Foraging in internal and external environments: developing behavioural assays for boredom proneness.

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners. I understand that my thesis may be made electronically available to the public.

Statement of Contributions

This work has been conducted in collaboration with my supervisor Dr. James Danckert and PhD student Andriy Struk.

Abstract

Previous research has shown that boredom proneness is associated with failures of self-regulation. As yet few studies have directly explored the behavioural consequences of this relationship. The goal of this study was to examine the behavioural constituents of boredom proneness and various self-regulatory traits. Foraging represents a common goal directed behaviour that emphasises exploration and attainment of valued outcomes. As such, foraging tasks were used as behavioural assays of self-regulatory behaviour. Foraging can be thought of as either internal or external: an internal forging task, emphasizes exploration of problem spaces with a goal of determining as many solutions as possible. The Boggle game, in which participants made as many words as possible from a grid of 9 letters, was used as an internal foraging task. An external foraging task, on the other hand, emphasizes exploration of physical or virtual environments, with a goal of maximizing provisions. A spatial foraging task, in which participants explored a virtual environment collecting as many red "berries" as possible, served as an external foraging task. Results suggest that although each self-regulatory trait was associated with a specific set of behaviors, self-regulatory traits seem to be better characterized as behavioral preferences. When individuals behaved contrary to what would be preferred under a given self-regulatory trait, it reflects a recurrent lack of regulatory fit. Instances of non-fit in the current study were associated with increased trait boredom proneness. These findings suggest that how goals are pursued may be an important determinant of boredom proneness.

Keywords: Boredom proneness, Self-regulation, Regulatory- fit, Foraging

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CHAPTER 1: Introduction

1.1 What is Boredom?

Boredom is a ubiquitous human experience characterised as a disengaged state and is associated with a range of negative affective states such as sadness, depression and anxiety (Eastwood, Frischen, J, & Smilek, 2012; Goetz, et al., 2014). Other research suggests that boredom is strongly associated with the tendency to feel unsatisfied, unchallenged and a feeling that current activities lack a sense of meaning (van Tilburg & Igou, 2012; Gerritsen, Toplak, Sciaraffa, & Eastwood, 2014). Here we define boredom as an agitated state of wanting, but failing, to engage in a meaningful activity.

The prevalence of boredom has led researchers to posit that the experience may serve some adaptive function (Bench & Lench, 2013; Elpidorou, 2014). Pain provides a useful metaphor: pain does not function to simply cause distress and/or physically damage tissue. Rather, pain is there to signal that a change in behaviour is required. A burn from the stove functions not to induce a painful experience but to initiate an action – remove your hand from the flame! Indeed, individuals with congenital analgesia – a rare genetic disorder characterised by an inability to feel pain, lead very dangerous lives as their inability to experience pain leads to failures in modifying their behaviour to prevent further harm. With respect to boredom, the experience does not function to make us bored, but signals a need for change in behaviour. Bench and Lench (2013) propose that the function of boredom is to regulate one's behaviour – perhaps by motivating individuals to seek out alternative activities, goals or environments that are more satisfying and meaningful to them than their current activity. Recent literature also emphasises that experiencing boredom can prompt individuals to change their activity or modify their behaviour to maintain optimal levels of engagement, interest, challenge and meaning (Sansone, Weir, Harpster, & Morgan, 1992; van Tilburg & Igou, 2011; Elpidorou, 2014). Thus, boredom operates as a self-regulatory signal letting us know that what we are doing now is failing to satisfy and giving us the 'push' needed to explore our environment for alternatives (Elpidorou, 2014).

1.2 Boredom and self-regulation

Previous work from our laboratory has shown that boredom proneness is related to lower levels of self-control and distinct profiles of self-regulation (Struk, Scholer, & Danckert, 2015). To pursue goals effectively, we exert a considerable amount of effort in part to overrule certain affective reactions to bring our actions in line with our goals. Self-regulation therefore, does not only entail behavioural regulation, it also requires regulation of emotions, thoughts and impulses (Baumeister, Heatherton, & Tice, 1994). Self-regulatory failures have been implicated in numerous personal and social problems including alcoholism, gambling and crime, while self-regulatory successes have been linked to numerous well-being dimensions including greater achievements in education, health and wealth (Moffitt, et al., 2011; Tangney, Baumeister, & Boone, 2004). Regulatory mode theory highlights two prominent ways in which people regulate their behaviour in pursuit of goals: Locomotion and Assessment. Locomotion refers to the implementation of action states (i.e., individuals "getting on with it"), while Assessment refers to a comparative mode of goal pursuit in which alternative action choices are contrasted in order to "do the right thing" (Kruglanski et al., 2000). In this sense, locomotors prefer to initiate and maintain engagement, whereas assessors tend to want to optimise reward associated with task engagement.

In addition to differences in how goals are pursued, individuals can also differ in the types of goals they pursue and the strategies they employ in pursuit of those goals. This differentiation is highlighted in regulatory focus theory that distinguishes between self-regulation in the pursuit of nurturance (Promotion focus), and self-regulation in the pursuit of security (Prevention focus; Higgins, 1997). Promotion focused individuals represent goals as hopes and aspirations, and are sensitive to opportunities for gains, whereas Prevention focused individuals represent goals as duties and obligations, prefer vigilant strategies and are sensitive to loss and threats (Crowe & Higgins, 1997). Previous research has shown that successful goal pursuit through *either* self-regulatory system leads to lower levels of boredom proneness (Struk et al., 2015), presumably because both modes of goal pursuit involve individuals being engaged with their goals, albeit in distinct ways.

Goal directed behaviour in general, regardless of particular regulatory mode or foci, involves two distinct stages: goal selection and goal engagement (O'Reilly, Hazy, Mollick, Mackie, & Herd, 2014). One can think of these as representing the distinction between exploration (seeking a particular goal to engage with) and exploitation (maximising the resources or outcomes of a particular activity). Boredom prone individuals may fail at one or both of these stages. In this sense, boredom prone individuals may experience boredom and realise that their current task does not align well with their goals, but may also experience difficulties in selecting something new to engage with (i.e., a failure of goal selection or exploratory behaviour). On the other hand, boredom prone individuals may fail to efficiently engage in a given task thus, making them more prone to the experience of boredom (i.e., a failure of engagement or exploitative behaviour). Failures in goal selection or engagement therefore, warrant a change in behaviour in order to more effectively pursue personally relevant goals and boredom acts as a signal for this change.

1.3 Current study:

One caveat of the studies looking at the various associations between boredom and self-regulation is the lack of an objective, quantitative measure that addresses differences in goal pursuit. That is, prior work is based almost entirely on self-report measures of self-regulation rather than on actual behavioural metrics. For example, experimental evidence shows attentional difficulties and time perception problems in boredom prone individuals and while these may be indicative of poor self-regulation, nothing has been done to directly test these notions (Eastwood, Frischen, J, & Smilek, 2012; Malkovsky, Merrifield, Golberg, & Danckert, 2012; Danckert & Allman, 2005; Watt, 1991). What is needed, therefore, is a behavioural assay of self-regulation (Locomotion, Assessment, Promotion and Prevention) to explore how goal pursuit differs as a function of boredom proneness.

The current study attempts to behaviourally differentiate between various levels of self-regulation through the use of foraging tasks. Foraging represents a common goal directed behaviour that balances exploration and exploitation. Explored extensively in the animal kingdom, foraging balances the animal's need to *explore* their environment for resources (e.g., food) to *exploit*. Unchecked exploitation of a given resource runs the risk that the animal misses other, potentially more plentiful sources of that resource (i.e., opportunity costs). As it turns out, foragers do not exhaust resources in this way, instead deciding to cease exploitation in favour of continued exploration of their environment. Using berry picking as an example, an animal will move on from one patch of berries when the reward level drops below some threshold (see Marginal value theorem; Charnov, 1976).

Foraging represents an ideal behavioural assay to explore distinct patterns of goal-directed behaviour as they relate to differences in self-regulatory profiles. For example, those high in Locomotion may be more likely to move from berry patch to berry patch more readily than those high in Assessment. Indeed, research in Drosophila and other species, have shown that foraging related behaviour differs along two phenotypes of the so-called foraging gene – labelled the rover and the sitter (Sokolowski, 1980). Animals with a dominant rover allele have longer foraging paths and tend to leave a patch of food to explore their environment more fully compared to those with a dominant sitter allele (Sokolowski, 2001). On a surface level, this difference maps well onto behaviours associated with Locomotion and Assessment respectively. That is, rovers are similar to Locomotors in that they are more likely to move from one situation to another, whereas sitters are similar to Assessors as they are more likely to exploit a local area more fully.

Foraging, as characterised here, can be considered within both external and internal spaces. That is, foraging for food (e.g., berries) could be considered an externally driven foraging task in that the individual's search behaviour is driven by factors in the external environment (e.g., density of berries, cost for moving from patch to patch, etc.). In other words, the individual must balance the needs of exploration and exploitation in an external search space to achieve their goals. For so-called internal foraging, participants need to search an internal space (e.g., memory, semantic knowledge, etc.) in order to achieve a particular goal. Indeed, Hills and colleagues (2008) examined external and internal foraging behaviour and found that searches in external spaces influenced subsequent search in internal cognitive space. They had participants go through a pre-test session followed by a spatial foraging task and then a post-test session. During the pre- and post-test sessions, participants were given an internal foraging task in the form of a scrabble game in which they had to find as many words of 4-letters or more as they could from the given letters. During the pre-test, participants went through three letter sets before moving on to the spatial foraging task. In the post-test session, participants were told to find 30 correct words across any number of letter sets before they could finish the experiment. The spatial foraging task consisted of a virtual berry picking task with environments that were either sparsely or densely populated. Results showed that participants who were primed for goal-directed exploitation by searching through densely populated external spaces subsequently spent more time per letter set during the internal search task compared to participants who searched a sparsely populated external search space. To this end, this study found that performance in a spatial foraging task could prime behaviour in an internal foraging task.

The current study employed two types of foraging tasks to explore whether patterns of performance could be differentiated by self-regulatory profiles and boredom proneness. The first is an external spatial foraging task in which individuals move around a virtual berry patch with the goal of picking as many berries as possible within a set time limit. The second is an internal, cognitive foraging task similar to the Boggle game. In this game, individuals are required to form as many words of 4-letters or more as possible within a set timeframe (and a variety of other constraints). Exploration within the foraging task can be measured by examining how participants move through the space collecting berries. According to the marginal value theorem, participants would move from one patch to another when the cost of picking berries within the present patch outweighs the cost of moving to another patch (Charnov; 1976). Similarly, exploration within the Boggle game can be measured using various metrics including how many words are made and how quickly participants move from one problem space to another. In both tasks, the various metrics – outlined in more detail below – can be used to differentiate distinct self-regulatory profiles.

This line of research is exploratory and hypotheses regarding foraging behaviours within each self-regulatory mode and foci and the performance of boredom prone individuals are necessarily speculative. High boredom prone individuals may exhibit behaviours that are suboptimal in either environment—indicative of their purported difficulties with goal-selection (exploration) and engagement (exploitation). Those high in Locomotion may explore their environment more (e.g., longer path lengths in the external foraging task) and move from one patch to another fairly quickly compared to those high in Assessment. Similar patterns should emerge in the cognitive foraging task (i.e., Boggle); those high in Locomotion may move from one solution space to another fairly quickly, while those high in Assessment may be more likely to spend more time per patch in the foraging task, diligently exploiting the environment. With regards to self-regulatory foci, previous research showed that boredom proneness is negatively correlated with both Promotion and Prevention modes of goal pursuit (Struk et al., 2015).Those with a strong Promotion focus are more likely to move around in the foraging environment (internal or external) in order to maximise gains compared to those with a weak Promotion focus. In contrast, those with a strong Prevention focus will be more sensitive to losses and are more likely to exhaust an environment before moving on.

CHAPTER 2: Methods

2.1 Participants and procedure

Three hundred undergraduates (220 females, mean age = 20 years) from the University of Waterloo, participated in this study in exchange for course credit. As part of a larger genetic project (the results of which will not be discussed here), data was collected over the fall term of 2015 and the winter term of 2016. It was determined, a priori, that data collection would continue until the required total number of participants for the genetic study was met (300). Due to some technical difficulties, data from four participants was corrupted; thus the final sample reported on was N = 296 (219 females; mean age = 19.98 years). This study was approved by the University of Waterloo, Office of Research Ethics and participants gave written consent prior to participating.

2.2 Materials

Participants completed a battery of questionnaires online prior to the laboratory study. These questionnaires indicated trait measures of boredom proneness and self-regulatory profile. The short boredom proneness scale (sBPS) was used as a measure of an individual's propensity to experience boredom (Struk, Carriere, Cheyne, & Danckert, 2015). The sBPS was developed as a short version of the Boredom Proneness Scale (BPS) developed by Farmer & Sundberg (1986). This shorter version addressed several of the shortcomings of the BPS, with factor analysis suggesting the scale taps into a single explanatory factor (Struk et al., 2015). The sBPS is a self-report questionnaire consisting of 8 items rated on a 7-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree" (e.g., "I find it hard to entertain myself"). High scores on this questionnaire indicate a higher proneness to experience boredom. Struk and colleagues (2015) report that the sBPS has an internal consistency of 0.88.

The Brief Self-Control Scale (BSCS) was used as a general measure of trait Self-Control (Tangney, Baumeister, & Boone, 2004). It is a self-report questionnaire that consists of 13 items rated on a 5-point Likert scale ranging from “not at all” to “very much” (e.g., “I am good at resisting temptation”). Items measure the ability to control one’s thoughts, feelings, impulses, and performance. High scores on this questionnaire indicate a stronger capacity to exert Self-Control. Tangney and colleagues (2004) report that the Self-Control Scale has an internal consistency of 0.83 and a test-retest reliability of 0.89.

The Regulatory Model Questionnaire (RMQ) was used as a measure of individual differences in regulatory mode: that is, Locomotion and Assessment orientations (Kruglanski et al., 2000). This questionnaire consists of 24 items, 12 assessing the Locomotion mode (e.g., “By the time I accomplish a task, I already have the next one in mind”), and 12 addressing the Assessment mode (e.g., “I often critique work done by myself and others”) rated on a 6-point Likert scale ranging from “Strongly Disagree” to “Strongly Agree.” High scores on each subscale reflect greater endorsement of Locomotion or Assessment regulatory profiles respectively. Kruglanski and colleagues (2000) reported an internal consistency of 0.82 for the Locomotion and 0.78 for the Assessment scales and, a test-retest reliability of 0.77 and 0.73 for the Locomotion and Assessment scales respectively.

The Regulatory Focus Questionnaire (RFQ) assessed previous successes or failures at implementing either a Promotion or Prevention focus (Higgins, et al., 2001). This questionnaire consists of 11 items: 6 Promotion focus items (e.g., “I feel like I have made progress towards being successful in life.”), and 5 Prevention focus items (e.g., “Not being careful enough has gotten me into trouble at times.”) rated on a 5-point Likert scale ranging from “never or seldom” to “very often.” Higgins and colleagues (2001) report an internal consistency of 0.73 and 0.80 and a test-retest reliability of 0.79 and 0.81 for the Promotion and Prevention scales respectively.

2.3 Apparatus and procedure

Participants completed two types of foraging task conceptualised here as foraging in internal (the Boggle game) or external (berries task) space (see Hills et al., (2008) for a similar distinction). A computerised version of the Boggle game and a foraging task were programmed using python 2.7.3 and a pygame library. The games were displayed on a 27” touchscreen monitor with a screen resolution of 2560 x 1440 pixels and a refresh rate of 60 hertz. All tasks were counterbalanced between participants.

2.3.1 Boggle Game

In the Boggle game, participants were presented with a 3 x 3 grid of squares, each containing a single letter. The central letter of the grid was highlighted in grey (Figure 1). Participants were asked to make as many words of 4 letters or more, with each individual word containing the central letter. Plurals and proper nouns were not permissible. Participants used their fingers to select individual letters from a given problem set in the appropriate order to make words. When an individual letter is selected, it appears in an answer box at the bottom left hand side of the grid so that participants do not have to remember which letter they had already selected. Once a word is created, participants tapped an ‘Enter’ button and the word then appeared in the answer box located to the right of the display. Participant responses appeared in a

180x30 pixel box next to the problem set on the screen. They could also tap on the ‘Clear’ button if they made a mistake. Participants were free to move from one problem set to another (and back again) by simply tapping the ‘Previous’ or ‘Next’ buttons located below the grid. There were a total of 23 problem sets generated from an online game (http://nineletterword.tompaton.com). The number of words that can be created from the problem sets ranged from a minimum of 80 words to a maximum of 253 words and an average of 120 words. Participants were told that each problem set contained at least one 9-letter word. Each participant had 10 minutes to complete this task and their goal was to make as many words as they could from each problem set. Time on the task was indicated by a clock above the 3x3 grid display which counted down from 10 minutes using a digital counter indicating seconds and minutes (Figure 1).

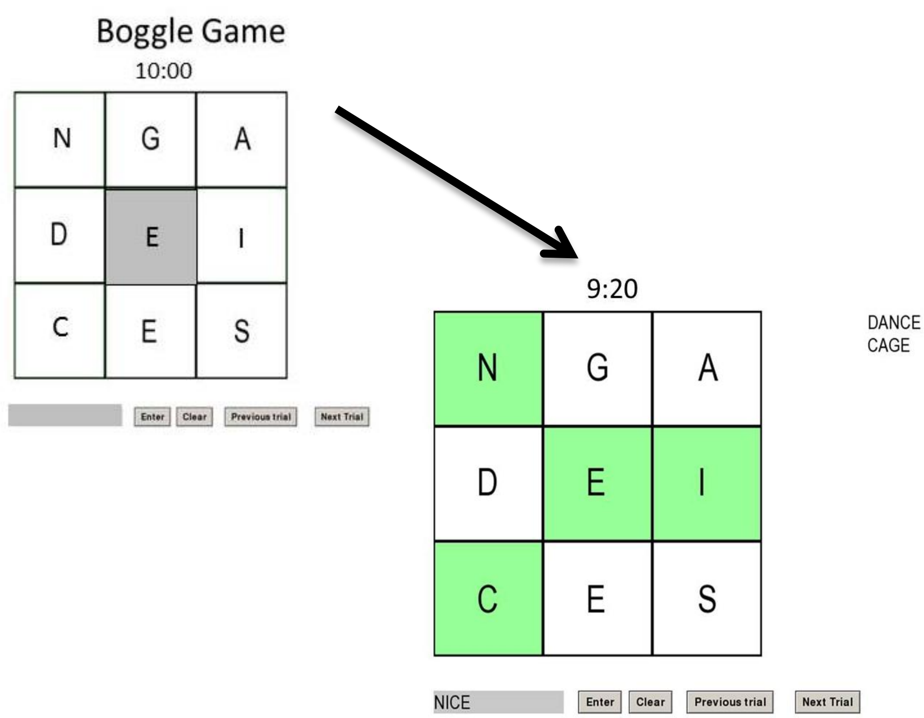


Figure 1: Top left is a screenshot of the Boggle game. Bottom right is a screenshot of the Boggle game showing the word “NICE” being created. Participants can see the words that they have already entered on the right of the letter grid.

2.3.1 Foraging Task

For the foraging task, participants were exposed to an environment meant to mimic searching for berries in a bush. The background was a grass texture (512 x 512 pixels) replicated in a 20,000 x 20,000 pixel environment (Figure 2). The 'berries' were red circles and varied in size from a radius of 4 to 16 pixels. A total of 384 berries were distributed evenly throughout the environment. Participants were instructed to collect as many berries as possible with a counter showing how many berries had been collected displayed in the upper right corner of the screen. The screen displayed only a portion of the environment at a time - encompassing 1850 x 1850 pixels. Participants navigated through the environment using their finger to swipe the screen. In order to collect berries participants tapped on the berries. The goal for each participant was to collect as many berries as possible in 5 minutes. A clock counting down the remaining time was displayed in the upper middle part of the screen.

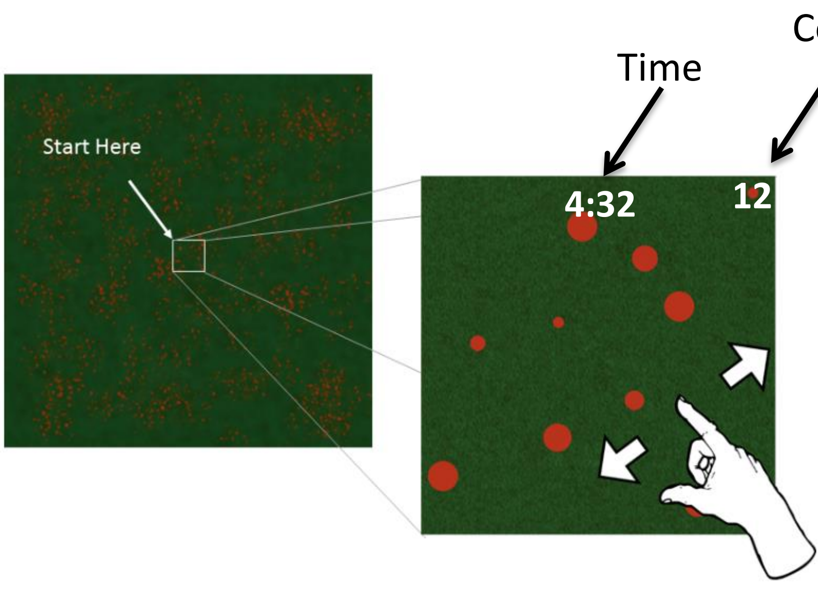


Figure 2: Foraging task. The left image shows the full environment with the berries represented as red dots. The right image shows a portion of the environment that participants saw with a counter located in the top right hand corner and a timer located in upper middle section of the screen.

2.4 Data Analysis

All data analyses were conducted in R statistical software package 3.2.4 (R Core Team, 2016). Examples of dependent variables within the Boggle game included the number of words entered, the average time per problem set, the number of times participants ‘moved’ from one problem set to another (and the direction of their movement – towards a new problem or back to a previous problem), and the number of errors made. Examples of dependent variables for the foraging tasks included path length, number of moves, number of successful picks, number of misses defined as number of failed attempts at berry picking, the average angle between moves and the average angle between berry picks (as measures of search pattern).

Correlational analyses between all self-report measures were calculated to replicate previous research findings concerning the relationships between boredom proneness and self-regulatory profiles. Correlations between self-report measures and the forging metrics on both tasks were then conducted. Next, the sample was split on the basis of high and low scores on each self-report measure separately, with t-tests used to examine differences on the foraging metrics. Additional exploratory analyses were conducted to investigate the potential for interactions between self-regulatory profiles and performance metrics on trait boredom proneness. Finally, we used classification algorithms to classify performance behaviours into specific groups and explore whether these groups differentiated between self-regulatory profiles and boredom proneness.

CHAPTER 3: Results

Table 1 shows the correlations between all self-report measures with results corroborating those of Struk and colleagues (2015) such that boredom proneness was significantly negatively correlated with Self-Control, Locomotion, Promotion and Prevention and positively correlated with Assessment.

Table 1: Correlation coefficients between all self-report measures

	sBPS	BSCS	Locomotion	Assessment	Promotion	Prevention
sBPS	1	-0.521**	-0.373**	0.178*	-0.563**	-0.182*
BSCS		1	0.397**	-0.207**	0.367**	0.366**
Locomotion			1	0.223**	0.567**	0.006
Assessment				1	0.061	-0.103
Promotion					1	0.046
Prevention						1

Note: *p < 0.005, **p < 0.001 BPS = Boredom Proneness Scale, BSCS = Brief Self-Control scale

3.1 Boggle game:

We examined the correlation between self-report measures and metrics from the Boggle game including the mean amount of time participants spent per problem set (mean block-time), total number of times participants pressed enter (sum enter; this equates to the total number of words including errors), total number of times participants pressed next or previous (sum next; sum previous), total number of errors (sum error), the total number of caught errors (which represents the total number of words that participants created but cleared once they realised it was a mistake), the total number of correct answers, and the proportion of correct words as a function of the total words entered (what we are calling ‘efficiency’). Results from a Pearson correlation analysis showed that there was a small but significant negative correlation between the brief Self-Control scale and sum next (r = -0.12, p – 0.04) and sum words correct (r = -0.12, p = 0.04). There was also a small positive correlation between Promotion focus and mean block-time (r = 0.15, p = 0.01). Marginal correlations were found between boredom proneness and mean block-time (r = -0.11, p = 0.07) and sum next (r = 0.1, p = 0.09). However, none of these relationships survived Bonferroni correction. No other significant correlations were found between Boggle metrics and the other self-report measures.

For each of the trait measures, participants were divided into 8 equal groups. Based on this division, there were a minimum of 35 and a maximum of 37 participants in each group with group 1 consisting of participants who scored lowest on a specific trait measure and group 8 consisting of those who scored highest on the same trait measure (Table 2). This division meant that those in the lowest and highest groups on each measure were on average 1.63 standard deviations outside the overall group mean (Table 2). This allowed for the exploration of behaviours for those participants scoring on the more extreme ends of each trait measure.

Table 2: Mean and standard deviations of the Low and High group

	Mean (N= 300)	Group 1: Mean scores (n = ~36) (SD)	Group 8: Mean scores (n = ~36) (SD)
Boredom	26.6	12 (1.5)	43.2 (1.7)
Self-Control	37.6	23.2 (1.7)	51.1 (1.6)
Locomotion	46.5	34.5 (1.7)	58.1 (1.6)
Assessment	48.2	37.4 (1.6)	58.9 (1.6)
Promotion	19.9	14 (1.6)	25.9 (1.7)
Prevention	16.6	9.5 (1.7)	23.5 (1.6)

Note: The standard deviation (SD) is the degree to which the mean for the low and high groups deviate from the whole sample mean.

Independent samples t-tests were used to examine differences on each of the Boggle metrics between low/high groups for each trait measure. Results showed that those with a strong Promotion focus spent more time per solution space ($m = 115.35$ seconds) than those with a weak Promotion focus ($m = 71.83$ sec; $t(49) = -2.27$, $p = 0.03$, $d = 0.54$). However, this relationship did not survive a Bonferroni correction. No other significant differences were found between groups, perhaps in part due to the low sample sizes. Effect sizes for each comparison were calculated with effect sizes equal to or greater than 0.3 considered small to medium and effect sizes equal to or greater than 0.5 considered moderate to high (Cohen, 1988). Cohen suggests that effect sizes of 0.3 indicate a true difference between groups that may fail to reach significance using traditional statistics due to factors such as sample size. Furthermore, Cohen (1988) suggests that an effect size of 0.3 or greater indicates a non-overlap of 21.3% or more between the distributions for the two groups. Recent developments in psychological research have also suggested that traditional null hypothesis significance testing may be less informative than examination of effect sizes and confidence intervals (Cumming, 2013).

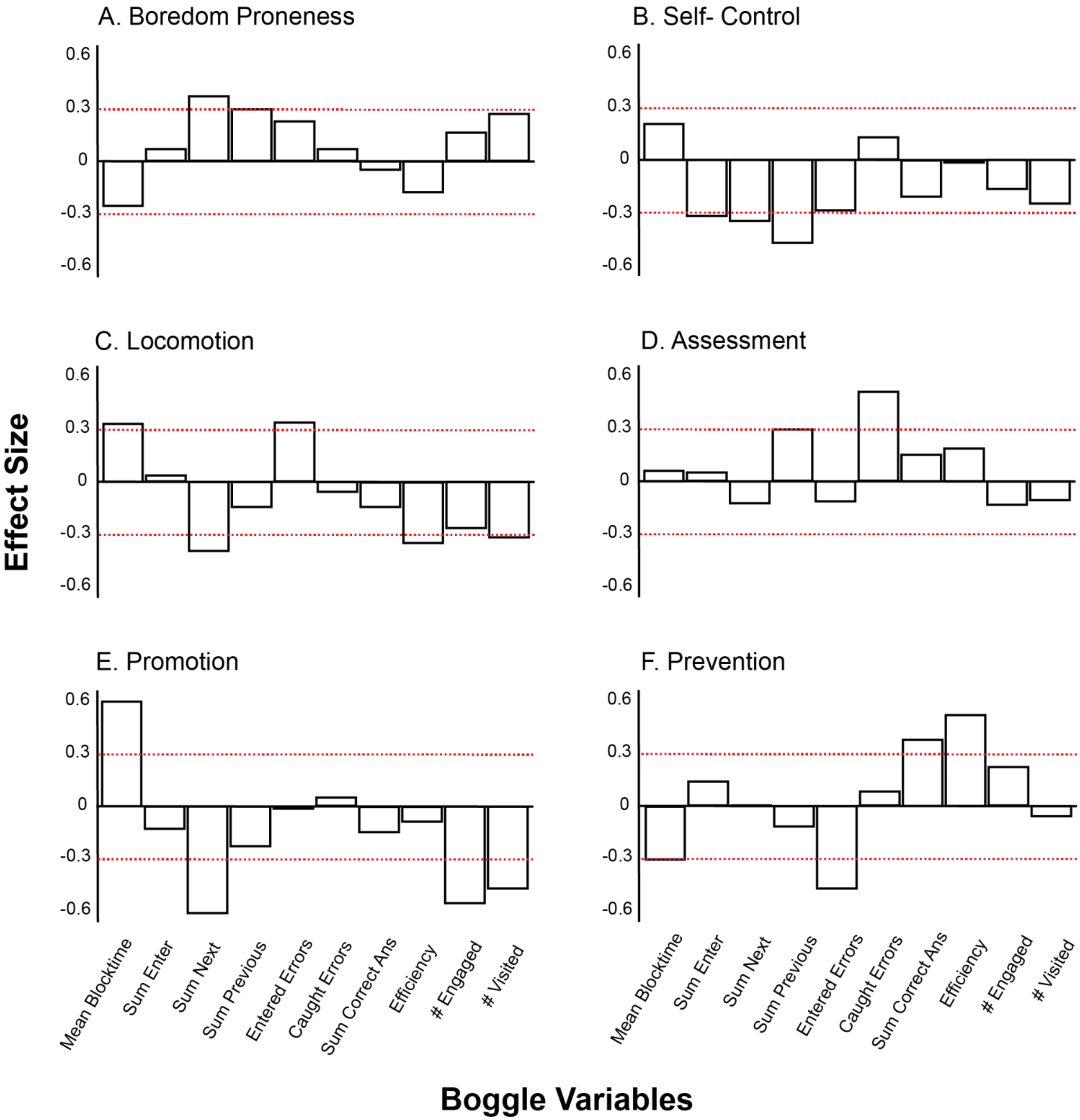


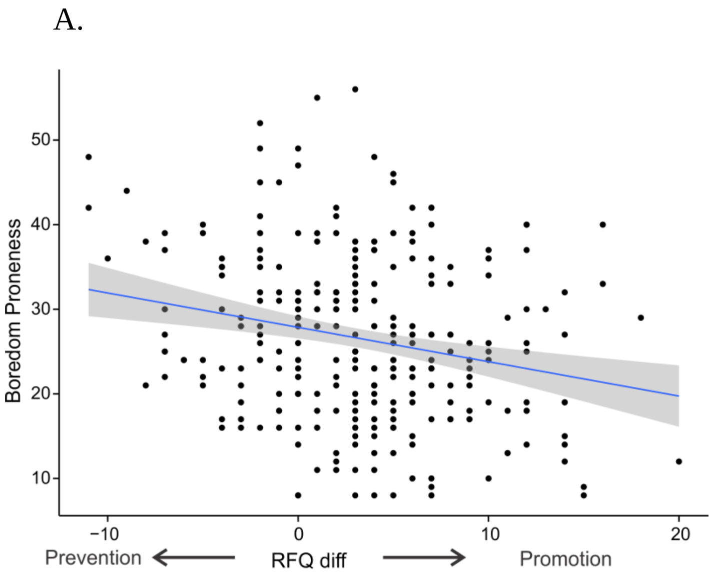
Figure 3A-F: Effect size for each comparison on each Boggle variable. Positive effect sizes reflect an effect in favour of those <u>high</u> in trait measures and vice versa. The red dotted lines represent an effect size of (+/-) 0.3 which is considered a small- moderate effect size. See Appendix A for comparison statistics and effect size table.

Of note, those high in boredom proneness tended to move back and forth more than those low in boredom proneness. Those high in Self-Control tended to enter fewer words compared to those low in Self-Control. This may reflect an influence of the parameters of the game. Participants were told that each word they made had to contain the central letter, had to be of 4-letters or more and could not be plural or a proper noun. Given these rather restrictive parameters, it may be that those high in Self-Control were more diligent in their answers compared to those low in Self-Control (although there were no difference in the number of errors made between those high and low in Self-Control). As far as regulatory mode is concerned, those high in Locomotion tended to spend more time per block, entered more errors, moved forward less often and hence visited fewer unique problem sets, and were less efficient compared to those low in Locomotion – suggesting that Locomotors attitude of 'getting on with it' has a cost. High Assessors on the other hand tended to catch their errors more often and were more likely to go back to previous problem sets compared to low assessors – highlighting their attitude of 'doing the right thing'.

For regulatory focus, those with a strong Promotion focus are typically goal driven and tended to spend more time per problem set, were less likely to move forward to the next problem set, and visited and engaged with fewer problem sets compared to those with a weak Promotion focus. Finally, those with a strong Prevention focus tended to enter fewer errors, created more correct answers, were more efficient and spent less time per problem set compared to those with a weak Prevention focus – reflecting their want to prevent losses and represent things as duties and obligations. To this end, this analysis suggests that different performance strategies are invoked relative to distinct self-regulatory profiles, perhaps suggesting that any single metric on this task is not sensitive on its own to detect differences. Indeed, each self-regulatory variable highlights specific behavioural *patterns* that are either congruent or incongruent to the trait measure. It could be that the Boggle game elicits certain behavioural patterns and these behaviours interact with participants' self-regulatory profiles resulting in instances of self-regulatory fit or failures of self-regulatory fit. Instances of fit would arise when the behaviours engaged in a task are in conjunction with the individual participant's self-regulatory profile. In contrast, failures of self-regulatory fit would arise when the behaviours engaged during a task are incongruent with an individual's self-regulatory profile (Higgins, 2000). This 'non-fit' may lead to maladaptive performances or evaluations (e.g., boredom proneness) as participants are failing to execute actions in line with how they would normally interact with their environment. Indeed, Higgins (2000) suggests that the value of an activity decreases if individuals experience regulatory non-fit. To test the idea of fit/non-fit further, regression analyses were conducted to determine whether behavioural metrics on the Boggle task would interact with self-regulatory traits to predict boredom proneness. Significant interactions from the regression analyses are shown in Table 3.

Two new variables were calculated for this analysis: Regulatory focus difference (RFQ diff) and Regulatory mode difference (RMS diff). Regulatory focus (Promotion and Prevention) and regulatory mode (Locomotion and Assessment) are both orthogonal, meaning that participants can be high on both subscales of the regulatory focus and regulatory mode questionnaires. The difference score provides a rough metric for which regulatory focus or mode an individual might *prefer* to adopt when pursuing goals. RFQ diff signifies the difference in scores between Promotion and Prevention with positive scores representing a greater tendency to adopt a Promotion focus, while negative scores represent a greater tendency to adopt a Prevention focus. RMQ diff signifies the difference in scores between Locomotion and

Assessment with positive scores representing a greater tendency to adopt a Locomotion orientation and negative scores representing a greater tendency to adopt an Assessment orientation. Correlational analyses between RFQ diff, RMS diff and boredom proneness suggest that boredom prone individuals are more likely to be high on Prevention compared to Promotion focus ($r = -0.23$, $p < 0.001$; Figure 4a) and are also more likely to adopt an Assessment as compared to a Locomotion orientation ($r = -0.45$, $p < 0.001$; Figure 4b).



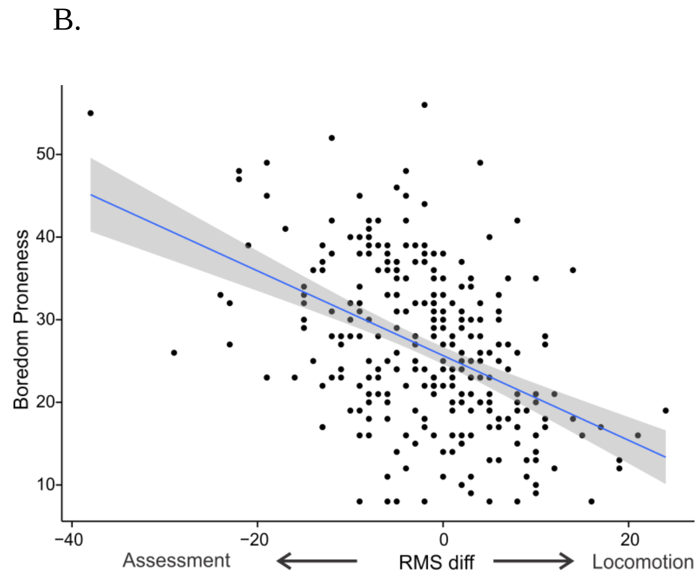


Figure 4a-b: Correlation between RFQ diff, RMS Diff and Boredom proneness

Table 3a: Significant interactions between self-regulatory traits and Boggle behaviours in predicting boredom proneness.

Model #	Predictor 1	Predictor 2	DV	β1	SE1	β2	SE2	Int.	SE Int.	p1	p2	int p
1	Sum next	Promotion	BPS	0.062	0.050	-0.586	0.051	-0.099	0.050	0.217	<0.001	0.051
2	Sum previous	Promotion	BPS	0.088	0.049	-0.584	0.050	-0.120	0.060	0.073	<0.001	0.047
3	Sum enter	Locomotion	BPS	0.003	0.055	-0.367	0.055	-0.112	0.052	0.959	<0.001	0.032
4	Sum enter	RFQ diff	BPS	0.009	0.059	-0.221	0.059	-0.12	0.055	0.883	0.0002	0.030
5	Caught Errors	Prevention	BPS	-0.054	0.058	-0.17	0.059	0.143	0.063	0.355	0.004	0.023

Note: BPS = Boredom proneness; B = beta coefficients from Regression analyses; SE = Standard error of the mean; Int. = Interaction coefficient; p = p-value; int p = p-value for interaction term

Table 3b: Model fit for each interaction

Model #	F	Df1	Df2	Model sig
1	46.163	3	282	<0.001
2	47.010	3	282	<0.001
3	17.136	3	283	<0.001
4	6.71	3	282	<0.001
5	5.22	3	283	<0.001

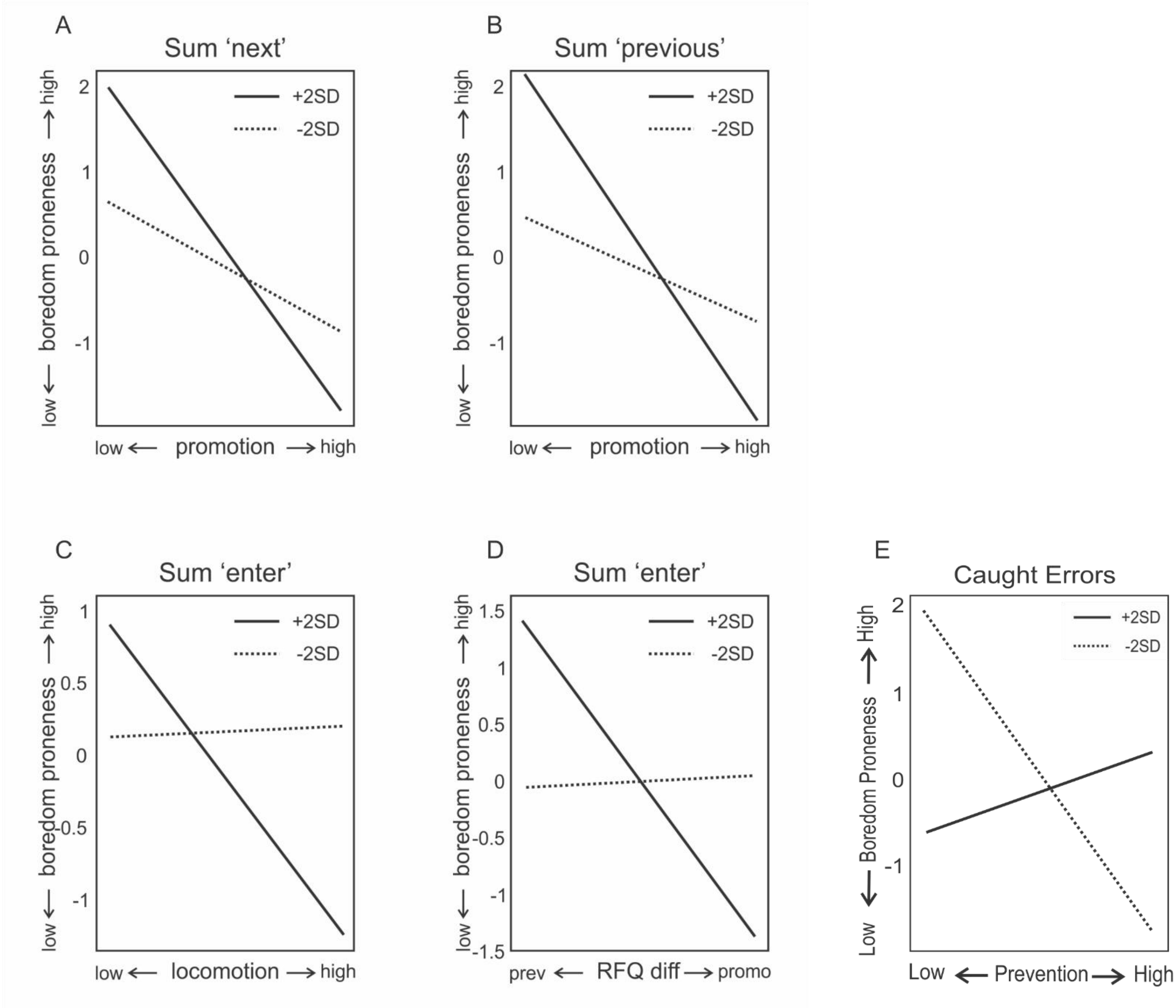


Figure 5a-e: Significant interactions between self-regulatory trait measures and Boggle performance metrics to predict boredom proneness. A—interaction between Promotion focus and Sum 'next' in predicting boredom proneness. B – Interaction between Promotion focus and Sum 'previous' in predicting boredom proneness. C – Interaction between Locomotion and Sum 'enter' in predicting boredom proneness. D – Interaction between RFQ diff and Sum 'enter' in predicting boredom proneness. F – Interaction between Prevention focus and caught errors in predicting boredom proneness.

As expected, the regression analyses indicated a main effect for each self-regulatory trait measure in predicting boredom proneness. There were no main effects for Boggle metrics predicting boredom proneness. However, there were several significant interaction terms exploring the influence of self-regulatory profile on boredom proneness. The first two interactions suggest that moving back and forth between problem sets interacts with Promotion focus to predict boredom proneness, such that those with a strong Promotion focus who also demonstrate a strong tendency to move back and forth between problem sets are less likely to be boredom prone. Put another way, an individual with a strong Promotion focus who engages in this kind of strategy (moving back and forth between problem sets) experiences regulatory fit and is less prone to boredom (Figure 5). The opposite is also true – individuals demonstrating a weak Promotion focus who nevertheless engage in a Promotion type strategy, experience poor regulatory fit and are thus more prone to boredom (solid lines in Figures 5a and b). The third interaction term suggests that the number of words entered (i.e., Sum Enter) interacts with Locomotion to predict boredom proneness, such that those with a strong Locomotion orientation who also entered a lot of words could be said to be experiencing regulatory fit and as a consequence are less boredom prone. Those participants who exhibit a weak Locomotion orientation but who nevertheless enter many words experience poor regulatory fit and are more prone to boredom (solid lines Figure 5c). The fourth interaction indicates that individuals demonstrating a strong preference for a Promotion focus, experienced regulatory fit when entering a lot of words and are generally less boredom prone (Figure 5d). The same strategy implemented by an individual with a strong preference for a Prevention focus increased the likelihood of boredom proneness. The final interaction term suggests that the number of caught errors interacts with Prevention focus to predict boredom proneness, such that those with a strong Prevention focus who catch fewer errors are less likely to be boredom prone. This may sound counterintuitive. However, effect size calculations suggest that those with a strong Prevention focus enter fewer errors and tend to create and enter more correct answers compared to those with a weak Prevention focus. That is, individuals with a strong Prevention focus do not create ‘wrong’ answers and therefore do not need to catch them. Nevertheless, catching few errors may still be a preferred strategy for those with a strong Prevention focus. Catching a lot of errors, on the other hand, is a strategy that may not be preferred by individuals with a strong Prevention focus as they have a preference not to make errors in the first place. In other words, individuals with a strong Prevention focus who catch fewer errors experience regulatory fit and are less boredom prone. The opposite is also true – individuals demonstrating a weak Prevention focus who nevertheless engage in this strategy experience poor regulatory fit and are thus more prone to boredom.

Together, these results suggest that goal pursuit is a multi-faceted behaviour. Both the effect size calculations (Figure 3) and the regression analyses (Figure 5) examine self-regulatory profiles and interactions with boredom proneness from the perspective of single metrics. In other words, patterns of performance on the Boggle task may be more informative than any given metric taken in isolation. Participants were therefore classified based on their performance on the Boggle using the classic finite Gaussian Mixture Model (GMM; Redner & Walker, 1984; Ming-Hsuan & Narendra, 1998). This probabilistic model assumes that all data points are generated from a finite number of Gaussian distributions with finite parameters (see sklearn.mixture package for more information about GMM; Pedregosa, et al., 2011). Using the GMM algorithm, a Bayesian Information Criterion (BIC) was computed. The BIC is a means of selecting from among a finite set of parameters or models, the model that best fits the data. Essentially, this method will take Boggle variables as independent parameters to determine the number of distinct groups that best characterises performance on the task (Schwarz, 1978). Generally, the fit of the model can be improved by adding more groups, with a penalty term included in the algorithm for each additional group in order to avoid over fitting the data. To select the appropriate number of groups, the model with the lowest BIC was selected. An a priori distinction was made between classes of variables representing performance within and between problem spaces on the Boggle task. Thus, two classification analyses were run with the first classifying participants based on their performance *within* problem sets using the following Boggle variables: the number of words entered (sum enter), number of correct words, number of entered errors and the number of caught errors. This classification successfully categorized 292 out of 296 participants into 5 groups. The remaining 4 participants did not adequately fit in any of the 5 groups and were removed from further analyses. The second classification analysis categorized participants based on their performance *between* problem sets and included the following variables: the number of times participants moved back and forth between problems (i.e., sum next and sum previous), number of problems visited and the number of problems engaged with. This classification successfully classified 293 of 296 participants into 5 groups. The remaining 3 participants did not adequately fit in any of the groups and were removed from further analyses[12].

[1] Two Boggle variables were not included in the classification analyses: Mean Blocktime (the amount of time spent per each problem set) and Efficiency (the proportion of correct words as a function of the total words entered). Mean Blocktime rendered the BIC unstable and was therefore removed from the *between* problem classification. Efficiency is comprised of the number of words entered and the number of correct answers which were already part of the *within* problem classification

[2] A third classification analysis was also conducted to classify participants based on their performance within and between problem sets and used all eight variables mentioned above. However, this classification remained unstable and was not able to consistently classify participants into a set number of groups. As such, we removed this classification from all other analyses.

3.1.1 Within problem classification

The *within* problem classification yielded 5 groups of participants with one group consisting of only 4 participants. Due to the lack of power associated with this low sample size, this group was excluded from further analyses. Groups 1 and 2 were characterised by entering many words – a high proportion of which were correct; what differentiated the two groups was the number of errors entered and the ability to catch any errors made with Group 1 outperforming Group 2 on this variable. Among all 4 groups, Group 3 was by far the most diligent in catching errors, although this may have been born of the fact that they made many more errors than either group 1 or 2. Finally, Group 4 entered the most words of any group and made the most errors (Figure 6 – top panel). Proposing singular descriptive labels for these groups is challenging. However Table 4 provides an overview of all groups.

Table 4: Overview of similarities and differences between groups from the *within* problem classification – the four groups are being compared against each other

	Group 1	Group 2	Group 3	Group 4
# of entered words	High	High	High	Highest
# of Correct answers	High	High	High	High
# of entered errors	Small- Moderate	Small	Moderate-High	High
# of caught errors	Moderate	Small	High	Moderate

To determine what proportion of participants who scored high/low on trait measures were classified in each group of the *within* problem classification, all participants were divided into quartiles with the lower quartile consisting of participants who scored lowest on a specific trait measure and the upper quartile consisting of those who scored highest on the same trait measure. Table 5 shows the percentage of participants from the upper and lower quartile represented in each classified group. This was calculated by taking the number of participants that represent a given quartile in each group and dividing it by the total group size. Chi square tests were then conducted to see if there were any significant differences between the classified groups for each trait measures. No significant difference were found between groups. However it seems that group 1 consists of the majority of those high and low in Locomotion- suggesting that perhaps this classification does not differentiate the behaviours of Locomotors well. Those high in Assessment were more likely to employ group 3’s behavioural strategy while those low in Assessment were more likely to employ group 2’s strategy. Low boredom prone individuals were more likely to employ group 1’s strategy and there was a higher proportion of high boredom prone individuals employing group 4’s strategy. Individuals high in self-control were more likely to engage with group 1’s strategy while individuals low in self-control were more use the behavioural strategies of group 4. The majority of individuals with a strong Promotion focus employed group 2’s strategy while the mass of those with a weak Promotion focus used group 1’s strategy. Finally, a higher proportion of individuals with a strong Prevention focus engaged with group 2’s strategy while a higher proportion of individuals with a weak Prevention focus engaged with group 3’s strategy.

Table 5: percentage of participants from the upper and lower quartile that are present in each *within* problem classified group

		Group 1	Group 2	Group 3	Group 4
Locomotion	Low	32.3	19	13.9	27.5
	High	29.2	21.9	22.2	21.6
Assessment	Low	24	27.6	19.4	21.6
	High	27.1	19	30.6	23.5
Boredom Proneness	Low	27.1	26.7	25	17.6
	High	20.8	26.7	19.4	29.4
Self-Control	Low	25	22.9	22.2	29.4
	High	27.1	26.7	22.2	15.7
Promotion	Low	30.2	21.9	13.9	25.5
	High	21.9	27.6	25	19.6
Prevention	Low	27.1	21	27.8	23.5
	High	22.9	29.5	19.4	21.6

Hierarchical regression models were used to test whether the four groups would interact with the individual self-regulatory traits (Locomotion, Assessment, Promotion, Prevention, Self-control, RFQ diff and RMS diff) to predict boredom proneness. Results indicated that the addition of groups to the model of Prevention predicting boredom proneness did not significantly improve the model fit [$F(3,274) = 0.482$, $SS = 131.54$, $p = 0.695$]. However, the addition of an interaction term between groups and Prevention focus yielded a marginally significant model [$F(3,271) = 2.57$, $SS = 701.63$, $p = 0.055$]. Simple effects correlations suggest that groups 2 and 4 demonstrated significant relationships between Prevention and boredom proneness ($r = -0.396$,

$p = 0.005$ and $r = -0.44$, $p= 0.022$ respectively) such that those with a strong Prevention focus were less boredom prone compared to those with a weak Prevention focus when employing the strategies used by groups 2 and 4. However, the simple effects for group 4 did not survive a Bonferroni correction. No other significant correlations were found.

The addition of groups to the model of RFQ diff predicting boredom proneness did not significantly improve the model fit [$F(3,273) = 0.691$, $SS = 183.59$, $p = 0.558$]. However, the addition of the interaction term between groups and RFQ diff yielded a significant model [$F(3,270) = 2.98$, $SS = 791.01$, $p = 0.032$]. Simple effects correlations including a Bonferroni correction suggest that group 1 demonstrated a significant relationship between RFQ diff and boredom proneness ($r = -0.42$, $p = 0.003$) such that those who are more Promotion focused are less boredom prone whereas those who are more Prevention focus are more boredom prone when employing the strategies use by group 1 (Figure 6). No other significant correlations were found. Model fit did not significantly improve with the addition of groups to the individual model of Locomotion, Assessment, Promotion, Self-control and RMS difference predicting boredom proneness; nor did the addition of interaction terms between groups and each of the above mentioned self-regulatory variables improve model fit.

3.1.2 Between problem classification

Classification of between problem performance yielded 5 groups of participants with two groups consisting of 4 and 8 participants respectively. Due to the lack of power associated with these low sample sizes, these groups were excluded from further analyses. Groups 1 and 2 moved forward to the next problem set more than did group 3 and therefore visited and engaged in more problem sets compared to group 3 (Figure 7- top panel). What sets the groups 1 and 2 apart is that group 1 re-visited some previous problem sets, while the other two groups did not. Group 2 visited and engaged in more problems compared to the other two groups while group 3 had the lowest mean scores on the performance metrics. The similarities and differences are further outlined in Table 6.

Table 6: Overview of similarities and differences between groups from the *between* problem classification – the three groups are being compared against each other

	Group 1	Group 2	Group 3
# of forward moves (Next)	High	High	Moderate
# of backward moves (Previous)	Moderate	Low to None	Low to None
# of problem visited	High	High	Moderate
# of engaged problems	High	High	Moderate

Once again, the proportion of participants who scored high/low on trait measures who were classified in the *between* problem classification was calculated. Table 7 shows the percentage of participants from the upper and lower quartile represented in each classified group. This was calculated by taking the number of participants that represent a given quartile in each group and dividing it by the total group size. Chi square tests were conducted to see if there were any significant differences between the classified groups for each trait measures. No significant difference were found between groups. Nevertheless, it seems that individuals high in Locomotion were more likely to employ group 2's strategy while those low in Locomotion were more likely to employ group 1's strategy. The majority of high Assessors employed group 3's strategy while the majority of low Assessors used that of group 2's strategy. High boredom prone individuals were more likely to employ group 1's strategy while low boredom prone individuals were more likely to employ group 3's strategy. A higher proportion of those high in self-control engaged in group 2's strategy while a higher proportion of those low in self-control engaged in group 1's strategy. Those with a strong Promotion focus were more likely to engage in group 3's strategy while the majority of those with weak Promotion focus used group 1's strategy. Finally, those with a strong Prevention focus were more likely to engage in group 1's strategy while those with a weak Prevention focus were more likely engage in group 2's strategy.

Table 7: percentage of participants from the upper and lower quartile that are present in each *between* problem classified groups

		Group 1	Group 2	Group 3
Locomotion	Low	26.7	22.6	25
	High	16.7	27.4	23.9
Assessment	Low	13.3	33.9	22.9
	High	23.3	17.7	25.5
Boredom Proneness	Low	13.3	24.2	27.7
	High	33.3	24.2	22.3
Self-Control	Low	40	17.7	23.9
	High	26.7	30.6	21.8
Promotion	Low	40	24.2	21.3
	High	13.3	19.4	27.7
Prevention	Low	23.3	25.8	23.9
	High	33.3	25.8	22.9

Hierarchical regression models were used to test whether the three larger groups would interact with individual self-regulatory traits to predict boredom proneness. Results indicated that the addition of groups to the model of Assessment predicting boredom proneness did not significantly improve the model fit [$F(3,266) = 1.95$, $SS = 348.44$, $p = 0.14$]. However, the addition of the interaction term between groups and RFQ diff yielded a marginally significant model [$F(3,264) = 2.996$, $SS = 527.47$, $p = 0.052$]. Simple effects correlations with a Bonferroni correction suggest that group 3 bears a significant relationship between Assessment and boredom proneness ($r = 0.37$, $p = 0.0003$) such that those who score higher on the measure of Assessment are more boredom prone compared to those who score low on the measure of Assessment when employing the strategies used by group 3 (Figure 7). No other significant correlations were found. The addition of groups to the individual model of Locomotion, Promotion, Prevention, Self-control, RMS diff and RFQ diff predicting boredom did not significantly improve the model fit, nor did the addition of interaction terms between groups and each of the self-regulatory trait variables.

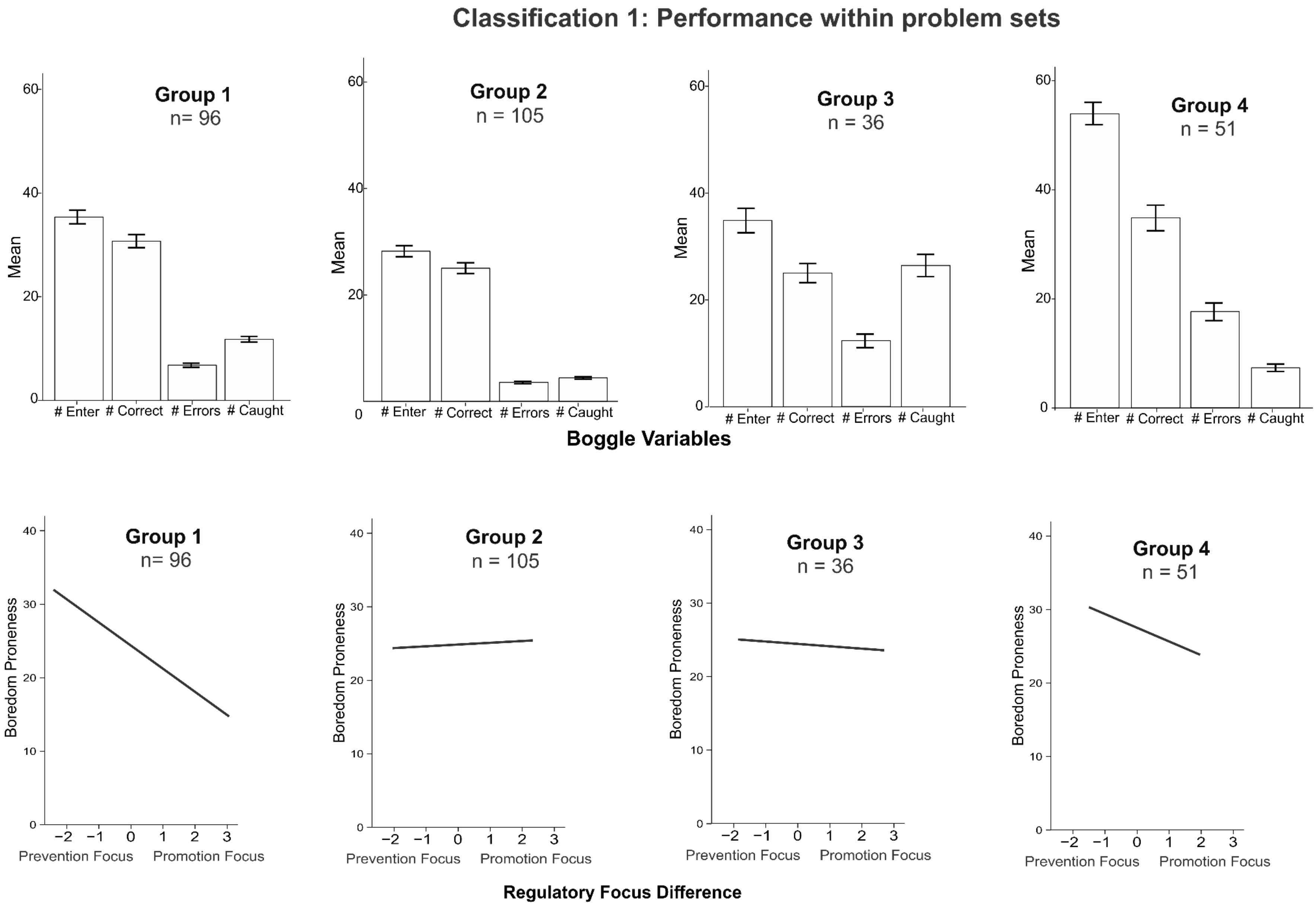


Figure 6: Classification 1 (based on performance within problem set). Top panel- classified groups and their specific performance behaviours (# Enter = number of words entered, # Correct = number of correct words, # Errors = number of entered errors, # Caught = number of Caught errors). Bottom panel- relationship between regulatory focus difference and boredom proneness for each classified group

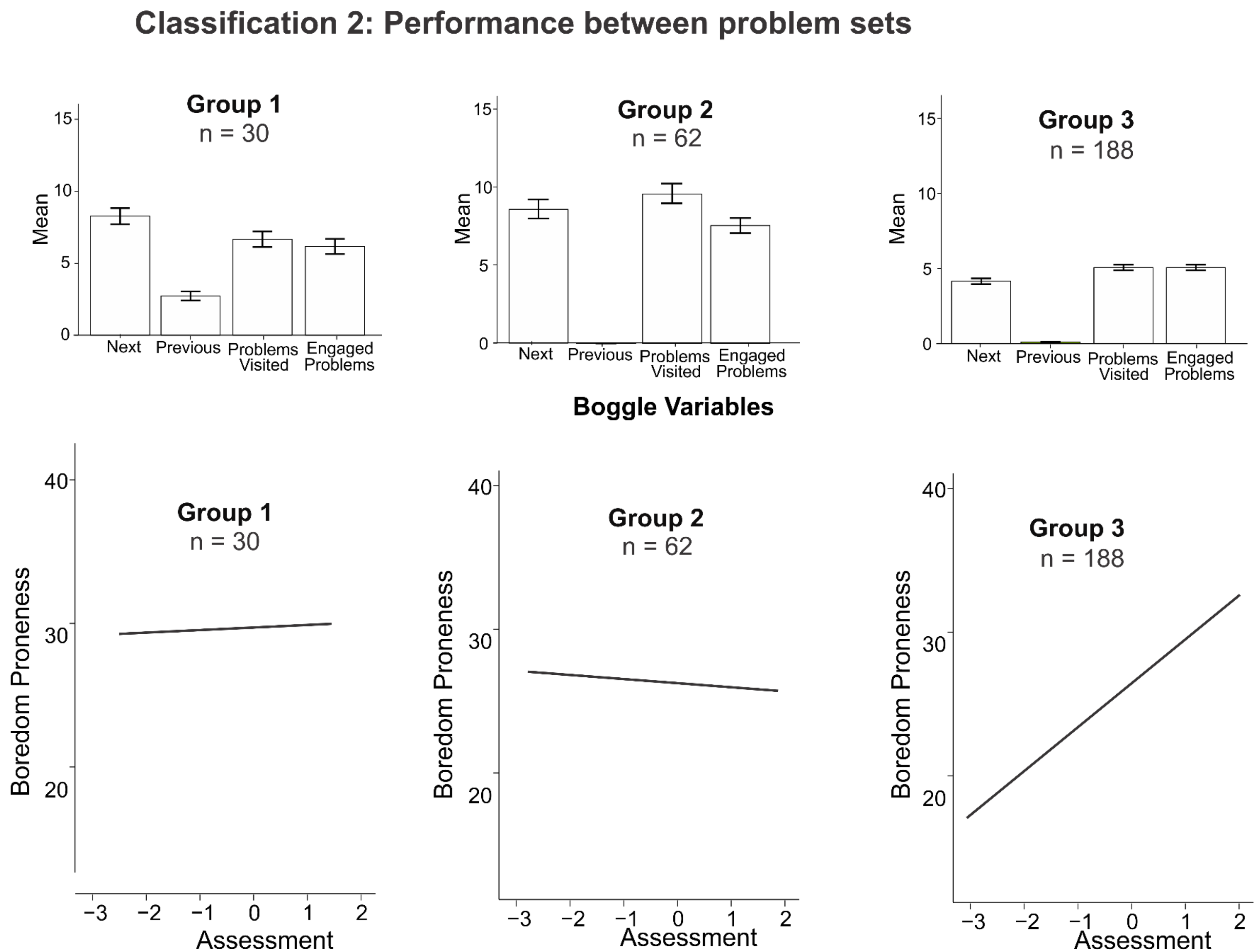


Figure 7: Classification 2 (based on performance between problem set). Top panel- classified groups and their specific performance behaviours. Bottom panel- relationship between Assessment and boredom proneness for each classified group

As mentioned above, the goal of the classifications was to explore the interplay between participants' self-regulatory traits and their performance strategies in predicting boredom proneness. The end results suggest that the use of certain strategies over others are likely to affect how boredom prone an individual is given individual differences on self-regulatory measures. More specifically, in the *within* problem classification, high Prevention individuals are less likely to be boredom prone when using a strategy exemplified by group 2. Furthermore, the *within* problem classification also suggested that Promotion focused individuals who employ a strategy of entering more words and getting more words correct (i.e., group 1) were less likely to be boredom prone than Prevention focused individuals – highlighting the behaviours that are either conducive or unconducive to an individual's self-regulatory foci. The between group classification suggested that, compared to low assessors, high assessors are more likely to be boredom prone when using utilising group 3's performance strategy.

3.1.3 Boggle Classifications: Similarities and differences

A total of 277 out of 292 classified participants were present in both classifications. The division of participants suggests that the majority classified in groups 2 and 3 of the *between* problem classifications were also classified as belonging to groups 1 and 2 of the *within* problem classification (Table 8). This highlights the preferred strategy for the group of participants.

Table 8: Number of participants from the *within* problem classification who were also present in the *between* problem classification

		Between groups Classification			
		Group 1	Group 2	Group 3	**Total**
Within groups Classification	Group 1	8	22	62	**92**
	Group 2	8	21	72	**101**
	Group 3	6	9	21	**36**
	Group 4	7	10	31	**48**
	Total	**29**	**62**	**186**	**277**

3.2 Foraging task:

Next we examined the correlation between self-report measures and metrics from the foraging task including path length, number of moves, misses in berry picking (defined as an unsuccessful attempt at picking a berry), successful berry picks, the average angle between moves and the average angle between berry picks. Pearson correlation analysis showed that there was a small significant negative relationship between Assessment and the average angle between picks ($r = -0.12$, $p = 0.04$). There was also a small negative correlation between Promotion and the average angle between picks ($r = -0.15$, $p = 0.01$) and between Prevention and the number of misses in berry picking and the number of successful picks ($r= -0.16$, $p = 0.007$ and $r = 0.16$, $p = 0.007$ respectively). However, none of these relationships remained significant when a Bonferroni correction was applied to the analysis. No other significant correlations were found.

Using the same method to split groups based on self-regulatory traits as was used for the Boggle game (Table 2), independent samples t-tests explored differences between low/high groups for each trait measure among the foraging variables. A significant difference was found between those high and low on Assessment and average angle between picks ($t(69)= -2.57$, $p = 0.012$, d = -0.61) such that high assessors generally employed lower turning angles between picks (m= 39.7°) compared to those low in Assessment (m= 48.1°). This is indicative of a linear search pattern where high assessors tend to move around the foraging environment in straight lines compared to low assessors. A significant difference was found between those high and low in Promotion focus and the average angle between picks ($t(68)= -2.01$, $p = 0.048$, d = -0.48) such that those with a strong Promotion focus had lower turning angles between picks (m = 39.6°) compared to those with a weak Promotion focus (m= 45.6°) – again indicating that individuals with a strong Promotion focus exhibit a preference for linear search patterns. A significant difference was also found between those high and low in Prevention focus and misses in berry picking (t(64)= -2.07, p = 0.04, d= -0.49) such that those with a strong Prevention focus tended to miss berries less often (m= 72.3 misses) compared to those with a weak Prevention focus (m = 89.9). Those with a strong Prevention focus were also more successful at picking berries (t(69)= 2.2, p = 0.03, d= 0.52, m= 156.9) compared to those with a weak Prevention focus (m = 146.3). Together, this is consistent with what one would expect from strong Prevention focus individuals motivation to avoid losses. However, these relationships did not survive Bonferroni correction. No other significant differences were found between groups. As with the Boggle game, effect sizes were calculated and are shown in Figure 8.

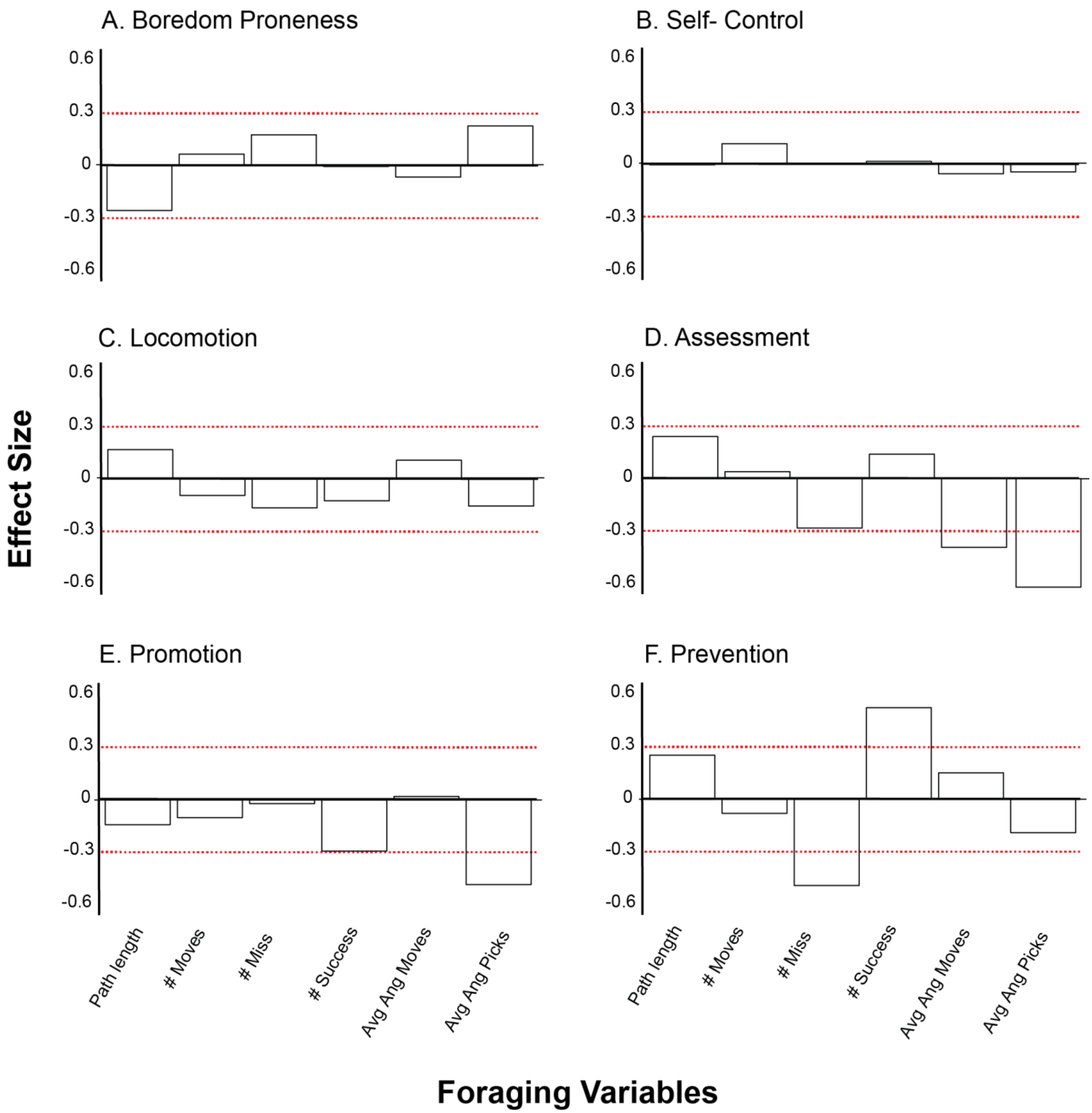


Figure 8a-f shows the effect size for each comparison on each foraging variable. Positive effect sizes reflect an effect in favour of those <u>high</u> in trait measures and vice versa. The red dotted lines represent an effect size of (+/-) 0.3 which is considered a small- moderate effect size. See Appendix B for comparison statistics and effect size table.

Aside from the effect sizes reported above, high assessors had smaller average angles per moves (m = 33.5°) compared to low assessors (m = 38.1°, d = -0.39) again highlighting their preference for a linear search pattern. Although the effect sizes were slightly smaller than 0.3, high assessors were also less likely to miss a berry (m = 75.8 misses) compared to low assessors (m = 87.9 misses, d= -0.28) and those with a strong Promotion focus were less successful at berry picking (m = 149 berries) compared to those with a weak Promotion focus (m = 154.6, d= -0.29). Like the Boggle game, this analysis suggests that each individual self-regulatory trait has a preferred strategy. It could also be that the foraging task elicits certain behavioural patterns and these behaviours interact with participants' self-regulatory profiles resulting in instances of fit or non-fit. To test the idea of fit/non-fit in the foraging task, regression analyses were conducted to examine whether foraging metrics would interact with self-regulatory traits (including the variables RFQ diff and RMS diff) to predict boredom proneness.

Two new foraging variables were also calculated. The variable 'Accuracy' refers to the proportion of times participants successfully picked a berry as a function of the number of attempted picks. High numbers reflect higher accuracy in berry picking. The variable 'Berries per move' refers to the number of times participants successfully picked berries for each movement made. This is a measure of how exhaustively participants picked berries each time they moved. This is somewhat equivalent to the 'efficiency' variable calculated for the Boggle game. The newly created variables were included as performance strategies that participants used. The results corroborated our initial correlational findings that each self-regulatory trait variable was significantly related to boredom proneness. Table 9 shows the significant interactions found between self-regulatory traits and foraging variables in predicting boredom proneness.

Table 9a: Significant interactions between self-regulatory traits and foraging behaviours in predicting boredom proneness.

Model #	Predictor 1	Predictor 2	DV	β1	SE1	β2	SE2	Int.	Int. SE	p1	p2	Int. p
1	Success	Prevention	BPS	-0.016	0.059	-0.176	0.059	0.138	0.060	0.790	0.003	0.021
2	Success	BSCS	BPS	-0.063	0.050	-0.525	0.050	0.103	0.051	0.210	<0.001	0.043
3	Miss	RFQ diff	BPS	0.080	0.059	-0.217	0.059	-0.144	0.064	0.176	<0.001	0.025
4	Success	RFQ diff	BPS	-0.074	0.059	-0.235	0.059	-0.131	0.062	0.211	<0.001	0.036
5	Success	RMS diff	BPS	-0.058	0.054	-0.474	0.054	0.134	0.059	0.283	<0.001	0.023
6	Berries per move	RMS diff	BPS	-0.035	0.054	-0.454	0.054	0.119	0.059	0.518	<0.001	0.042

Note: BPS = Boredom proneness; B = beta coefficients from Regression analyses; SE = Standard error of the mean; Int. = Interaction coefficient; p = p-value; int p = p-value for interaction term

Table 9b: Model fit for each interaction

Model #	F	Df1	Df2	Model sig
1	5.151	3	284	0.0018
2	37.924	3	286	<0.001
3	7.377	3	283	<0.001
4	7.276	3	283	<0.001
5	26.260	3	282	<0.001
6	25.448	3	282	<0.001

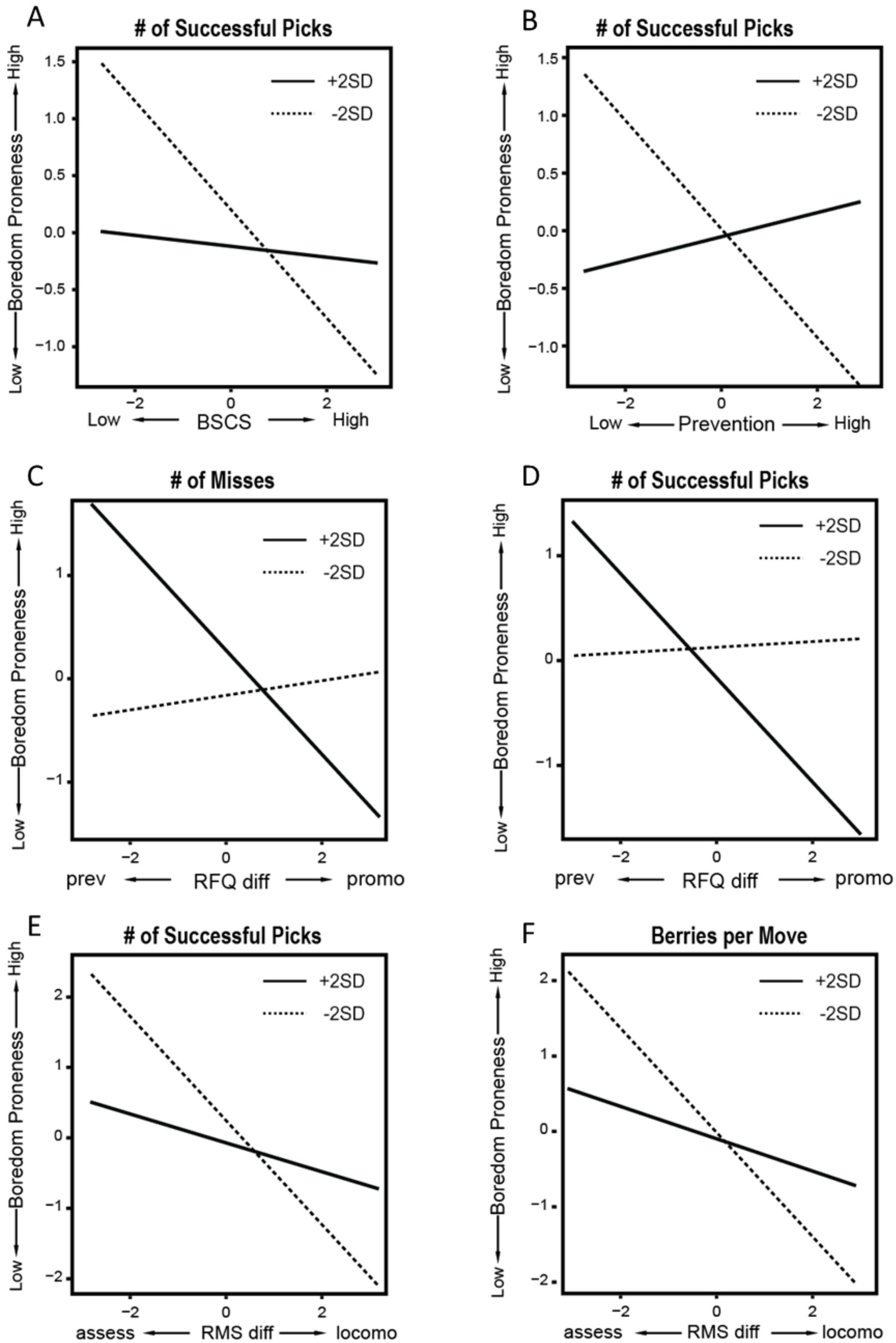


Figure 9a-f: Interactions between self-regulatory trait measures and foraging performance metrics to predict boredom proneness. A— Self-control interacts with # of Misses to predict boredom proneness. B – Prevention interacts with # of Successful Picks to predict boredom proneness. C & D – # of Miss and # of Successful Picks Interact with RFQ diff to predict boredom proneness. E-F – # of Successful Picks and Berries per Move interacts with RMS diff to predict boredom proneness

The first interaction term indicates that those high in self-control who have fewer successful picks are less boredom prone, whereas those low in self-control who have fewer successful picks are more boredom prone. A similar pattern is observed for the second interaction – those with a weak Prevention focus are more boredom prone when they have fewer successful picks while those with a strong Prevention focus are less boredom prone when they have fewer successful picks. The third and fourth interactions highlight the behaviours that are either conducive or unconducive to an individual's self-regulatory foci such that those who are Promotion focused are less boredom prone regardless of the fact that they miss a lot of berries or when they have a high number of successful picks. Conversely, Prevention focused individuals are more boredom prone when they miss a lot of berries or when they have a high number of successful picks. The fifth and sixth interactions point to distinct regulatory mode behavioural preferences such that Locomotors are least boredom prone when they have fewer successful picks or pick fewer berries per move whereas Assessors are more likely to be boredom prone when they have fewer successful picks or pick fewer berries per move.

As with the Boggle, these interactions highlight that goal pursuit is a multi-faceted behaviour and that individual performance variables from the foraging task may not be sensitive enough to capture differences in goal pursuit as they relate to self-regulation and boredom proneness. Using the same probabilistic model and procedures used for the Boggle game, participants were classified using the surface metrics of the foraging task. This classification successfully classified 293 of 296 participants and yielded two groups (Figure 10). The remaining 3 participants did not adequately fit in any of the two groups and were removed from further analyses. Group 1 has longer path length, higher successful berry picks and greater average angles per move compared to group 2 whereas 2 has a higher number of moves and tend to miss more berries compared to those in group 1 (Table 10).

Table 10: Overview of similarities and differences between groups from the Foraging classification—the two groups are being compared against each other

	Group 1	Group 2
Path length	High	Low
# of moves	Low	High
# of misses	Low	High
# of successful picks	High	Low
Average angle between moves	High	Low
Average angle between picks	Moderate	Low

Again, the proportion of participants who scored high/low on trait measures who were also classified in the above foraging classification was calculated. Table 11 shows the percentage of participants from the upper and lower quartile represented in each classified group. Chi square tests were conducted to see if there were any significant differences between the classified groups for each trait measures. No significant differences were found between groups. Nevertheless, it seems that a higher proportion of those low in Locomotion, Assessment, boredom prone and those with a strong Promotion and Prevention focus, were more likely to employ group 1’s strategy. On the other hand, a higher proportion of those high in Locomotion, Assessment, boredom proneness and those with a weak Promotion and Prevention focus, were more likely to employ group 2's strategy.

Table 11: percentage of participants from the upper and lower quartile that are present in each foraging classified groups

		Group 1	Group 2
Locomotion	Low	27.9	17.6
	High	23.7	24.5
Assessment	Low	26.3	20.6
	High	22.6	26.5
Boredom Proneness	Low	27.9	19.6
	High	24.2	25.5
Self-Control	Low	24.7	24.5
	High	24.7	23.5
Promotion	Low	23.7	25.5
	High	24.7	22.5
Prevention	Low	22.6	27.5
	High	27.4	18.6

Hierarchical regression models were used to test whether the two groups would interact with individual self-regulatory traits (Locomotion, Assessment, Promotion, Prevention, Self-control, RFQ diff and RMS diff) to predict boredom proneness. Results indicated that the addition of groups to the model of Assessment predicting boredom proneness did not significantly improve model fit [$F(1,280) = 0.902$, $SS = 82.76$, $p = 0.343$]. However, the addition of an interaction term between groups and Assessment yielded a significant model [$F(1,279) = 6.287$, $SS = 576.76$, $p = 0.0123$]. Simple effects correlations with a Bonferroni correction suggests that group 1 bears significant relationships between Assessment and boredom proneness ($r= 0.36$, $p = 0.0003$) such that those high in Assessment were more boredom prone than those low in Assessment when employing group 1's strategy (Figure 11A). No other significant correlations were found.

The addition of groups to the model of RMS diff predicting boredom proneness did not significantly improve the model fit [$F(1,279) = 1.36$, $SS = 103.02$, $p = 0.244$]. However, the addition of the interaction term between groups and RMS diff yielded a significant model [$F(1,279) = 5.18$, $SS = 391.68$, $p = 0.024$]. Simple effects correlations including a Bonferroni correction suggest that group 1 bears significant relationships between RMS diff and boredom proneness ($r = -0.58$, $p < 0.001$) such that those who are predominantly high in Locomotion are less boredom prone than those who are predominantly high in Assessment when employing a strategy that emphasises longer path length, greater turning angles between moves and a higher number of successful berry picks (i.e., group 1's strategy; Figure 11B). Group 2 shows a marginally significant relationship between RMS diff and boredom proneness ($r = -0.26$, $p = 0.07$; no Bonferroni correction). It is possible that the two above mentioned hierarchical regressions are similar in that the RMS diff variable does include the Assessment measure. The addition of groups to the individual model of Locomotion, Promotion, Prevention, Self-control and, RFQ diff predicting boredom did not significantly improve the model fit nor did the addition of interaction terms between groups and each of the above mention self-regulatory variables.

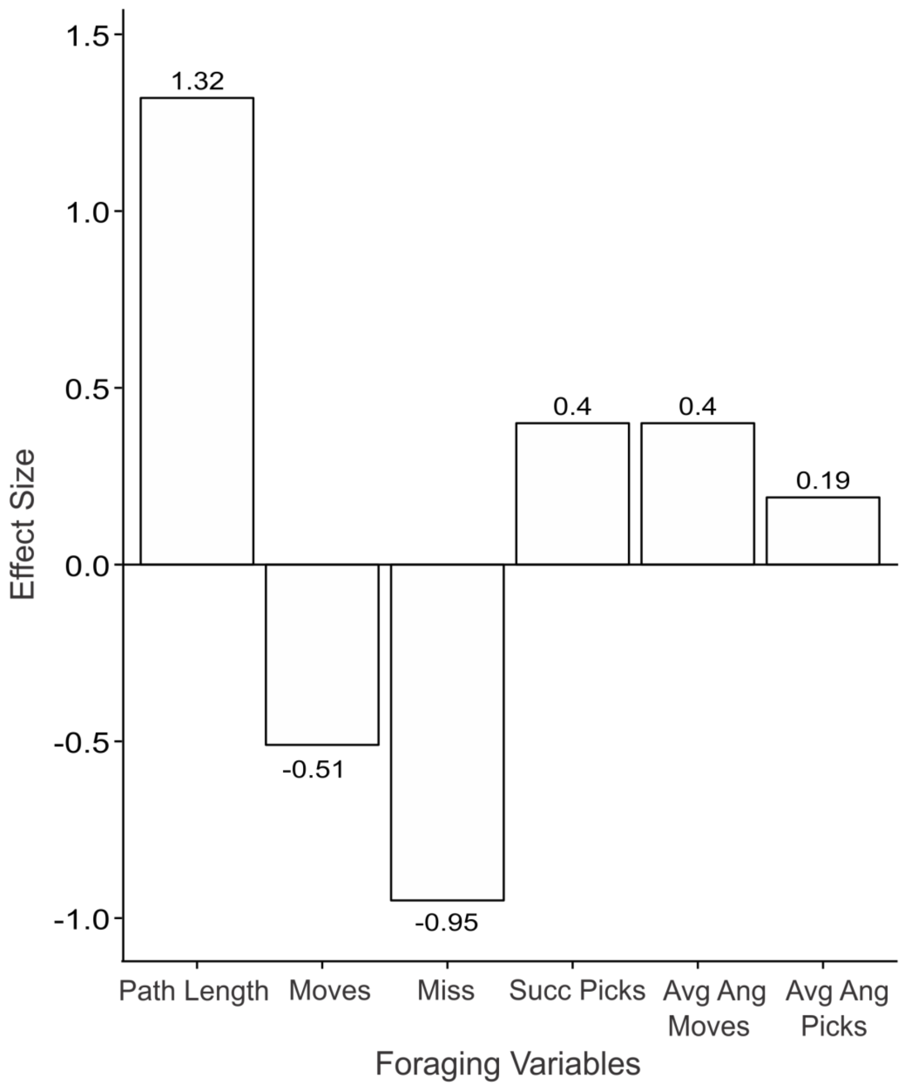


Figure 10: differences between classification group 1 and group 2. The foraging variables differed in measurement scale. In order to portray the specific behavioural strategies that is favored by each group, t-tests and effect size were conducted between group 1 and group 2 for each foraging surface metric. A positive effect signifies that group 1 has a higher mean compared to group 2 and vice-versa.

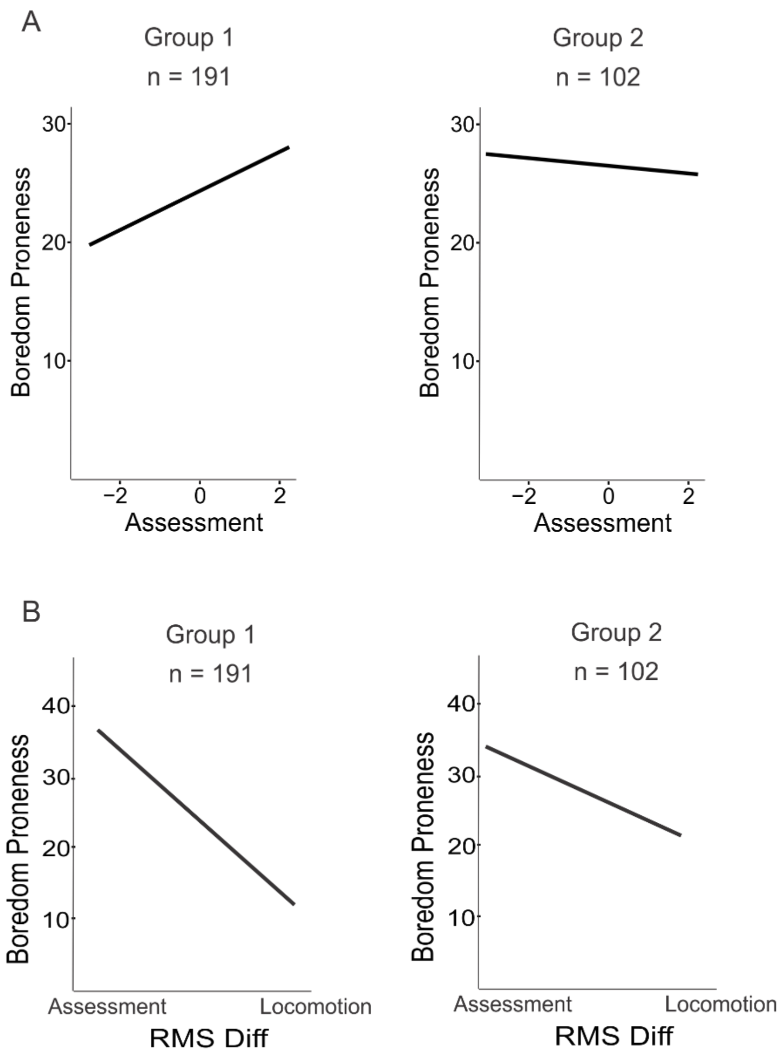


Figure 11: A – Relationship between Assessment and boredom proneness for each classified group. B – Relationship between RMS diff and boredom proneness for each classified group.

The classification results suggest that certain behavioural strategies are not conducive to certain self-regulatory profiles and can affect the likelihood of being boredom prone. More specifically, the relationship between Assessment and Boredom proneness is exacerbated when using the behavioural strategy used by group 1. Correlational findings also suggest that boredom proneness is negatively associated with Locomotion (r = -0.37). The second hierarchical regression model suggests that the use of group 1's strategy (having longer path length and picking a lot of berries) is conducive to those high in Locomotion but may not be the ideal choice for those high in Assessment.

3.3 Similarities and differences between tasks

To find out whether the two tasks were comparable, we looked at the correlations between the foraging task and the Boggle game (Table 12). A positive relation was observed between path length and successful berry picks from the foraging task and the number of correct answers from the Boggle game ($r = 0.226$ and $r = 0.214$ respectively). A negative correlation was observed between number of Misses and the average angles between picks from the foraging task and how efficient participants were on the Boggle game ($r = -0.195$ and $r = -0.203$ respectively).

Furthermore, we calculated the proportion of participants who were classified into groups on the Boggle game and who were also present in the foraging groups. A total of 277 out of 292 classified participants were present in all 3 classifications. The distribution of participants suggest that the majority of those who were part of group 1 and 2 from the *within* Boggle classification and group 2 and 3 from the *between* Boggle classification were also part of group 1 of the foraging classification. The majority of those who were part of group 2 from the *within* Boggle classification and group 3 from the *between* Boggle classification were also part of group 2 of the foraging classification.

Table 12: Correlations between the Foraging and Boggle metrics.

		Foraging metrics					
		Path Length	# Moves	# Miss	Successful Picks	Avg Ang Moves	Avg Ang Picks
Boggle Metrics	Mean Blocktime	-0.053	-0.045	0.011	-0.059	0.074	0.040
	Sum Enter	0.184	0.040	0.035	0.175	-0.019	-0.016
	Sum Next	-0.014	-0.052	-0.022	0.024	-0.098	-0.070
	Sum Previous	-0.025	-0.061	0.028	0.087	-0.051	-0.037
	Entered Errors	-0.018	-0.001	0.139	0.001	0.100	0.103
	Caught Errors	0.073	0.024	0.090	0.078	0.099	0.017
	Sum Correct Ans	**0.226**	0.046	-0.035	**0.214**	-0.090	-0.091
	Efficient	0.094	-0.005	**-0.195**	0.097	-0.170	**-0.203**
	# Engaged	0.028	-0.029	-0.085	-0.003	-0.083	-0.049
	# Visisted	-0.011	-0.034	-0.045	-0.029	-0.094	-0.039

Note: Significant correlations after a Bonferroni correction are bolded. P =< 0.0008.

Table 13a: Number of participants who classified on both the *within* and *between* Boggle classification and who formed part of **group 1** from the foraging classification

Foraging Group 1 (n = 183)	Boggle *between* groups Classification				
Boggle *within* groups Classification		Group 1	Group 2	Group 3	**Total**
	Group 1	4	18	47	**69**
	Group 2	8	13	40	**61**
	Group 3	3	4	14	**21**
	Group 4	3	7	22	**32**
	Total	**18**	**42**	**123**	

Table 13b: Number of participants who classified on both the *within* and *between* Boggle classification and who formed part of **group 2** from the foraging classification

Foraging Group 2 (n= 94)	Boggle *between* groups Classification				
Boggle *within* groups Classification		Group 1	Group 2	Group 3	**Total**
	Group 1	4	4	15	**23**
	Group 2	0	8	32	**40**
	Group 3	3	5	7	**15**
	Group 4	4	3	9	**16**
	Total	**11**	**20**	**63**	

CHAPTER 4: Discussion

Previous findings suggest that effective goal pursuit through specific self-regulation systems is associated with lower levels of boredom proneness (Struk et al., 2015). However, few studies have examined the behavioural consequences of trait self-regulation and boredom proneness. The aim of this study was to develop a behavioural assay capable of differentiating between various self-regulatory profiles. To this end, an internal foraging task – the Boggle game and an external foraging task – berry picking, were designed to explore the consequences of various self-regulatory profiles, as well as boredom proneness levels, on performance. Foraging represented an ideal behavioural task to capture complex goal pursuit styles that are specific to each self-regulatory profile. Our results replicated previous research findings regarding the relationship between various self-report measures of self-regulation and boredom proneness such that boredom proneness was negatively related to self-control, each aspect of regulatory foci and the Locomotion aspect of regulatory mode. However, boredom proneness was positively related to an Assessment focus. Surface metrics from both tasks did not strongly differentiate those individuals high/low on self-regulatory variables. This suggests that different performance strategies are used during goal pursuit and focusing on any one of them may not be particularly useful or sensitive for understanding goal pursuit. Regression analyses and classification techniques were used to better understand the complexity of goal pursuit behaviours and the interplay between self-regulatory profiles and behaviours evoked by the tasks. Our findings suggest that trait measures are indicative of *preferences* for specific goal pursuit styles as opposed to the tendency or frequency with which a given strategy is employed. Thus instances where individuals' preference in goal pursuit and their actual behaviour were not well aligned, may be more likely to be associated with higher boredom proneness. Such incongruences (described below) represented a lack of fit that may have reduced engagement and increased boredom proneness. In particular, the relationship between boredom proneness and Assessment is exacerbated when non-fit strategies are employed. In other words, Assessors who do not adopt a behavioural strategy conducive to their trait preference are more likely to be boredom prone. This differentiating factor may help address the conundrum of boredom – that bored individuals are motivated to engage but unwilling (or perhaps unable) to do so. Bored individuals might indeed be using a strategy that is not conducive to their self-regulatory preferences and therefore remain stuck in a state of ennui.

4.1 Internal foraging and Boredom proneness

Contrary to our hypothesis that those high in Locomotion would move from one solution space to another fairly quickly, results from the Boggle game suggest that high locomotors were less likely to move to the next problem set, made more errors and were less efficient than low locomotors. While this is contrary to our hypothesis, the behaviours are congruent with the essential nature of locomotion – which is to move from one state to another without any pre-determined destination or goal (Kruglanski et al., 2007; Pierro, Kruglanski, & Higgins, 2006). This explains the higher number of errors made by those high in Locomotion – they were concerned with moving from one word to another rather than the correctness of their answers. Higgins (2000) suggested that when behaviours are in line with self-regulatory profile, individuals experience regulatory fit and a greater value is associated with the activity. Conversely, when there is a non-fit, the value of the activity decreases. We propose that boredom may arise as a consequence of a mismatch between how one approaches a goal and their intrinsic preference for goal pursuit. Results supported this with those who experienced fit (e.g., high locomotors who entered a lot of words; Figure 5c) were less likely to be high in boredom proneness and those on the other end of the spectrum (low Locomotors entering a low number of words) being more prone to boredom.

Effect size findings suggest that high Assessors were more likely to catch an error and go back to a previous problem set within the Boggle game than low Assessors. While these behaviours are suggestive of Assessors ensuring they are ‘doing the right thing’, they could have also been evoked by the Boggle game. Kruglanski and colleagues (2000) define Assessment as the comparative aspect of self-regulation that allows one to evaluate all available options and ensure the right thing is done. The Boggle game did not present Assessors with all the problem sets in one go – participants had to move back and forth between problems to engage with them. The comparative nature of Assessors would mean that those high in Assessment would want to move back and forth between problem sets to determine which is the best problem to engage with. Any failure to fully assess the available problem spaces may result in lack of regulatory fit for high Assessors. Indeed, the *between* group classification, where participants were classified based on their performance between problem sets, suggested that high Assessors who employed group 3’s strategy (not moving back and forth between problem set and in engaging and visiting fewer problem sets) were more likely to be boredom prone compared to low Assessors who employed the same strategy. In this framework, high Assessors experienced a lack of regulatory fit by not moving between problem sets to determine which one would be the best problem to engage with. This lack of regulatory fit was associated with increased boredom proneness (r = 0.37 for group 3). Conversely, those low in Assessment could be said to have experienced regulatory fit as they were not focused on doing the right thing. Indeed, previous research suggests that when high Assessors were made to reach a decision using a comparative strategy, they were willing to pay more for an object compared to when they were made to reach the decision using an elimination strategy (Avnet & Higgins, 2003). This further points to the fact that the value of an object or task can increase if the strategy used is in line with the regulatory orientation.

As for the regulatory foci, individuals with a strong Promotion focus tended to spend more time per problem set, were less likely to move forward to the next problem set and engaged and visited fewer problem sets compared to those with a weak Promotion focus. This may be due to the parameters of the Boggle task that required participants to create as many words as they can within the set time limit, encouraging Promotion focused individuals to stay longer within a set. Roney and colleagues (1995) found that participants who were induced into a Promotion focus were more likely to persist and spend more time on unsolvable anagrams than those who were induced into a Prevention focus. It seems that while Promotion focus individuals have an inclination towards gains and accomplishments (Crowe & Higgins, 1997), they do not realise when it might be more fruitful to move on. Within the Boggle game, those with a strong Promotion focus might have been more successful in reaching their goal had they moved on more readily between problem sets. Indeed, results suggest that those who went against the trend and moved back and forth more between problem sets were less likely to be boredom prone than those with a strong Promotion focused who did not move a lot between problem sets. It could be that those with a strong Promotion focus experienced a greater degree of fit by moving back and forth between problem sets. Conversely, those with a weak Promotion focus who moved more between problem sets was associated with an increased likelihood of being boredom prone. This suggests that the use of an inappropriate strategy – in this case those with a weak Promotion focus using a strong Promotion focus strategy, resulted in a regulatory non-fit and hence reduces the engagement of any activity for those with a weak Promotion focus.

With regards to Promotion focus behaviours within each problem set, regression analyses suggested that entering a lot of words was associated with decreased boredom proneness for those who were predominantly Promotion focused, while the reverse was true for those who were predominantly Prevention focused. This was further exemplified in the within problem classification where group 1 and 4 (both of which entered a lot of words) were associated with less boredom proneness if they were also predominantly Promotion focused as compared to being predominantly Prevention focus (although only trending for group 4). In other words, the performance strategies of group 1 were conducive to a promoter's attitude towards gains and therefore individuals with a strong Promotion focus experienced fit when employing such strategy. On the other hand, those who are predominantly Prevention focus experienced a lack of fit when employing the same strategy. Prevention focused individuals are sensitive to losses and prefer a vigilant strategy (Higgins, 1997). As such, Prevention focused individuals are less likely to enter errors and are more likely to get a higher number of correct answers compared to individuals with a weak Prevention focus. Previous research has shown that there is a speed accuracy trade-off such that Prevention focused individuals are more likely to value accuracy, while Promotion focused individuals value speed (Forster, Higgins, & Bianco, 2003; Shah, Higgins, & Friedman, 1998). The use of group 1's strategy was associated with increased boredom proneness for those who were predominantly Prevention focused. However, the use of either group 2 or 3's strategy was not associated with increased boredom proneness for Prevention focused individuals, suggestive that Prevention focused individuals might be better off using these strategies.

Effect size calculations did not differentiate between high and low Prevention groups on the number of caught errors. However, for those with a strong Prevention focus, a tendency to catch errors was associated with increased boredom proneness, whereas catching fewer errors was associated with a decrease in boredom proneness. Prevention focused individuals are averse to making errors (Crowe & Higgins, 1007). While catching the errors before entering them seems to be a vigilant strategy in that they are preventing themselves from making an error, it also represents a loss of some kind. The caught errors can no longer be considered as potential answers for the game. Individuals with a strong Prevention focus are also sensitive to losses and may experience a lack of fit when they realize their answers are not correct.

4.2 External foraging and Boredom proneness

Looking at the behavioural differences in the foraging task, for those low in self-control, having fewer successful picks was associated with higher boredom proneness, whereas the opposite was true for those high in self-control. According to the theory of self-control, those high in self-control would delay smaller rewards that are available sooner for larger rewards that would be available later (Logue, 1988; Madden & Bickel, 2010). By having fewer successful picks, it could be that those high in self-control continue to forage through the environment in search of larger rewards (although high/low self-control individuals do not significantly differ in path length). Conversely, those low in self-control would prefer the immediate rewards and having fewer successful picks is not conducive to their preference. Those low in self-control may therefore experience a lack of fit associated with increased boredom proneness.

A similar pattern can be observed for Prevention focused individuals. Effect size calculation suggested that individuals with a strong Prevention focus have a higher number of successful picks and are less likely to miss berries when attempting to pick them. This highlights the nature of a Prevention focused individual – use of a vigilant strategy in berry picking and a greater value placed on accuracy as indicated by the tendency to miss fewer berries (Higgins, 1997; Forster, Higgins, & Bianco, 2003; Shah, Higgins, & Friedman, 1998). Regression analyses suggest that for those with a strong Prevention focus, having fewer successful picks is associated with low boredom proneness, whereas having a higher number of successful picks was associated with an increase in boredom proneness. By picking fewer berries, those with a strong prevention focus are emphasising accuracy and thus may experience regulatory fit. Conversely, having fewer successful berry picks is not conducive to the preference for low Prevention focused individuals as those low in Prevention focus do not value accuracy and a vigilant strategy. As a result, low Prevention focused individuals may experience lack of regulatory fit associated with increased boredom proneness.

The notion that regulatory fit plays an important role in boredom proneness is further exemplified when looking at the behavioral preferences for those who demonstrate either a predominantly Promotion or Prevention foci. For those who are Promotion focused, successfully picking a lot of berries or missing a lot of berries was associated with lower levels of boredom proneness, whereas for those who are Prevention focused, successfully picking or missing a lot of berries was associated with increased boredom proneness. As mentioned above, Promotion focused individuals value gains and opportunities, whereas Prevention focused individuals are sensitive to losses and value accuracy more (Higgins, 1997; Forster, Higgins, & Bianco, 2003; Shah, Higgins, & Friedman, 1998). Therefore, Prevention focused individuals may have experienced a lack of fit when they experience a high number of misses. Similarly, they might experience a lack of fit when having a high number of successful picks as they are not being selective and are just picking any and all berries. Promotion focused individuals on the other hand experienced fit as instances of misses or successful picks might simply represent an opportunity for them to move on and explore another patch.

As for regulatory mode, results suggested that for those who are predominantly Locomotors, having fewer successful picks or picking fewer berries per move was associated with a decrease in boredom proneness, while the same behaviours were associated with an increase in boredom proneness for those who are predominantly Assessors. This may be because Locomotors value moving from one state to another regardless of gains and therefore experience fit when engaging in such behaviors (Kruglanski, Pierro, Higgins, & Capozza, 2007). Conversely, Assessors like to compare all available options and ensure they are making the right choice (Kruglanski, et al., 2000). Assessors therefore may have experienced a lack of regulatory fit as neither behaviour (picking fewer berries and fewer successful picks) were conducive to an Assessment orientation. That is, by picking fewer berries per move, Assessors would be exploring the environment more – a strategy not conducive to the Assessment orientation. Furthermore, having fewer successful picks is also suggestive of an explorative strategy which is not conducive to an Assessors preference of ensuring the right thing is done. This behavioral pattern is further reinforced in the classification analyses where assessors who employed group 1’s performance strategies (having longer path length, greater successful picks and greater angles between moves) was associated with higher levels of boredom proneness.

At first glance, these results may seem to be the opposite of each other: regression analyses suggested that for Assessors, having fewer successful picks is associated with more boredom proneness and having greater successful picks is associated with less boredom proneness. Classification analyses on the other hand suggest that Assessors whose performance strategy involved a combination of greater path length, greater successful picks and greater angles between moves tended to be more boredom prone. The critical component in understanding these conflicting results is that the classification analyses accounts for the multi-faceted nature of goal pursuit, whereas the regression analyses only take into account one behavior. Clearly, more research is warranted to explore this relationship further.

Finally, the classification analysis also suggested that for Locomotors, the use of group 1's strategy was associated with lower levels of boredom proneness. This may be because longer path lengths and a higher number of successful berry picks highlights the Locomotors preference for 'getting on with it.'

4.4 Relationship between internal and external foraging

Hills and colleagues (2008) showed that priming participants using either a densely or scarcely populated spatial foraging task affected how participants subsequently behaved on a cognitive task. While the goal of this study was not to test whether one task would prime performance in the other (i.e., the tasks were counterbalanced), we did find some relations between the internal and external foraging tasks. More specifically, the greater the number of successful picks in the foraging task, the more likely participants were to get more correct answers in the Boggle game and the more participants missed berries in the foraging game, the less efficient they were likely to be on the Boggle game. Even though the correlations were small, these results do point the possibility that common underlying cognitive mechanisms are at play in both tasks.

4.3 Limitations and future directions

At the end of the Boggle game and the foraging task, participants were asked to rate how boring each of the tasks were. Relative to a 1-back cognitive task, participants rated the two task as not boring. However, no measure of participants' state boredom was collected. While the analyses point to the potential for participants to be boredom prone if they experience a lack of fit, no conclusions can be drawn for state boredom. It would be worthwhile to examine whether such instances of incongruence lead to an increase in state boredom relative to baseline. As such, future studies should attempt to get a measure of state boredom in instances where participants experience a lack of fit.

Furthermore, this study was a correlational study. No attempt was made to manipulate either state boredom or any of the self-regulatory profiles. As such, the direction of causality is as yet unclear. Future studies could induce participants into either of the regulatory foci or regulatory modes to examine whether performance on the foraging tasks interacts with the induced states to predict state boredom.

Finally, this study did not account for variables such as motivation, frustration, value, or fatigue – all of which can drastically affect a participant's behaviour. These highlight some of the variables that are often at play when we interact with our environment and are influential in which goals we pursue and how we pursue them. One way to explicitly manipulate motivation and frustration is to reward or punish participants for collecting as many berries or creating as many correct words as possible. Alternatively, certain berries or word lengths could be given greater value than others.

Conclusion

Different self-regulatory profiles have different behavioural preferences. Having a preference for a specific approach to goal pursuit does not ensure that the individual will enact that behaviour. Environmental constraints and interactions could result in a behaviour that is not conducive to the self-regulatory profile preference –as demonstrated here. It is this mismatch between goal-pursuit preferences and actual behaviours that is theorised to be associated with higher levels of boredom proneness.

References

Avnet, T., & Higgins, T. E. (2003). Locomotion, assessment, and regulatory fit: Value transfer from ‘‘how’’ to ‘‘what’’. *Journal of Experimental Social Psychology, 39*, 525-530.

Baumeister, R. F., Heatherton, T. F., & Tice, D. M. (1994). *Losing control: How and why people fail at self-regulation.* San Diego, CA: Academic Press.

Bench, C. W., & Lench, H. C. (2013). On the function of boredom. *Behavioural Sciences, 3*(3), 459-472.

Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population biology, 9*(2), 129-136.

Cohen, J. (1988). *Statistical power analysis for the behavioural sciences* . New Jersey: Lawrence Earlbaum Associates.

Crowe, E., & Higgins, T. E. (1997). Regulatory focus and strategic inclinations: Promotion and prevention in decision-making. *Organizational behavior and human decision processes, 69*(2), 117-132.

Cumming, G. (2013). Cumming, G. (2013). The new statistics why and how. *Psychological science*. doi:10.1177/0956797613504966

Danckert, J., & Allman, A.-A. (2005). Time flies when you’re having fun: Temporal estimation and the experience of boredom. *Brain and Cognition, 59*(3), 236-245. doi:10.1016/j.bandc.2005.07.002

Eastwood, J. D., Frischen, A., J, F. M., & Smilek, D. (2012). The unengaged mind defining boredom in terms of attention. *Perspectives on Psychological Science, 7*(5), 482-495.

Elpidorou, A. (2014). The bright side of boredom. *Frontiers in Psychology, 5*, 1245. doi:10.3389/fpsyg.2014.01245

Farmer, R., & Sundbert, N. (1986). Boredom proneness--the development and correlates of a new scale. *Journal of personality assessment, 50*(1), 4-17.

Forster, J., Higgins, E. T., & Bianco, A. T. (2003). Speed/accuracy decisions in task performance: Built-in trade-off or separate strategic concerns? *Organizational Behavior and Human Decision Processes, 90*(1), 148-164.

Gerritsen, C. J., Toplak, M. E., Sciaraffa, J., & Eastwood, J. (2014). I can't get no satisfaction: Potential causes of boredom. *Consciousness and cognition, 27*, 27-41.

Goetz, T., Frenzel, A. C., Hall, N. C., Nett, U. E., Pekrun, R., & A, L. A. (2014). Types of boredom: An experience sampling approach. *Motivation and Emotion, 38*(3), 401-419.

Higgins, E. T. (1997). Beyound pleasure and pain. *American psychologist, 52*(12), 1280.

Higgins, E. T., Friedman, R. S., Harlow, R. E., Idson, L. C., Ayduk, O. N., & Taylor, A. (2001). Achievement orientations from subjective histories of success: Promotion pride versus prevention pride. *European Journal of Social Psychology, 31*(1), 3-23. doi:10.1002/ejsp.27

Higgins, T. E. (2000). Making a good decision: Value from fit. *American Psychologist, 55*(11), 1217-1230. Retrieved from http://dx.doi.org/10.1037/0003-066X.55.11.1217

Hills, T. T., Todd, P. M., & Goldstone, R. L. (2008). Search in external and internal spaces evidence for generalized cognitive search processes. *Psychological Science, 19*(8), 802-208.

Kruglanski, A. W., Pierro, A., Higgins, T. E., & Capozza, D. (2007). "On the Move" or "Staying Put": Locomotion, Need for Closure, and Reactions to Organizational Change. *Journal of Applied Social Psychology, 37*(6), 1305-1340.

Kruglanski, A. W., Thompson, E. P., Higgins, E. T., Atash, M. N., Pierro, A., Shah, J. Y., & Spiegel, S. (2000). To "do the right thing" or to "just do it": Locomotion and assessment as distinct self-regulatory imperatives. *Journal of Personality and Social Psychology, 79*(5), 793-815.

Logue, A. W. (1988). Research on self-control: An integrating framework. *Behavioral and Brain Sciences, 11*(4), 665-679. doi:10.1017/S0140525X00053978

Madden, G. J., & Bickel, W. K. (2010). *Impulsivity: The behavioral and neurological science of discounting.* Washington, DC: American Psychological Association. doi:10.1037/12069-000

Malkovsky, E., Merrifield, C., Golberg, Y., & Danckert, J. (2012). Exploring the relationship between boredom and sustained attention. *Experimental Brain Research, 221*(1), 59-67. doi:10.1007/s00221-012-3147-z

Ming-Hsuan, Y., & Narendra, A. (1998). Gaussian mixture model for human skin color and its applications in image and video databases. *Proc. SPIE 3656, Storage and Retrieval for Image and Video Databases VII, 458*. doi:10.1117/12.333865

Moffitt, T. E., Aeseneault, L., Belsky, D., Dickson, N., Hancox, R. J., Harrington, H., . . . Caspi, A. (2011). A gradient of childhood self-control predicts health, wealth, and public safety. *Proceedings of the National Academy of Sciences, 108*(7), 2693-2698.

O'Reilly, R. C., Hazy, T. E., Mollick, J., Mackie, P., & Herd, S. (2014). *Goal-driven cognition in the brain: a computational framework.* arXiv preprint.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., . . . Perrot, M. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research, 12*, 2825−2830.

Pierro, A., Kruglanski, A. W., & Higgins, T. E. (2006). Progress Takes Work: Effects of the Locomotion Dimension on Job Involvement, Effort Investment, and Task Performance in Organizations. *Journal of Applied Social Psychology, 36*(7), 1723-1743.

R Core Team (2016). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/.

Redner, R. A., & Walker, H. F. (1984). Mixture densities, maximum likelihood and the EM algorithm. *SIAM review*, 195-239.

Roney, C. J., Higgins, E. T., & Shah, J. (1995). Goals and framing: How outcome focus influences motivation and emotion. *Personality and Social Psychology Bulletin, 21*(11), 1151-1160.

Sansone, C., Weir, C., Harpster, L., & Morgan, C. (1992). Once a boring task always a boring task? Interest as a self-regulatory mechanism. *Journal of personality and social psychology, 63*(3), 379.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics, 6*(2), 461-464.

Shah, J., Higgins, E. T., & Friedman, R. S. (1998). Performance incentives and means: how regulatory focus influences goal attainment. *Journal of personality and social psychology, 74*(2), 285.

Sokolowski, M. B. (1980). Foraging strategies of Drosophila melanogaster: A chromosomal analysis. *Behavior Genetics, 10*(3), 291-302. doi:10.1007/BF01067774

Sokolowski, M. B. (2001). Drosophila: Genetics meets behaviour. *Nature Reviews Genetics*, 879-890. doi:10.1038/35098592

Struk, A. A., Carriere, J. S., Cheyne, J. A., & Danckert, J. (2015). A Short Boredom Proneness Scale Development and Psychometric Properties. *Assessment*. doi:10.1177/1073191115609996

Struk, A. A., Scholer, A. A., & Danckert, J. (2015). A self-regulatory approach to understanding boredom proneness. *Cognition and Emotion*, 1-14. doi:10.1080/02699931.2015.1064363

Tangney, J. P., Baumeister, R. F., & Boone, A. L. (2004). High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *Journal of Personality, 72*(2), 271-324. doi:10.1111/j.0022-3506.2004.00263.x

van Tilburg, W. A., & Igou, E. R. (2012). On boredom: Lack of challenge and meaning as distinct boredom experiences. *Motivation and Emotion, 36*(2), 181-194.

van Tilburg, W., & Igou, E. (2011). On boredom and social identity: a pragmatic meaning-regulation approach. *Personality & Social Psychology Bulletin, 37*(12), 1679-1691. doi:10.1177/0146167211418530

Watt, J. (1991). Effect of boredom proneness on time perception. *Psychological Reports, 69*(1), 323-327. doi:10.2466/pr0.1991.69.1.323

Appendix A.

Table 14: T-tests and Effect size calculations for high/low groups for each trait measure on Boggle Game.

Predictor	DV	t	df	p	sig	High	Low	d
Locomotion	**Mean Blocktime**	**1.380**	**54.30**	**0.17**	**-**	**98.09**	**74.18**	**0.33**
Locomotion	Sum Enter	0.117	63.70	0.91	-	39.86	39.33	0.03
Locomotion	**Sum Next**	**-1.641**	**67.83**	**0.11**	**-**	**1.91**	**2.32**	**-0.39**
Locomotion	Sum Previous	-0.585	64.30	0.56	-	0.23	0.32	-0.14
Locomotion	**Entered Errors**	**1.434**	**66.09**	**0.16**	**-**	**10.46**	**7.72**	**0.34**
Locomotion	Caught Errors	-0.191	68.96	0.85	-	9.51	9.89	-0.05
Locomotion	Sum Corrrect Ans	-0.594	67.23	0.55	-	30.51	32.92	-0.14
Locomotion	**Efficiency**	**-1.471**	**68.82**	**0.15**	**-**	**0.77**	**0.83**	**-0.35**
Locomotion	# Engaged	-1.088	68.95	0.28	-	5.14	6	-0.26
Locomotion	**# Visited**	**-1.304**	**67.28**	**0.20**	**-**	**5.46**	**6.75**	**-0.31**
Assessment	Mean Blocktime	0.242	65.99	0.81	-	89.99	85.50	0.06
Assessment	Sum Enter	0.218	68.82	0.83	-	37.69	36.75	0.05
Assessment	Sum Next	-0.534	66.19	0.60	-	2.06	2.22	-0.13
Assessment	**Sum Previous**	**1.272**	**53.33**	**0.21**	**-**	**0.48**	**0.21**	**0.3**
Assessment	Entered Errors	-0.453	65.27	0.65	-	7.54	8.47	-0.11
Assessment	**Caught Errors**	**2.151**	**54.92**	**0.04**	*****	**10.63**	**7.06**	**0.51**
Assessment	Sum Corrrect Ans	0.618	68.78	0.54	-	31.34	29.14	0.15
Assessment	Efficiency	0.748	61.14	0.46	-	0.83	0.80	0.18
Assessment	# Engaged	-0.563	68.70	0.58	-	5.31	5.78	-0.13
Assessment	# Visited	-0.411	68.52	0.68	-	6.26	6.75	-0.1
Boredom Proneness	Mean Blocktime	-1.033	58.58	0.31	-	76.95	94.28	-0.25
Boredom Proneness	Sum Enter	0.301	68.23	0.76	-	40.19	38.92	0.07
Boredom Proneness	**Sum Next**	**1.589**	**70.90**	**0.12**	**-**	**2.37**	**1.98**	**0.37**
Boredom Proneness	**Sum Previous**	**1.298**	**61.63**	**0.20**	**-**	**0.38**	**0.17**	**0.3**
Boredom Proneness	Entered Errors	0.996	56.32	0.32	-	9.28	7.24	0.23
Boredom Proneness	Caught Errors	0.285	70.76	0.78	-	10.94	10.30	0.07
Boredom Proneness	Sum Corrrect Ans	-0.216	70.14	0.83	-	31.94	32.78	-0.05
Boredom Proneness	Efficiency	-0.756	69.03	0.45	-	0.80	0.83	-0.18
Boredom Proneness	# Engaged	0.724	70.68	0.47	-	6.00	5.43	0.17
Boredom Proneness	# Visited	1.186	69.83	0.24	-	6.89	5.73	0.28

Self-Control	Mean Blocktime	0.771	59.68	0.44	-	95.88	82.37	0.18
Self-Control	**Sum Enter**	**-1.405**	**69.14**	**0.16**	**-**	**33.03**	**38**	**-0.33**
Self-Control	**Sum Next**	**-1.355**	**70.09**	**0.18**	**-**	**1.96**	**2.35**	**-0.32**
Self-Control	**Sum Previous**	**-2.013**	**48.01**	**0.05**	*****	**0.12**	**0.53**	**-0.47**
Self-Control	**Entered Errors**	**-1.319**	**59.44**	**0.19**	**-**	**5.72**	**7.51**	**-0.31**
Self-Control	Caught Errors	0.380	61.25	0.71	-	8.67	8.08	0.09
Self-Control	Sum Corrrect Ans	-0.913	69.81	0.36	-	28.53	31.51	-0.21
Self-Control	Efficiency	0.038	70.52	0.97	-	0.84	0.83	0.01
Self-Control	# Engaged	-0.555	70.74	0.58	-	5.36	5.78	-0.13
Self-Control	# Visited	-0.937	69.25	0.35	-	5.86	6.84	-0.22
Promotion	**Mean Blocktime**	**2.387**	**46.80**	**0.02**	*****	**118.16**	**71.83**	**0.57**
Promotion	Sum Enter	-0.354	64.44	0.72	-	39.34	40.89	-0.08
Promotion	**Sum Next**	**-2.417**	**65.90**	**0.02**	*****	**1.77**	**2.40**	**-0.57**
Promotion	Sum Previous	-0.936	68.13	0.35	-	0.19	0.33	-0.22
Promotion	Entered Errors	0.415	67.08	0.68	-	8.54	7.86	0.1
Promotion	Caught Errors	0.185	68.85	0.85	-	10.14	9.81	0.04
Promotion	Sum Corrrect Ans	-0.614	66.16	0.54	-	31.57	34.08	-0.15
Promotion	Efficiency	-0.822	66.41	0.41	-	0.79	0.82	-0.2
Promotion	**# Engaged**	**-2.081**	**65.15**	**0.04**	*****	**4.60**	**6.17**	**-0.49**
Promotion	**# Visited**	**-1.806**	**65.74**	**0.08**	**-**	**5.23**	**7.14**	**-0.43**
Prevention	Mean Blocktime	-1.215	64.04	0.23	-	75.35	94.93	-0.29
Prevention	Sum Enter	0.645	65.74	0.52	-	36.67	34.36	0.15
Prevention	Sum Next	-0.093	65.11	0.93	-	2.24	2.27	-0.02
Prevention	Sum Previous	-0.518	67.02	0.61	-	0.39	0.54	-0.12
Prevention	**Entered Errors**	**-1.887**	**49.09**	**0.07**	**-**	**5.25**	**8**	**-0.44**
Prevention	Caught Errors	0.349	67.95	0.73	-	9.25	8.58	0.08
Prevention	**Sum Corrrect Ans**	**1.627**	**69.27**	**0.11**	**-**	**32.42**	**27.19**	**0.38**
Prevention	Efficiency	2.140	59.15	0.04	*	0.88	0.81	0.5
Prevention	# Engaged	0.805	69.80	0.42	-	5.64	5.11	0.19
Prevention	# Visited	-0.278	64.32	0.78	-	6.56	6.89	-0.07

Note: Effect sizes equal to or greater than 0.3 are bolded

Appendix B

Table 15: T-tests and Effect size calculations for high/low groups for each trait measure on foraging variable.

predictor	DV	t	df	p	sig	x1	x2	d
Locomotion	Path Length	0.883	68.02	0.38	NA	146198.24	141039.94	0.21
Locomotion	# Moves	-0.917	67.85	0.36	NA	247.69	257.69	-0.22
Locomotion	# Miss	-0.545	67.60	0.59	NA	72.97	77.78	-0.13
Locomotion	# Success	-0.744	67.02	0.46	NA	145.78	150.03	-0.18
Locomotion	Avg Ang Moves	-0.251	68.71	0.80	NA	33.36	34.02	-0.06
Locomotion	Avg Ang Picks	-0.932	63.77	0.36	NA	47.57	50.31	-0.22
Assessment	Path Length	0.362	66.91	0.72	NA	143804.92	141626.51	0.09
Assessment	# Moves	0.950	68.85	0.35	NA	255.69	245.28	0.23
Assessment	**# Miss**	**-1.291**	**64.60**	**0.20**	**NA**	**68.34**	**80.17**	**-0.31**
Assessment	**# Success**	**-1.258**	**66.01**	**0.21**	**NA**	**149.43**	**156.00**	**-0.3**
Assessment	**Avg Ang Moves**	**-2.300**	**68.99**	**0.02**	*****	**32.20**	**38.21**	**-0.55**
Assessment	Avg Ang Picks	-0.915	68.92	0.36	NA	47.98	50.85	-0.22
Boredom proneness	Path Length	0.773	69.65	0.44	NA	148662.04	143212.76	0.18
Boredom proneness	# Moves	0.650	62.91	0.52	NA	256.81	249.81	0.15
Boredom proneness	# Miss	0.557	70.96	0.58	NA	81.75	76.30	0.13
Boredom proneness	# Success	0.053	71.00	0.96	NA	147.92	147.59	0.01
Boredom proneness	Avg Ang Moves	-0.228	70.63	0.82	NA	35.98	36.52	-0.05
Boredom proneness	Avg Ang Picks	0.399	68.64	0.69	NA	51.90	50.75	0.09
Self-Control	Path Length	-0.587	68.37	0.56	NA	143557.35	146796.91	-0.14
Self-Control	# Moves	0.158	69.45	0.88	NA	262.56	260.62	0.04
Self-Control	# Miss	0.396	64.77	0.69	NA	73.86	70.08	0.09

Self-Control	# Success	-0.101	66.54	0.92	NA	149.81	150.43	-0.02
Self-Control	Avg Ang Moves	0.338	70.35	0.74	NA	32.83	32.18	0.08
Self-Control	Avg Ang Picks	0.399	66.45	0.69	NA	49.27	48.14	0.09
Promotion	Path Length	-0.434	64.69	0.67	NA	143558.95	146077.61	-0.1
Promotion	# Moves	-0.946	69.88	0.35	NA	254.83	267.67	-0.22
Promotion	# Miss	0.833	68.66	0.41	NA	83.83	75.50	0.2
Promotion	# Success	-0.308	65.59	0.76	NA	147.86	149.56	-0.07
Promotion	Avg Ang Moves	0.831	66.55	0.41	NA	34.08	32.14	0.2
Promotion	Avg Ang Picks	1.089	69.73	0.28	NA	50.25	46.74	0.26
Prevention	Path Length	0.699	67.87	0.49	NA	147132.41	142894.21	0.16
Prevention	# Moves	0.368	68.28	0.71	NA	253.28	248.51	0.09
Prevention	**# Miss**	**-2.326**	**67.91**	**0.02**	*****	**67.33**	**86.70**	**-0.54**
Prevention	# Success	0.947	70.94	0.35	NA	153.36	148.65	0.22
Prevention	Avg Ang Moves	0.595	65.40	0.55	NA	34.78	33.05	0.14
Prevention	Avg Ang Picks	-0.820	68.31	0.42	NA	46.98	49.63	-0.19

Note: Effect sizes equal to or greater than 0.3 are bolded