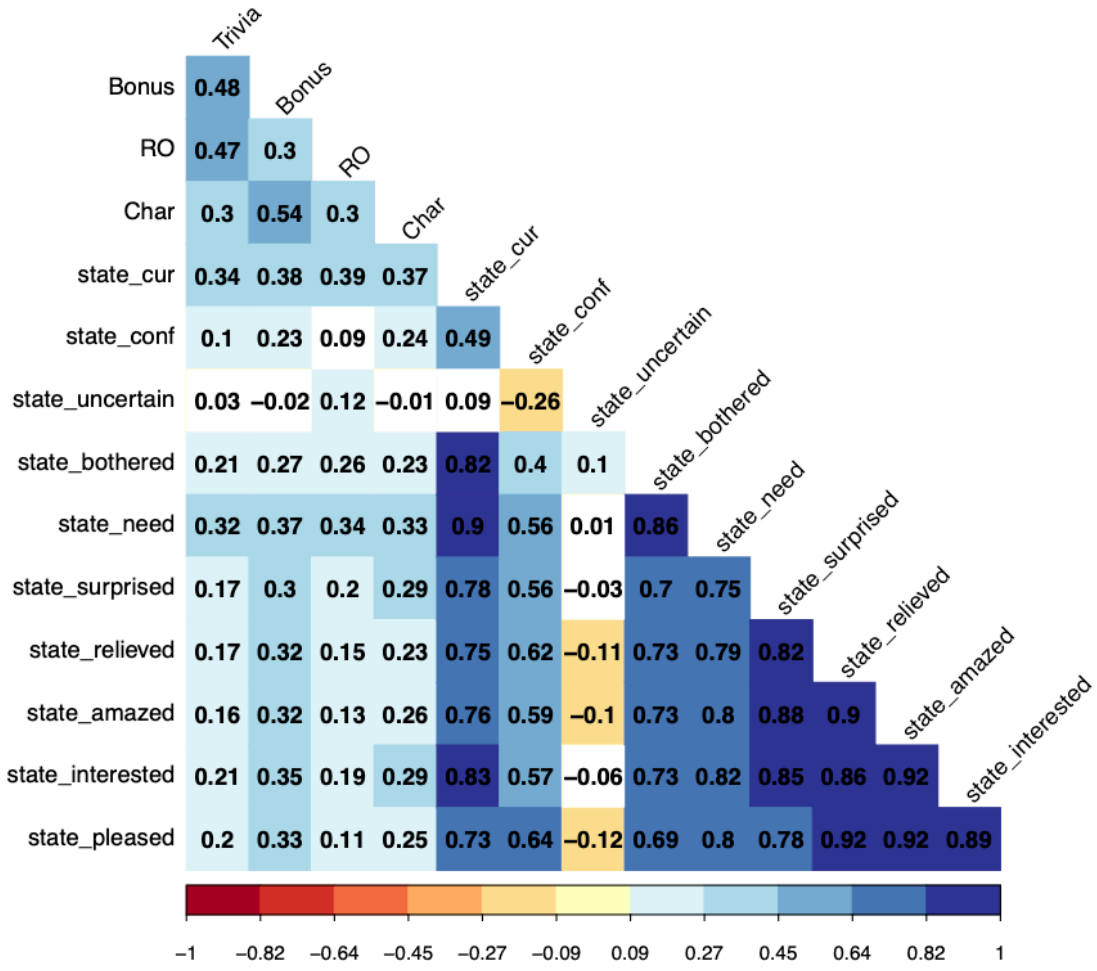
However, pre- and post- information state ratings were very highly intercorrelated, both comparing individual stimulus sets and averaged across stimulus sets. For pre-information ratings, curiosity, bother, and need were particularly highly correlated within and between stimulus sets, with the lowest correlation $r = .76$ (Trivia curiosity and Trivia bothered) and the highest $r = .90$ (Reward-Outcome need and Reward-Outcome curiosity). Post-information ratings follow a similar pattern, with Supplementary Figure 1 showing that mean correlations between all five of these variables were between $r = .78$ (surprised and pleased) and $r = .92$ (amazed and interested; amazed and pleased; pleased and relieved). When multicollinearity exceeds $r \sim .70$ the effects of each rating are challenging to separate statistically (Dormann et al., 2013). This perhaps suggests that these terms are imperfect estimates of the states that we were trying to elicit. We thus advise caution in drawing

inferences from results concerning pre- and post-information state responses, particularly curiosity, bothered, need, and predictions distinguishing between post-information responses.

To provide one example of the difficulty in drawing inferences from results, we had predicted that joyous exploration would not relate to feeling bothered after controlling for deprivation sensitivity. If feeling bothered reflects uncertainty-induced anxiety, then joyous exploration—which concerns positive emotions related to exploring the unknown—would not be expected to relate to feeling bothered except via its correlation with deprivation sensitivity. We thus computed a partial correlation from feeling bothered in each task, deprivation sensitivity, and joyous exploration, but observed that in the Trivia and Character stimulus sets, both joyous exploration and deprivation sensitivity were independently related to feeling bothered. However, these effects may be simply due to participants' lack of construct discrimination between feeling bothered and feeling curious, given the high intercorrelation of these ratings. We therefore cannot accurately infer degree of support for our hypothesis.

As an additional example, we had specified that the post-information emotion "relief" would be most related to the quiescence of negative emotions by obtaining information. That produced the hypothesis that neuroticism would be related to state relief after obtaining information. We did not find support for this prediction (Supplementary Table 3, last row). However, given that relief is correlated with being pleased, excited, surprised, and amazed and at a value of at least $r = .82$, we cannot distinguish between emotions of relief and these other positively-valanced emotions, and thus, responses could be reflecting any of these other emotions, or an unspecific feeling of general positive emotions.

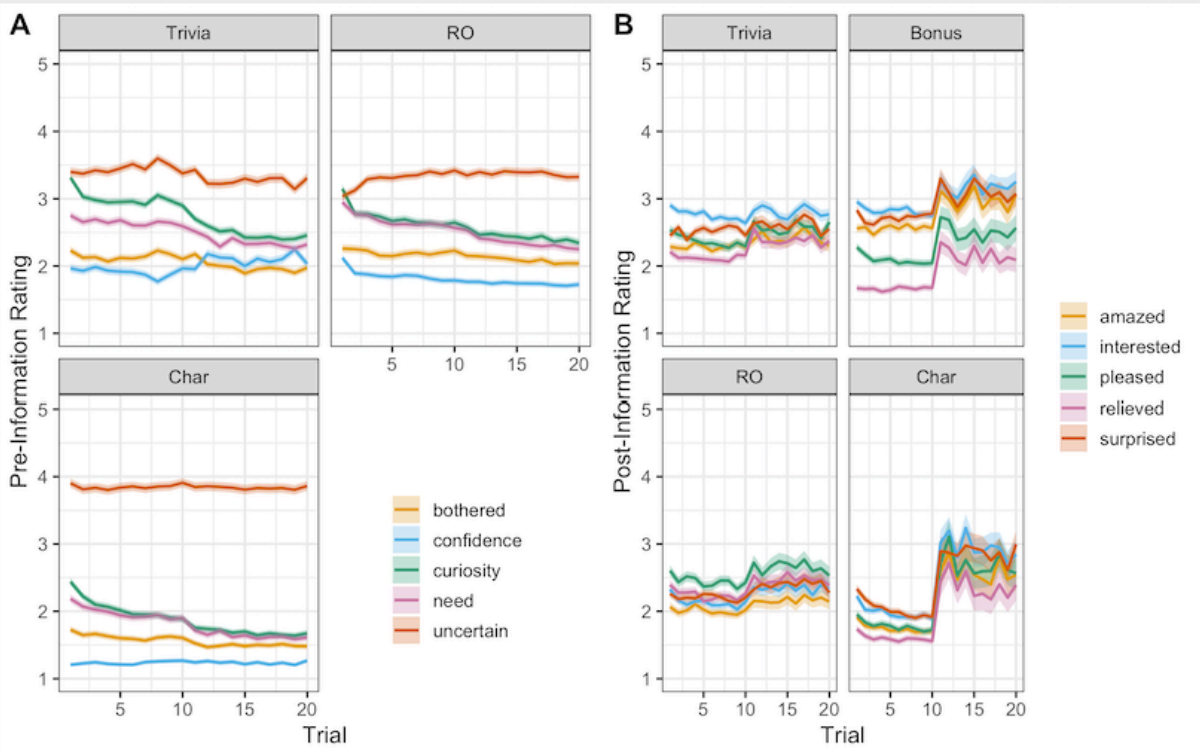
Despite these concerns, there are a few broad insights to be gleaned from the pattern of state responses. First, curiosity, bothered, and need are related to preferences for information in the stimulus sets (Supplementary Figure 1). This indicates that even if we cannot precisely distinguish between emotions, they are generally related to a broad preference for information. Similarly, post-information state responses for the first 10 trials relate to preference for information in the latter 10 trials. This suggests that when we feel positive emotions or surprise after receiving information, this makes us more likely to subsequently seek information.



Supplementary Figure 1. Zero-order Pearson correlations between information seeking stimulus sets, combined mean pre-information state ratings, and combined post-information state ratings. Unshaded correlations are statistically non-significant. Trivia = Trivia information-seeking stimuli, Bonus = Bonus information-seeking stimuli, RO = Reward-Outcome information-seeking stimuli, Char = Translated Characters information-seeking stimuli.

Finally, Supplementary Figure 2, Panel A displays pre-information state ratings as a function of time across all trials, averaged across participants. For all stimulus sets, pre-task ratings of curiosity, need, and bothered declined over the course of the trials, suggesting a general trend of reduced interest in information (and/or engagement with the task) over time. This is mirrored in post-information state ratings (Supplementary Figure 2, Panel B): for the first 10 trials, there are declines on all ratings for the Character stimuli, declines in interest and pleasure for the Trivia stimuli, declines in pleasure for the Bonus stimuli, and declines in

pleasure, relief, and interest for the Reward-Outcome stimuli. This may suggest that the average "information reward" is being reduced over the course of an experimental paradigm.



Supplementary Figure 2. Mean state ratings over time (trials). Shaded area shows the standard error of the mean. (A) Pre-information state ratings. (B) Post-information state ratings. Note that from Trial 11 onward, post-information ratings are only provided by people who chose to seek information.

Supplementary Table 3
Hypothesis 3 Results

State rating	Personality Trait or Situation Rating			
	Trivia	Bonus	Reward-Outcome	Character
Curious	+~~ **Cur joyous exploration (*r* = .30**)** +~~ **Cur deprivation (*r* = .24**)** +~~ **Open/Intel (*r* = .20**)** **!~~ IoU (*r* = .04, M_{01} = 6.79)** +~~ **pOsitivity (*r* = .47**)** +~~ **Intellect (*r* = .47**)**			+~~ **Cur joyous exploration (*r* = .31**)** +~~ **Cur deprivation (*r* = .16**)** +~~ **Open/Intel (*r* = .19**)** **!~~ IoU (*r* = .04, M_{01} = 6.63)** +~~ **pOsitivity (*r* = .57**)** +~~ **Intellect (*r* = .57**)**
Bothered	+~~ Neuroticism (*r* = .00) +~~ IoU (*r* = .08) +~~ **Cur deprivation (*r* = .25**)** !~~ Cur joyous exploration (partial *r* = .10*) after controlling for Cur deprivation +~~ **Negativity (*r* = .35**)**		+~~ Neuroticism (*r* = -.04) +~~ **IoU (*r* = .17**)** +~~ **Cur deprivation (*r* = .20**)** **!~~ Cur joyous exploration (partial *r* = .03) after controlling for Cur deprivation** +~~ **Negativity (*r* = .29**)**	+~~ Neuroticism (*r* = -.19**) +~~ IoU (*r* = .01) +~~ **Cur deprivation (*r* = .16**)** !~~ Cur joyous exploration (partial *r* = .20**) after controlling for Cur deprivation +~~ **Negativity (*r* = .26**)**
Need	+~~ **Cur deprivation (*r* = .24**)** +~~ Neuroticism (*r* = -.10*) +~~ IoU (*r* = .05) +~~ **Negativity (*r* = .27**)** +~~ **Intellect (*r* = .48**)**		+~~ **Cur deprivation (*r* = .20**)** +~~ Neuroticism (*r* = -.08) +~~ **IoU (*r* = .15**)** +~~ **Negativity (*r* = .21**)** +~~ **Intellect (*r* = .42**)**	+~~ **Cur deprivation (*r* = .15**)** +~~ Neuroticism (*r* = -.24**) +~~ IoU (*r* = -.02) +~~ **Negativity (*r* = .20**)** +~~ **Intellect (*r* = .56**)**
Uncertain	~~ Neuroticism < for RO (*r* = .16**)		+ ~~ Neuroticism (*r* = .02)	~~ Neuroticism < for RO (*r* = .04)
Confident	~~ Neuroticism < for RO (*r* = -.25**)		**-~~ Neuroticism (*r* = -.22**)**	~~ Neuroticism < for RO (*r* = -.20**)
Pleased and Interested	+~~ **Cur joyous exploration (*r* = .32**;.31**)**	+~~ **Cur joyous exploration (*r* = .31**;.33**)**	+~~ **Cur joyous exploration (*r* = .21**; .18**)**	+~~ **Cur joyous exploration (*r* = .31**; .32**)**

	+~~ Openness/Intellect (*r* = .23; 21**)** **+~~ pOsitivity (*r* = .52** .50**)**	**+~~ Openness/Intellect (*r* = .21**; .24**)** **+~~pOSitivity (*r* = .47**; .49**)**	**+~~ Openness/Intellect (*r* = .12*; .10*)** **+~~ pOsitivity (*r* = .59**; .60**)**	**+~~ Openness/Intellect (*r* = .23**; .25**)** **+~~ pOsitivity (*r* = .57**; .60**)**
Surprise	**+~~ Cur joyous exploration (*r* = .20**)** +~~ O/I (*r* = .08) **+~~ pOsitivity (*r* = .38**)**	**+~~ Cur joyous exploration (*r* = .26**)** **+~~ O/I (*r* = .16**)** **+~~ pOsitivity (*r* = .50**)**	**+~~ Cur joyous exploration (*r* = .17**)** +~~ O/I (*r* = .05) **+~~ pOsitivity (*r* = .49**)**	**+~~ Cur joyous exploration (*r* = .23**)** **+~~ O/I (*r* = .15**)** **+~~ pOsitivity (*r* = .50**)**
Relief	+~~ neuroticism (all trials *r* = -.20**)[16]		+~~ neuroticism (when correct *r* = .01; all trials *r* = -.11*)	

Note. Hypotheses supported by the data are presented in bold. +~~ = hypothesized positive correlation, -~~ = hypothesized negative correlation, !~~ = hypothesized null effect, * = $p < .05$, ** = $p < .01$.

[16] In our pre-registration, we predicted that this effect would occur when giving the correct response. However, this was not possible to compute with the entire sample due to some participants never guessing correct trivia responses, so we present solely the total trial responses.

Appendix D

Supplementary Materials for Chapter 5 (Jach, Feuerriegel, & Smillie, 2020)

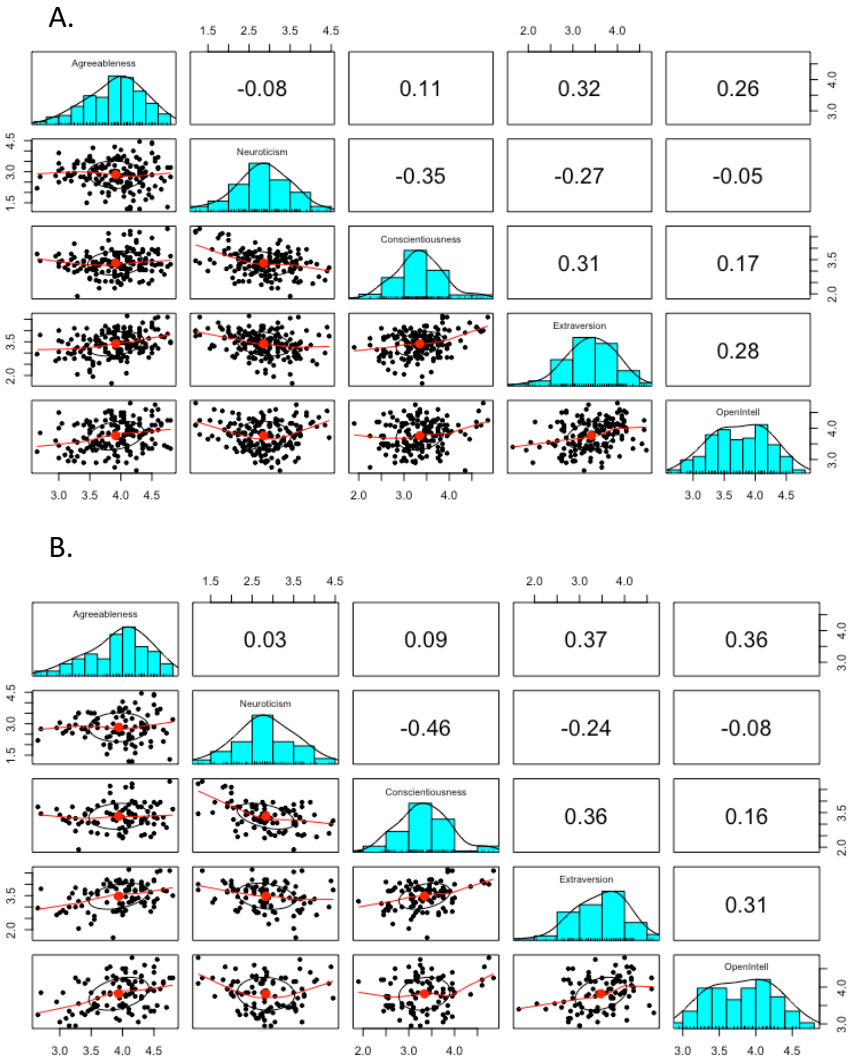


Figure S1. (A) Pre-task trait distribution and correlations between traits. (B). Post-task trait distribution and correlation between traits.

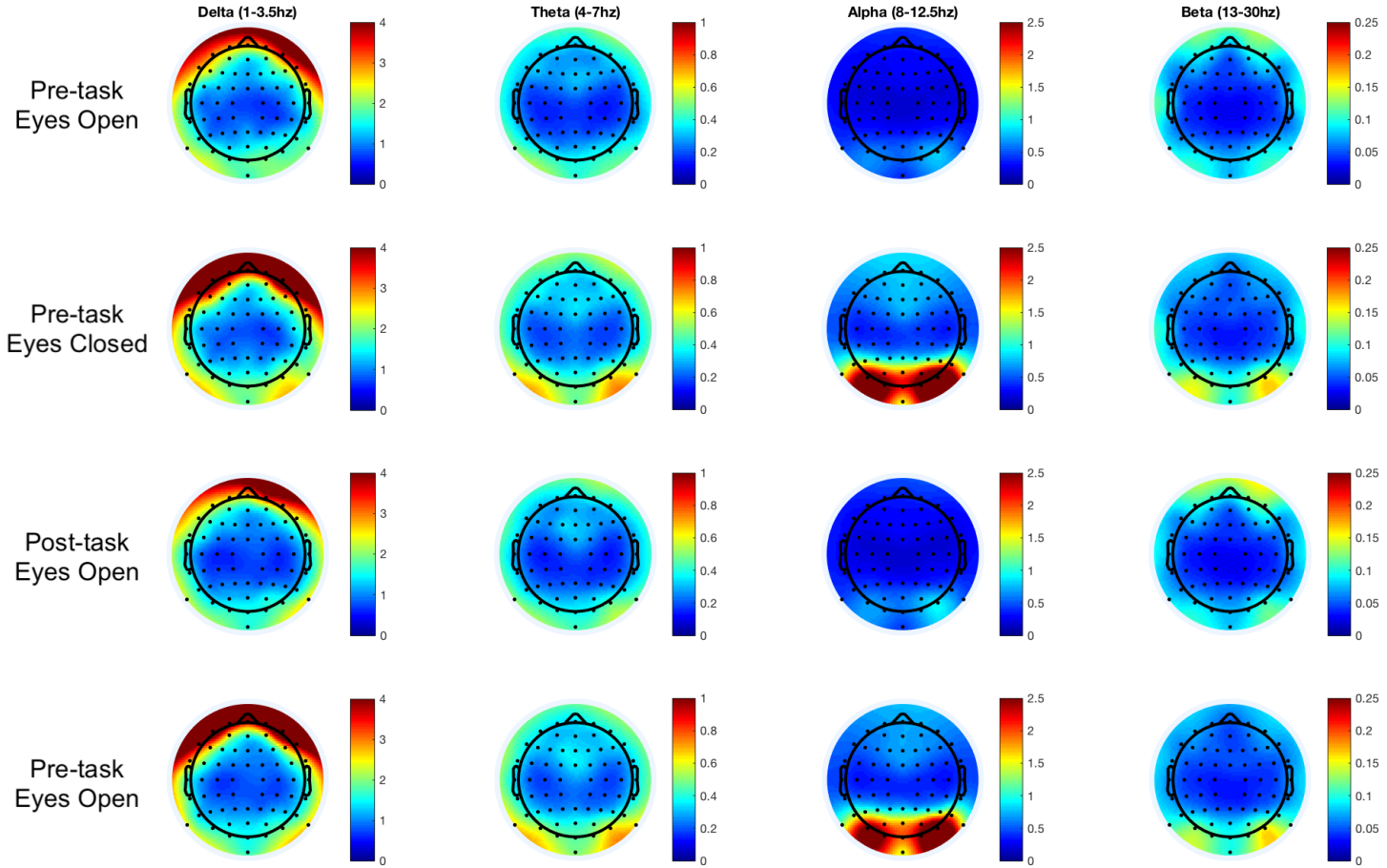


Figure S2. Scalp plots of power in selected frequency bands, averaged across all participants. Each row is a different condition (pre-task eyes open, pre-task eyes closed, post-task eyes open, and post-task eyes closed) and each column is a different frequency band (delta, theta, alpha, and beta). Colors depict the power in a given channel averaged across the frequency bins indicated. Colors correspond to the color-bar on the right side of the graph. Note that to facilitate visualization, different frequency bands have different scaling.

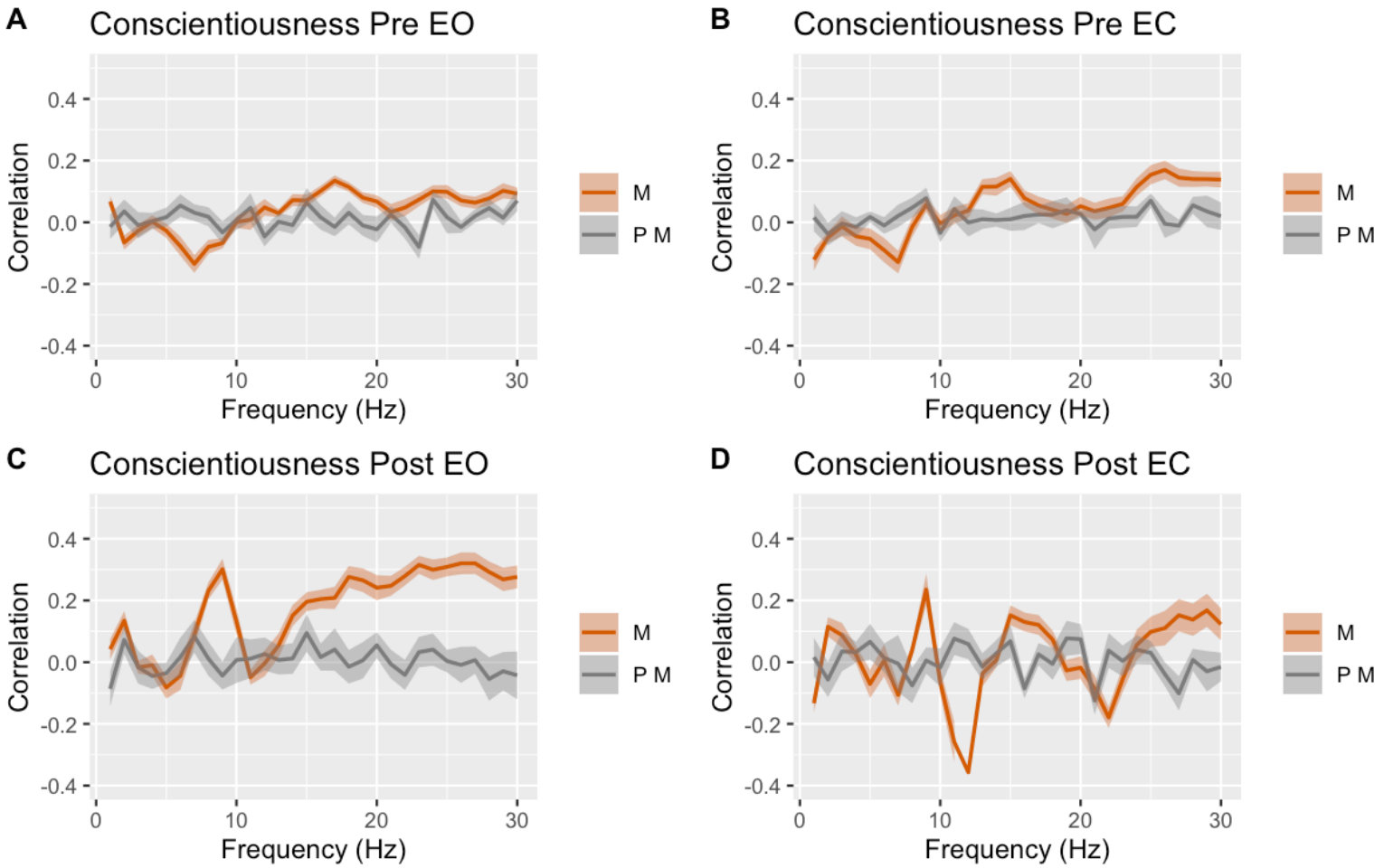


Figure S3. Model decoding for conscientiousness. The y-axis depicts the correlation between predicted personality labels (as given by power spectral values) and personality trait scores. The x-axis shows frequency bins from 1-30 Hz. M = Mean decoding performance, PM = Permuted labels mean decoding performance.

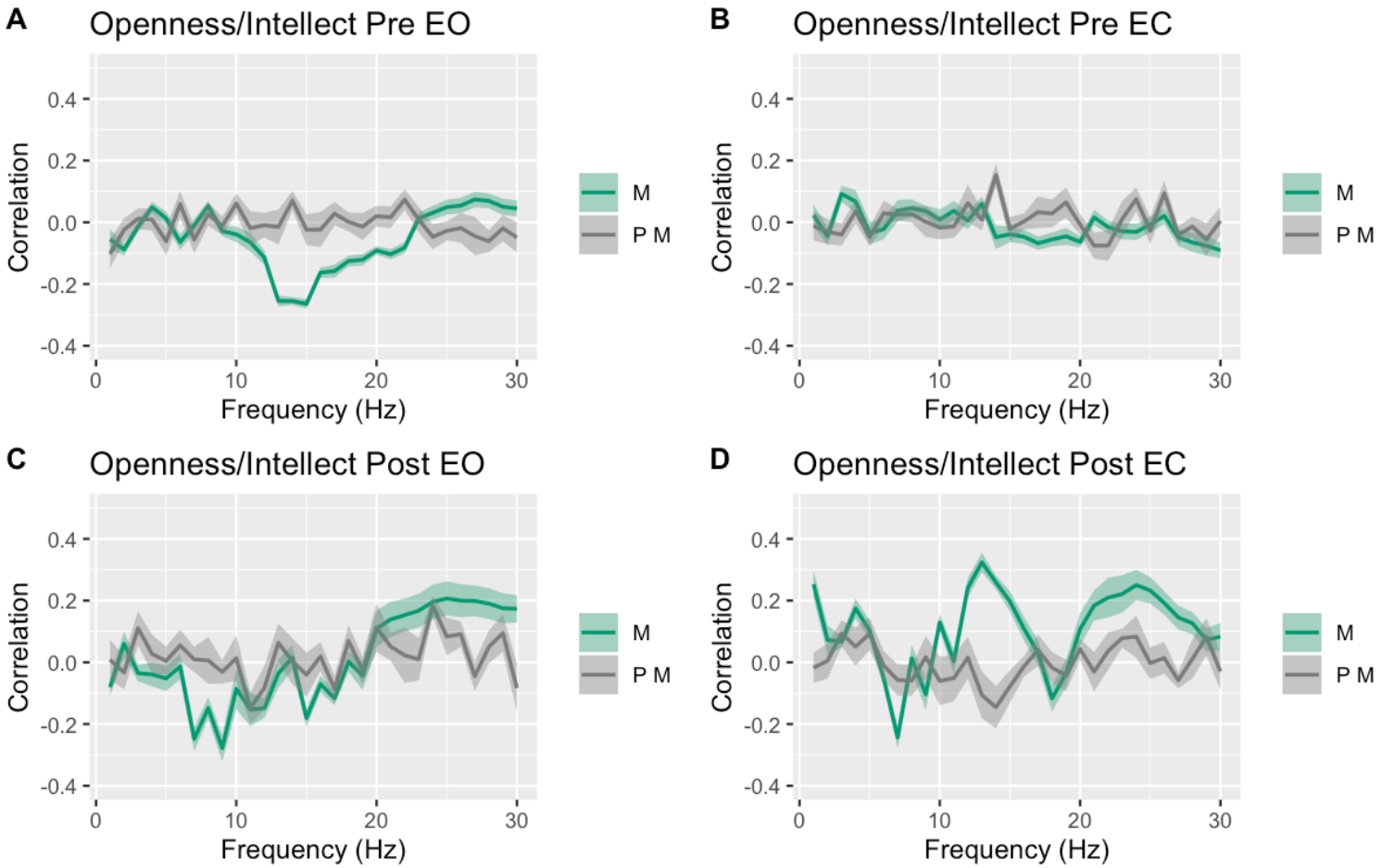


Figure S4. Model decoding for openness/intellect. Interpretation as per Figure S3. M = Mean decoding performance, PM = Permuted labels mean decoding performance.

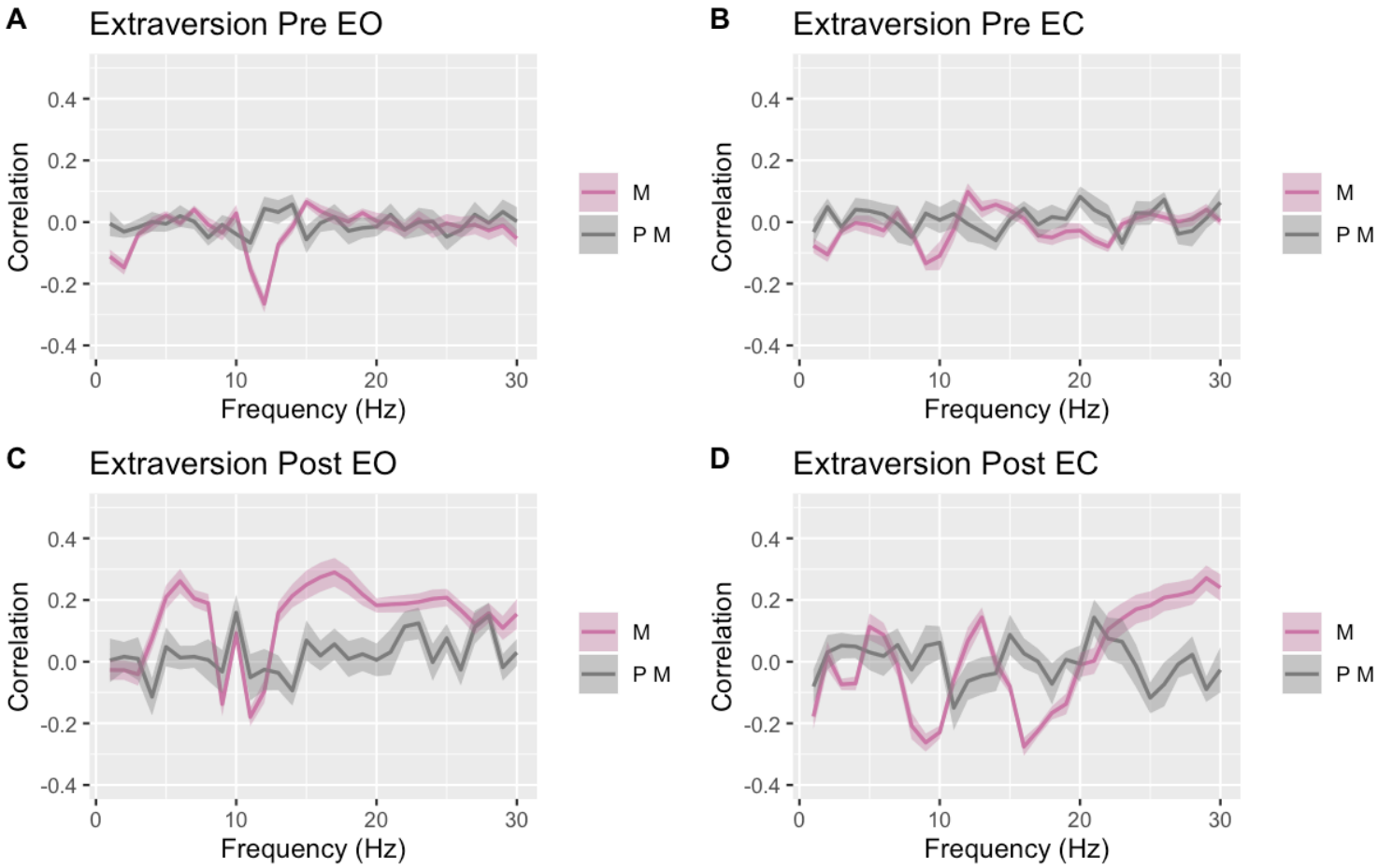


Figure S5. Model decoding for extraversion. Interpretation as per Figure S3. M = Mean decoding performance, PM = Permuted labels mean decoding performance.

Table S1.
Agreeableness and Conscientiousness Decoding Accuracy Across Frequency Bins 1-30hz

Frequency	A Post EC	A Post EO	A Pre EC	A Pre EO	C Post EC	C Post EO	C Pre EC	C Pre EO
1	0.31	0.2	0.05	0.07	-0.13	0.04	-0.12	0.07
2	0.24	0.08	-0.03	0.02	0.11	0.13	-0.05	-0.07
3	0.29	0.06	0.11	0.09	0.09	-0.02	-0.01	-0.03
4	0.19	0.14	0.12	0.16	0.02	-0.01	-0.05	0
5	0.29	0.16	0.08	0	-0.07	-0.08	-0.05	-0.03
6	0.37	0.15	0.01	-0.03	0.01	-0.04	-0.09	-0.08
7	0.32	0.14	0.07	0.02	-0.11	0.09	-0.13	-0.13
8	0.4	0.13	0.2	0.09	0.04	0.23	-0.02	-0.08
9	0.22	0.16	-0.05	0.07	0.24	0.3	0.06	-0.07
10	0.12	0.21	0.1	0.09	-0.06	0.13	0	0
11	0.32	0.32	0.17	-0.03	-0.26	-0.05	0.02	0.01
12	0.29	0.14	0.2	-0.07	-0.36	0	0.04	0.05
13	0.25	0.19	0.18	0.11	-0.04	0.05	0.12	0.03
14	0.26	0.27	0.17	0.08	0.01	0.15	0.12	0.07
15	0.35	0.18	0.2	0.19	0.15	0.2	0.14	0.07
16	0.26	0.19	0.2	0.22	0.13	0.2	0.08	0.1
17	0.26	0.14	0.22	0.21	0.12	0.21	0.05	0.14
18	0.22	0.22	0.24	0.17	0.07	0.28	0.04	0.11
19	0.22	0.2	0.21	0.15	-0.03	0.27	0.03	0.08
20	0.17	0.16	0.13	0.12	-0.02	0.24	0.05	0.07
21	0.08	0.07	0.16	0.02	-0.09	0.25	0.04	0.03
22	0.11	0.04	0.21	0.04	-0.18	0.28	0.05	0.05
23	0.17	0.04	0.25	0.1	-0.05	0.32	0.06	0.07
24	0.2	0.04	0.21	0.08	0.06	0.3	0.11	0.1
25	0.21	0.02	0.17	0.06	0.1	0.31	0.15	0.1

26	0.25	0.04	0.15	0.04	0.11	0.32	0.17	0.07
27	0.25	0	0.08	0.04	0.15	0.32	0.14	0.06
28	0.21	-0.07	0.07	0.03	0.14	0.29	0.14	0.08
29	0.2	-0.06	0.08	0.06	0.17	0.27	0.14	0.1
30	0.19	-0.03	0.06	0.04	0.12	0.28	0.14	0.09

Table S2.
Extraversion and Neuroticism Decoding Accuracy Across Frequency Bins 1-30hz

Frequency	E Post EC	E Post EO	E PreEC	E PreEO	N PostEC	N PostEO	N PreEC	N PreEO
1	-0.18	-0.03	-0.08	-0.11	0.12	0.02	0.01	0
2	0.02	-0.03	-0.11	-0.15	0.13	-0.01	0.07	0.02
3	-0.07	-0.04	-0.03	-0.04	0.18	0.06	0.13	0.15
4	-0.07	0.07	0	-0.01	0.14	0.1	0.23	0.21
5	0.11	0.21	-0.01	0.02	0.02	-0.03	0.23	0.29
6	0.09	0.26	-0.03	0	0.13	-0.04	0.15	0.2
7	-0.01	0.21	0.03	0.04	0.05	-0.24	0.09	0.14
8	-0.21	0.19	-0.04	-0.01	-0.04	-0.1	0	0.11
9	-0.26	-0.14	-0.13	-0.03	-0.06	-0.13	-0.05	-0.12
10	-0.23	0.09	-0.11	0.03	0.05	-0.19	-0.18	-0.1
11	-0.06	-0.18	-0.02	-0.15	-0.06	-0.24	-0.1	-0.16
12	0.07	-0.1	0.1	-0.26	0.12	-0.26	-0.12	-0.18
13	0.14	0.16	0.04	-0.07	-0.23	0.02	-0.02	-0.09
14	0	0.21	0.06	-0.02	-0.02	0.12	0.08	-0.07
15	-0.08	0.25	0.04	0.07	0.11	0.09	0.14	0
16	-0.28	0.27	0.01	0.04	0.07	0	0.07	-0.01
17	-0.22	0.29	-0.04	0.02	-0.08	-0.15	0.07	-0.05
18	-0.17	0.26	-0.05	0	-0.22	-0.23	0.02	-0.1

19	-0.14	0.22	-0.03	0.03	-0.23	-0.24	-0.07	-0.14
20	-0.01	0.18	-0.03	0	-0.03	-0.2	-0.05	-0.08
21	0	0.19	-0.06	0	0	-0.2	0.08	-0.16
22	0.11	0.19	-0.08	-0.03	-0.15	-0.18	0.07	-0.18
23	0.14	0.19	-0.01	0.01	-0.11	-0.12	-0.03	-0.14
24	0.17	0.2	0.01	-0.02	-0.02	-0.09	-0.04	-0.08
25	0.18	0.21	0.03	0	0.07	-0.09	-0.02	-0.07
26	0.21	0.17	0.02	-0.02	0.08	-0.08	0	-0.07
27	0.22	0.12	0	-0.01	0.08	-0.1	-0.01	-0.06
28	0.23	0.16	0.01	-0.03	0.05	-0.1	-0.04	-0.04
29	0.27	0.11	0.04	-0.01	0.08	-0.16	0	-0.05
30	0.24	0.15	0	-0.05	0.05	-0.16	-0.02	-0.05

Table S3.

Openness/Intellect Decoding Accuracy Across Frequency Bins 1-30hz

Frequency	OI PostEC	OI PostEO	OI PreEC	OI PreEO
1	0.25	-0.08	0.02	-0.06
2	0.07	0.06	-0.05	-0.09
3	0.07	-0.04	0.09	-0.01
4	0.17	-0.04	0.07	0.05
5	0.1	-0.05	-0.03	0.01
6	-0.05	-0.01	-0.02	-0.06
7	-0.24	-0.25	0.04	-0.01
8	0.01	-0.15	0.05	0.05
9	-0.1	-0.28	0.04	-0.03
10	0.13	-0.09	0.01	-0.04
11	0	-0.15	0.04	-0.06

12	0.24	-0.15	0.01	-0.11
13	0.32	-0.04	0.06	-0.25
14	0.26	0.02	-0.05	-0.26
15	0.2	-0.18	-0.04	-0.26
16	0.11	-0.07	-0.05	-0.16
17	0.03	-0.12	-0.07	-0.16
18	-0.12	0	-0.06	-0.13
19	-0.03	-0.04	-0.05	-0.12
20	0.11	0.11	-0.06	-0.09
21	0.18	0.14	0.02	-0.1
22	0.21	0.15	-0.02	-0.08
23	0.22	0.17	-0.03	0.01
24	0.25	0.2	-0.03	0.03
25	0.23	0.21	-0.01	0.05
26	0.19	0.2	0.02	0.05
27	0.15	0.2	-0.05	0.07
28	0.13	0.19	-0.06	0.07
29	0.07	0.18	-0.08	0.05
30	0.08	0.17	-0.09	0.04

Appendix E

Supplementary Materials for Chapter 6 (Jach et al., In Prep.)

Table S1

Decoding Performance for all traits, Combined and by Country

	Agreeableness			Conscientiousness			Extraversion			Neuroticism			Openness/Intellect		
Freq	A	G	C	A	G	C	A	G	C	A	G	C	A	G	C
1	.06	.03	-.07	-.12	-.04	-.13	-.08	-.05	-.07	.07	.09	.10	.08	.09	.09
2	.10	-.05	.06	-.21	.14	-.20	**-.22**	.10	-.14	.04	**.18**	.07	-.07	.11	.02
3	.02	-.01	.04	-.22	.15	-.22	**-.30**	.13	-.09	-.05	**.19**	.02	-.20	.09	.07
4	.03	.02	.03	-.12	**.18**	-.14	**-.29**	-.02	-.10	-.05	**.24**	.03	-.20	**.22**	.09
5	.10	-.03	.03	-.10	.13	-.13	-.16	-.23	-.09	-.01	**.21**	.09	-.29	**.22**	.13
6	**.24**	.02	.07	-.08	.07	-.11	.010	-.10	-.09	.11	.09	.10	-.27	.16	.11
7	**.24**	-.17	.03	.00	.01	-.11	**.19**	-.10	-.03	-.03	.12	.00	-.29	.07	.10
8	**.19**	-.05	.02	-.04	-.07	-.06	**.29**	-.03	.10	.05	**.20**	-.14	-.51	.04	.04
9	.03	-.02	.04	.03	.07	.04	.05	.10	**.18**	.10	.00	.04	-.11	.04	.05
10	.12	.00	.00	-.07	.01	-.10	.08	.04	.11	.08	.06	.04	-.31	.14	.11
11	.13	-.03	.09	.14	.14	-.11	**.24**	-.03	.03	.16	.00	.06	-.24	**.18**	.03
12	.08	-.08	.09	.04	.12	-.01	.07	-.08	.05	.08	.06	-.01	-.28	.02	-.07
13	.10	.00	.02	.12	.00	-.06	.14	-.17	.10	-.01	.05	.00	-.23	-.22	-.18
14	.12	-.07	-.01	.14	.09	.04	.12	.02	.10	-.08	-.20	-.11	-.13	-.17	-.02

15	.15	-.05	-.01	.15	.14	.08	**.19**	.10	.09	.05	.04	-.06	-.09	-.06	.09
16	**.23**	.04	.02	.12	.08	.12	**.27**	.09	.10	.12	**.19**	.01	-.03	.13	**.18**
17	**.28**	.00	.05	.13	.12	.15	**.23**	.06	.16	.12	**.22**	.14	-.02	.16	**.23**
18	**.18**	.02	.07	**.18**	.08	.14	**.31**	.16	**.26**	.02	.17	.17	-.11	.14	.14
19	.12	-.03	.08	.14	.01	.00	**.31**	.14	**.21**	.04	**.19**	.13	-.03	.08	.07
20	.14	.00	.03	.03	.02	-.08	**.33**	.11	.15	-.07	.06	.06	.00	.12	.17
21	.15	-.05	.07	.10	.04	.04	**.25**	.13	**.18**	.00	-.02	.04	.02	.11	**.24**
22	**.22**	-.12	.13	.15	-.03	-.01	**.20**	.15	.16	-.01	.06	.01	.15	.07	**.27**
23	**.21**	-.10	.13	.17	-.02	.05	.09	.10	.10	-.06	.08	.01	.13	.08	**.19**
24	**.27**	-.03	.09	**.20**	-.11	-.06	-.01	.01	.06	-.08	.08	.04	**.30**	.01	.14
25	**.32**	-.09	.13	**.28**	-.12	-.12	.04	.02	.05	-.12	.04	-.02	**.33**	-.03	.13
26	**.26**	-.11	.13	**.34**	-.12	-.11	.12	.04	.07	-.12	.01	-.02	**.27**	.02	.16
27	**.28**	-.06	.16	**.31**	-.09	-.14	**.19**	.03	.08	-.08	-.02	-.07	**.20**	.06	.17
28	**.39**	-.03	**.18**	**.34**	-.10	-.14	.17	.03	.08	-.08	.03	-.03	**.18**	.06	.16
29	**.41**	-.03	.17	**.31**	-.07	-.11	.09	-.01	.05	-.04	.09	-.04	**.22**	.07	.15
30	**.41**	-.01	**.21**	**.25**	-.01	-.10	.12	.02	.05	-.07	.12	-.01	**.24**	.07	.13

Note. Freq = Frequency bin, A = Australia, G = Germany, C = Combined. **Bold** values indicate correlations ≥ r = .18, our pre-specified threshold.

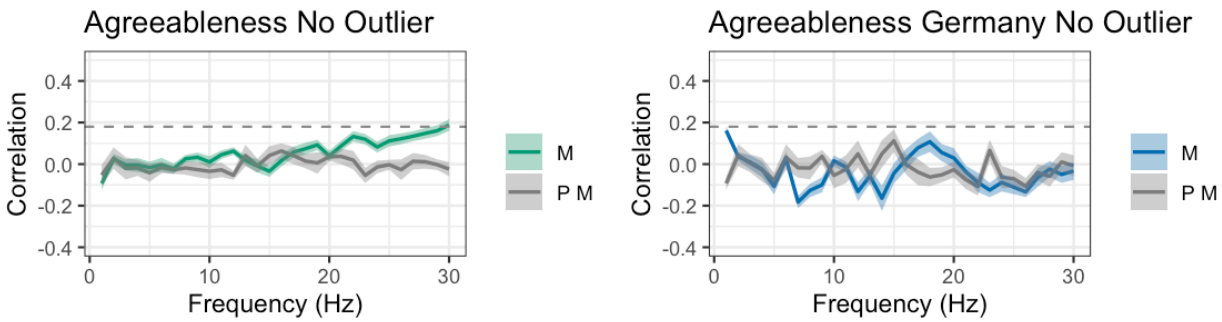


Figure S1. Decoding performance for agreeableness without the single outlying value in the German sample.