The London School of Economics and Political Science

Temporal drivers of heterogeneity: understanding the role of "when" in cognition and decision-making

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

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Statement of co-authored work

I confirm that Paper 1 was jointly co-authored with Matteo Galizzi, Rob Jenkins, and Jet G. Sanders; I contributed 60% of this work.

I confirm that Paper 2 was jointly co-authored with Matteo Galizzi, Benno Guenther, Rob Jenkins, and Jet G. Sanders; I contributed 60% of this work.

I confirm that Paper 3 was jointly co-authored with Barbara Fasolo, Matteo Galizzi, and Jet G. Sanders; I contributed 60% of this work.

I confirm that Paper 4 was jointly co-authored with Barbara Fasolo, Matteo Galizzi, and Claire Heard; I contributed 50% of this work.

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Abstract

Behavioural science researchers, practitioners, and policymakers have realised how important is to characterize the various drivers of heterogeneity of human behaviour within populations in order to understand intra- and inter-individual differences and create better interventions.

This thesis examines temporal drivers of heterogeneity, focusing on *when* decisions are made, especially looking at the day of the week. The day of the week has been shown to affect individual cognition and decision-making, and this is termed the ‘day of the week effect’.

This thesis examines the antecedents (paper 1), the potential causes (paper 2), the manifestations (paper 3), and extended applications (paper 4) of the day of the week effect.

The first paper reveals that at the start of the day, individual thoughts are largely uniform across the days of the week, focusing on the day ahead and on a to-do list. The second paper finds that both individual awareness of the days of the week as well as societal meaning of the days of the week are needed for the days to influence an individual. The third paper finds that the day of the week does not influence engagement with health information. The fourth paper finds that the day of the week does not affect established decision-making patterns or strategies, suggesting that it may only affect certain domains of cognition and decision-making.

Overall, this thesis contributes to the ongoing discussion of heterogeneity within behavioural science, in particular adding to the understanding of the day of the week effect.

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General Introduction

This introductory chapter discusses four relevant concepts in the literature, upon which this thesis builds. First, this begins with a discussion of what behavioural science is to orient this work within the context of the aims and methods of the field. Second, this introduction discusses behavioural science and individual heterogeneity, as the field continues to struggle with how to reconcile differences both within and between individuals with the typical broad-strokes implementation of many behavioural science interventions. Third, behavioural science and health is briefly discussed, as applications of behavioural science to health are common and widespread (including within the third paper of this thesis). Lastly, the weekly cycle is discussed to lay the groundwork for the temporal element of heterogeneity that is a cornerstone of this thesis' focus.

Broadly, this thesis sets out to understand and better characterize temporal drivers of individual heterogeneity within behavioural science. The motivation behind this investigation is that time is an inescapable feature of every behaviour an individual ever carriers out and scaffolds our understanding of the world around us. Therefore, this thesis contains four chapters that investigate time's effect on individual heterogeneity from different theoretical 'distances', from the antecedents, the manifestations, the first-order implications, and the second-order implications. Through this methodological examination, a multifaceted understanding of the temporal drivers of heterogeneity (and their effects) emerges that creates an understanding on how time cycles change individual behaviour. The diversified methodological approach taken in this research reflects a wider recognition in the social sciences: the questions I seek to answer require drawing from different disciplines and integrating their associated methods into a unified approach (Buyalskaya et al., 2021). By a thorough examination of (some of) what makes individuals different, especially focusing on different from *themselves* from one day to the next, a clearer understanding of heterogeneity and its implications for behavioural science, can be built.

1. What is behavioural science?

Behavioural science, as a field, seeks to understand and characterize actions and decisions made by people both individually and in groups (National Research Council, 1988). While this is an important goal, behavioural science is not unique in its interest in understanding individual action. Whether through economic modelling or neuroscience-based predictions, understanding human behaviour and its many (in)consistencies is a shared interest across many scientific disciplines (Glimcher & Fehr, 2013; Sanfey, 2007). One of the primary strengths of behavioural science as a field has been its willingness to draw from a wide variety of disciplines, incorporating their guiding principles, methods, and analytical toolkit (Gintis, 2007; Kwon & Silva, 2020). This creates an exciting and interdisciplinary field, as age-old questions—what makes us decide the way we do? —are tackled by groups of behavioural scientists with backgrounds as varied as their approaches.

One of the tenets of behavioural science lies in the acknowledgement that individual behaviour cannot be neatly predicted and categorized—further, individuals often act directly against best interests (both their own and collective ones) and their overarching intentions. Consider a non-exhaustive list of examples: not saving for retirement, continuing unhealthy behaviours, and more (Duckworth et al., 2018). While perhaps an intuitive proposition in the context of contemporary science, it is important to note that the very concept of human bounded rationality was in and of itself a revolution for many fields, for example economics (see Mill, 1824, for the original definition of *Homo economicus*). The very acknowledgement of human limited rationality, and the predictable ways from which we often go astray, has opened the door to the conception of behavioural science as a discipline.

Behavioural science has gone from strength to strength in all areas, from universities offering specialised degrees in the area, to integration within governments, to holding its own in both commercial and policy applications around the world (Benartzi et al., 2017). Through a robust, evidence-based examination of individual behaviours and biases, leaving long behind the idea of *Homo economicus*, behavioural science has allowed for light-touch modifications of existing systems to yield massive changes.

A prominent example of this integration is through the Behavioural Insights Team (BIT), an organization originally set up within the United Kingdom's cabinet to apply behavioural science methods to existing policy challenges. Now an international research consultancy working for a variety of private, public, and governmental bodies, BIT has paved the way for impactful integration of rigorous behavioural science methods to pressing questions. An early success for BIT involved invoking social norms in text messages regarding taxes (Hallsworth et al., 2007). Through small modifications to language, researchers were able to increase the proportion of taxpayers paying their taxes on time. While a small example in a sea of applications, the power of behavioural science to shape behaviour was recognized and embraced.

However, behavioural science has not been without its detractors. A large meta-analysis of behavioural science led interventions, both in the academic and the so-called 'nudge unit' sphere (i.e., government entities), showed that effect sizes in academic papers often are wildly beyond what can be expected in interventions in the wild (Dellavigna & Linos, 2022). The replicability crisis, an ongoing phenomenon within the social sciences including behavioural science (Pashler & Wagenmakers, 2012), centres around the finding that many famous social science studies, which have served as cornerstones of their respective subfields, do not replicate when other researchers attempt to conduct the same study. This has plagued many high-profile publications (see Camerer et al., 2018) and led to a questioning of what effects, if any, behavioural science can safely lay claim to. A blog post from BIT itself, provocatively titled "Behavioural Science or Bullsh*t?" (*Behavioural Science or Bullshit? | The Behavioural Insights Team*, 2022) sought to re-establish the importance of rigorous methodology and scientific grounding which some corners of behavioural science had lost.

It is important, therefore, to lend a critical eye to what we are asking when we think about using behavioural science as a tool to answer a question. What behaviours are we actually looking at, and what are we trying to measure?

What toolkit are we drawing from, and how robust are the conclusions we can draw? What are the limits of what we can claim, and how do we go about finding them? A review of the roots of behavioural science may seem out of place when setting the stage for new research, as the basics are well-known to experts within the field and may be perceived as rudimentary. I argue that it is indeed crucial to the proceedings of this discipline to remain in touch with its original conception and aims, to remind researchers and practitioners alike what behavioural science can and cannot do. Furthermore, it is critical to connect the present work, mentioned above and further presented in section 5 of this introduction, to one of the main domains where it can be applied, behavioural science.

2. Behavioural science and individual heterogeneity

Behavioural science and associated interventions are a powerful tool for inciting behavioural change on an individual and often collective level. However, its failure to account for the effects of individual heterogeneity (both within and between individuals) often leads to unexpected outcomes. A pivotal piece by Bryan et al. (2021) draws the connection between these issues in replicability and the unacknowledged heterogeneity that often underlies the samples used in various intervention studies. Briefly put, one cannot expect a behavioural science intervention to have a homogenous effect when applied to heterogeneous populations. This underappreciation for heterogeneity within populations can be reframed as a factor that can provide more insight into the causal mechanisms behind how these interventions affect the outcome behaviour.

In behavioural science, this is often borne out as much-lauded interventions failing to generate the expected significant effect size that had been found in other studies, particularly in the policy space. A well-known example of this phenomenon is the Opower case, originally put forth by Allcott (2011). Briefly, this intervention aimed to decrease electricity usage through a social norm approach. Homeowners were given information about the consumption levels of their neighbours, allowing them to see where they fell in energy consumption compared to similar households. The original experiment had a sample of roughly 600,000 homes and resulted in a 2% decrease in electricity usage. While this was a promising change, it did not carry over into subsequent expansions of the Opower intervention. It later emerged that differences in neighbourhood demographics were strong predictors of whether an Opower-style intervention would have a measurable effect on household energy consumption (Allcott, 2015).

This is one expression of how heterogeneity in a target population can be conflated with a replication crisis. The inability to replicate a finding may be misattributed to the research process versus a more nuanced understanding of the participants and causal mechanism behind the intervention itself. Bryan et al. (2021) therefore call for a "heterogeneity revolution", wherein such sources of heterogeneity are considered throughout the whole intervention design process. As expressed in Bryan et al. (2021):

> What if instead of treating variation in intervention effects as a nuisance or a limitation on the impressiveness of an intervention, we assumed that intervention effects should be expected to vary across contexts and populations? How would we design the research pipeline differently if we took seriously the challenge of using heterogeneity as a tool for building more complete theories and producing more robust and predictable effects across contexts and populations at the end of the line?

Implementation of these methodologies would further help to reveal the causal mechanism behind these interventions' effects, while further separating out between failures to replicate due to experimental error and unaccounted for heterogeneity in participant pools driving disparate results. This idea is central to the research presented here, as building an understanding of temporal drivers of individual heterogeneity is one step towards forming a more complete characterization of individual sources and manifestations of heterogeneity. As this thesis sets out to understand individual heterogeneity, the acknowledgement of its role within behavioural science-led interventions lays the groundwork for a crucial application in this space.

3. Behavioural science health applications

Behavioural science is applied to assess which principles are most effective for shifting health behaviour on a population scale (Livingood et al., 2011). There are a host of undesirable behaviours (or lack of desirable behaviours) that incur significant costs, both in terms of individual wellbeing and burdens to public services. These behaviours are not always driven by lack of information (i.e., a Gallup poll revealed 95% of Americans think smoking is harmful, yet 23% smoke (Moore, 1999)). This points to the need for an approach that tackles the underlying irrationality and contradictions that are often present in individual behaviours. For example, there is no strictly rational reason that a smoker should be more inclined to quit just through receiving information that changes the language to suggest images of diseased lungs are like their own. However, this is exactly the type of approach that is motivating a new intervention by Murray et al. (2020) that uses images of individuals' own lungs to motivate smoking cessation. This is an example of behavioural science needing to address less 'rational' aspects of decision-making within individuals.

By understanding irrationality and using an evidence-based approach, behavioural scientists have been able to introduce interventions that have included everything from citizen taxation (Larkin et al., 2019) and incentive structures within the NHS (*NHS England » NHS to Introduce New Financial Incentive to Improve Staff Health*, 2016) to text message content for appointment attendance (Arora et al., 2015) and modified supermarket layouts (Gittelsohn et al., 2012). This has shown that behavioural interventions are a feasible, cost-effective means to modify behaviours of the public, including in the healthcare space.

Evidence-based methods are often used to test the effect of physical or spatial alterations on behaviour. Behavioural scientists have successfully altered undesirable behaviour such as smoking and alcohol consumption (Gill & O'May, 2007; Robinson et al., 2019). However, current applications have focused only on the physical aspect of the decision space. This presents an opportunity for an enrichment of the method, by understanding the decision space as part of a larger context that has a temporal dimension. I argue that by integrating the temporal aspect into our current understanding of decision-making, we can gain a richer and more complete understanding of decision-making behaviour.

Behavioural science focuses on overcoming systematic decision-making bias in behaviours on an individual level, but often does not address the inter- and intra-personal fluctuations in any given behaviour and the role of individual heterogeneity. This is often described as noise in decision-making and can manifest in a diversity of cases. For example, when pathologists assessed the severity of biopsy results across two independent instances, the correlation between their ratings was only 0.61. In other words, their diagnoses were frequently inconsistent (Kahneman et al., 2016). An important step in better understanding these inconsistencies is to explore underlying systematic fluctuation as a driver of heterogeneity in preference and cognitive stability within individuals. Classifying these fluctuations could also inform the current push in behavioural science to understand why behavioural interventions have heterogeneous effects (see earlier discussion, as well as Bao & Ho (2015); Sunstein (2017)) and in turn pave the way for more effective interventions. Therefore, the understanding of individual heterogeneity is pivotal not just as something to understand within the context of psychological research—rather, it lays the groundwork for the creation of more effective interventions in the future.

4. Weekly fluctuations background

Time is often viewed as the backdrop against which human behaviour unfolds, and it seldom garners adequate attention in and of itself. However, it governs much of the rhythm of daily life, dictating plans, actions, and mindsets. For example, the beginning a new week has been found to increase goal-directed behaviour (Dai et al., 2014). Furthermore, the cyclical structure of modern Western society has given to time (namely, breaking it up into seven-day weeks) has become a pervasive scaffolding to which individuals fit in and organize their lives. This seven-day structure is an entirely 'artificial' one, as it is not based in a physical or biological rhythm (in contrast with the 24-hour day and the circadian rhythm)—however, it has existed in some form since the

Babylonians (Copeland, 1939). I argue that this imposed cyclical structure, by which society largely uniformly operates, has a greater effect on individual states and subsequent decision-making than is commonly recognized, hereafter referred to as the day of the week effect. Of note, the day of the week effect discussed herein is based in the predominantly Western understanding of the week; namely, Monday through Friday are weekdays associated with work and school for children, while Saturday and Sunday are weekends associated with time off and leisure activities.

One area in which these differences are pervasive is in individual subjective experience and affect on various days. Many naturally associate certain times of the day or week with different events, habits, and emotions (Ellis et al., 2015). And as many individuals can recognise anecdotally, Friday carries a sense of elation at the upcoming weekend, while Monday carries a sense of fatigue and a negative mood (Stone et al., 2012). This is an intriguing finding, as there is little materially different in a biological or geophysical sense between a Friday or a Monday of the same week—unlike comparing a December morning to a July morning, the differences are largely socially constructed. There is growing research into the effects these ubiquitous temporal patterns, especially the seven-day week, have on individual cognition, emotions, and the subsequent decisions.

These cyclical differences between weekdays, previously identified in affect, have been shown to have larger-scale impacts on behaviours across several domains. For example, the day of the week has been shown to have an effect in various behavioural domains, from the mundane such as traffic flow and coffee queues, and attendance to medical appointments (Ellis et al., 2022.) to suicide rates (Brådvik & Berglund, 2003), stock performance (Gibbons & Hess, 1981), political decision-making (Sanders & Jenkins, 2016), and surgical risk (Aylin et al., 2013). Interestingly, these fluctuations have also been found in incidence of acute illness, such as myocardial infarctions and stroke (Arntz, 2000; Gerber et al., 2006; Phillips et al., 1999; Wang et al., 2002). In the case of acute myocardial infarction, the increase in sympathetic nervous system activity (a driver of acute myocardial infarction) associated with the stress of

Monday has been proposed as a cause for the spike in incidence (Kloner, 2006). These “natural and unnatural triggers” (Kloner, 2006), mentioned in the context of causes of the cyclical nature of myocardial infarction, suggest an interplay between the societally formed seven-day weekly cycle and its tangible effects on individuals.

In sum, we are all influenced by time and the rites and structures built around it: the time of day (Roeser et al., 2016), day of the week (Stone et al., 2012), and the month of the year (Thaler, 1987) are influences present in every decision an individual will ever make. The effect of these influences has been briefly described above, including both affect, physical symptoms, and larger action patterns. Despite this, the effect of time is rarely considered when we seek to explain variance in human decision-making and behaviour. In my thesis, I explore whether some of what has previously been understood as ‘noise’ in action and decision-making patterns can be explained by underlying temporally driven small-scale fluctuations of decision-making and subsequently, behaviour.

Therefore, the perspective taken in this thesis marries the effect of the day of the week with an understanding on the role between situation and behaviour. The intuition for this is the following: if behaviours are dynamic and based upon a person-situation interaction, and large-scale differences have been found in behaviour over the course of the days of the week, the proposed research seeks to treat each day of the week as its own ‘situation’ (or functional equivalency class, borrowing the language of Mischel & Peake (1982)) and then examine the effects of the days of the week on individual behaviours.

5. The present work

The present work seeks to understand how temporal factors interplay with different individual drivers of heterogeneity. This work builds upon behavioural science and its power to change behaviour and the continuously building heterogeneity question facing the social sciences. By drawing on the insights garnered by each of these lines of inquiry (behavioural science, behavioural science and health, and the weekly cycle), this thesis seeks to refocus the discussion on temporal drivers of heterogeneity, examining how different individual traits and decisions are affected.

Each chapter in this thesis has a short one-page ‘in context’ introduction preceding it to orient the reader of where the research fits into the larger puzzle of temporal heterogeneity.

Overall, the questions guiding this line of research are the following.

1. Do the day of the week differences manifest at the beginning of one’s day?
2. How do alterations in the daily structure, like during COVID-19 lockdowns, change manifestations of the day of the week effects, especially within risk attitudes?
3. How does the day of the week effect change engagement with health information?
4. How does the day of the week affect existing decision-making patterns?

In conclusion, this novel research direction rests on two pillars: 1) the established fluctuations in said personality and cognitive traits (again, like risk or intellect) and 2) the role that these traits play in decision-making. This line of research draws together numerous fields of research with the goal to create a more comprehensive characterisation of population-wide patterns in small-scale fluctuations in cognitive traits.

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Paper 1: Penumbral Thoughts: Contents of consciousness upon waking

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Paper 1: In context

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The first paper in this thesis focuses on the antecedents of the day of the week effect by investigating individuals' thoughts at the start of the day. The motivation behind this research is to uncover *when* the day of the week effect emerges. Past research has shown that the day of the week can have outsized effects on a variety of behaviours, but at what point do these differentiations begin to emerge? This paper seeks to determine whether these are differences that can be found early in the day, in an individual's first waking thoughts.

The primary finding of this paper is the exceptional homogeneity of first waking thoughts, termed here *penumbral thoughts,* across the days of the week. Individuals primarily look toward the future in a short timescale, focusing on what needs to be done immediately and what the day ahead will look like. As such, there is no day of the week effect on content found in penumbral thoughts. This homogeneity in thought content across the days suggests that it is the answers to these penumbral thoughts, like the content of the to-do list and the activities of the day ahead, that lead to the cognitive (and behavioural) fluctuations we see across days of the week.

In sum, the antecedents of the day of the week effect are not found upon waking—penumbral thoughts are a surprisingly unifying category across individuals with different traits. The differences emerge as the days and the behaviour instead develops. This suggests a strong role of social influence (see more in Paper 2) in forming these cognitive predispositions that yield different day of the week effects. This paper begins the exploration of the weekly cycle from the very first moment of consciousness, paving the way for the rest of thesis to further investigate drivers of heterogeneity across days.

Abstract

Thoughts shape our experience, choice, and behaviour throughout the day. Yet the content of 'penumbral thoughts'—first thoughts upon waking—has received very little research attention. Across seven independent samples (total N = 829), we used recall and reflection methods, solicited the same day, to understand what individuals think as they regain consciousness. These penumbral thoughts show remarkable thematic consistency: individuals were most likely to reflect on their somatic or psychological state, focus on temporal orientation, and prioritise waking actions. Survey results demonstrate that temporal and spatial orientation are dominated by the current time and the day ahead, rather than the past or other future timescales. Our results provide some insight into the order of priority in consciousness. We conclude that establishing one's temporal position is important to the daily process of 'rebooting' conscious awareness.

1. Introduction

Humans wake up every day. What can we learn from their first waking thoughts? One possibility is that the earliest thoughts reveal levels of priority ascribed to the various constructs which play a role in consciousness. Following the metaphor of a rebooting computer, powering its most essential features (such as working memory) triggers the reboot of secondary features (such as stored memory). Once the system is up and running, new actions can be taken through its interface. When we extend this metaphor to the daily emergence of consciousness, a similar order of prioritisation may take place. Identifying which thoughts occur first allows us to identify which processes receive cognitive priority. Previous studies have shown that experiences of waking up can reverberate for several hours. For example, self-reported anticipation of stress first thing in the morning reduced that day's working memory [1]. Similarly, a workplace correlational study found that waking up positively left employees more likely to perceive interactions with their customers and work quality more positively too [2]. Such findings demonstrate how early thoughts can set the tone of the rest of the day and may predict variability between thoughts and behaviour over the course of that day.

The first thoughts emerge during a qualitatively different cognitive state from thoughts that emerge during normal wakeful cognition. This state, during the time window between sleeping and being awake, is sometimes known as sleep inertia— “the temporary time of sleepiness, disorientation and impaired cognitive performance experienced upon awakening” [3]. Studies of sleep inertia have emphasised its detrimental effects on performance. Although acute effects of sleep inertia have been shown to dissipate after 15–30 minutes of waking [3], performance on cognitively-challenging tasks during this time has been found to be worse immediately after waking than after 26 hours of sleep deprivation [4]. Similarly, complex planning of military strategy amongst junior officers was found to be impaired immediately after waking [5]. These behavioural findings suggest a relatively basic and primal level of cognition during the transitory period between sleep and wakefulness, devoid of sophisticated levels of thought.

Converging evidence comes from studies which have measured people’s physiological profile during this period. This transition between sleep and wakefulness is marked by a clear sequence of synchronised neurological activity comprising the thalamic nuclei and cingulate cortex [6] marking a large shift in patterns of neural activation. Cognition immediately after waking has been associated with a number of neural correlates, such as increased power of delta waves (the lowest frequency brain waves, associated with the deepest phases of sleep) [7] and decreased blood flow to frontal regions, relative to wakeful activity [8] These neural findings could explain the distinct cognition seen in sleep inertia.

In sum, the work on sleep inertia suggests that thoughts during the transition from sleep to wakefulness may have a distinct profile from thoughts during either full sleep or full wakefulness. We refer to these as *Penumbral Thoughts* by analogy to the boundary between shadow to light. If penumbral thoughts reflect cognitive rebooting, they may be less cognitively sophisticated and less variable across individuals, relative to typical wakeful thought [9,10]. To the best of our knowledge, however, no previous study has examined penumbral thoughts from a psychological science perspective. This omission is perhaps surprising, given 1) the ubiquity of regaining consciousness as a daily experience, 2) it is frequently studied in other disciplines i.e., through literary or cinematic representation (as in Proust's 'Swann's Way' [11], discussed in [12], or Charles Dickens' 'A Christmas Carol' [13], discussed in [14]), and 3) the insights gleaned from behavioural and physiological studies of sleep inertia. It reveals a gap in understanding between the content of thoughts during sleep (i.e., dreaming; [15,16]) [9,17–22], and the content of thoughts during full wakefulness—both of which have been studied intensively in psychological research.

The contrast with full wakefulness is particularly relevant here. Over the last decade, several studies have sought to characterise the content of wakeful thought, including its temporal and spatial orientation, protagonist focus, and affective valence [9,17–22]. For example, thought content is only on-task (in the present) about half of the time [9]. The other half is focused on the past (episodic memory) or planning of the future (episodic foresight) [9,22]. Estimates suggest that about two-thirds of wakeful thoughts are future-oriented, and one-third are past-oriented [17,18]. D'Argembeau, Renaud & van der Linden found that on a typical day, an average 42.5% of thoughts were future-oriented, with 31% of these future-oriented thoughts pertaining to later in the same day [18]. Other studies have found that the content of thought is often related to oneself, with the affective valence more often negative or neutral than positive [17,20,21]. These regularities matter, not least because they can affect the thinker's mood: future-orientation and positive mood tend to go together; and past-orientation and negative mood tend to go together [19]. These associations suggest that the temporal orientation of penumbral thoughts may shape the quality of conscious experience for the day ahead.

In the current study, we set out to categorise the content, valence, protagonist, and orientation of penumbral thoughts. To monitor the consistency of penumbral thoughts, we collected data in seven independent samples, one on each day of the week [23,24]. If penumbral thoughts reflect early prioritisation, we expect a degree of consistency across samples and person demographics, such that a small number of readily identifiable themes emerge. We also expect future orientation with a short horizon, geared towards ordering behaviour over the day ahead.

2. Methods

2.1. Participants

A total of 829 paid participants from the UK were recruited on the Prolific platform over two weeks in November 2020 (117-121 participants total per day of week; mean age = 32.7 years, age range = 18-75; 71.5% female). See Supplementary Material 1 for the age and gender distribution per sample. All participants provided informed consent (University Ethics approval number 07564).

2.2. Materials and procedure

The experiment was run entirely online using Prolific. The survey was created and compiled using Qualtrics, which was used to administer task instructions, present test materials, and record participants' responses. Participants accessed the experiment from their own devices.

2.2.1. Open recall question

Participants were first asked to complete a free recall question, "*What was your first thought when you woke up this morning?*", with waking up described as "*the first moment of consciousness after sleep*" in order to clarify the intended period of time. We opted to ask for the first thought as a thought could also refer to a direct thought process (i.e., where am I?), but also an experience (i.e. It's cold here) or emotional state ('I am tired'). The intention here was to capture information that participants volunteered when they were not led to any particular theme.

2.2.2. Reflections

Reflection items were used to elicit data on specific topics of interest. Participants were asked whether they (i) already knew, or (ii) sought to establish the time, day, or place when they first woke up (See Table 1A). We compared knowing or establishing of temporal information (time or day; which is typically different on successive wakings and therefore may be less known) to the baseline of spatial information (place; which is typically the same on successive wakings and therefore more known (1)). Participants responded on a Likert scale from Never (0), to Sometimes (1), to Usually (2) to Always (3). For example: *How often does the following statement apply: When I wake up, I want to establish the time.*

Next, participants were asked to reflect on an additional six statements to establish the temporal orientation of their penumbral thoughts. Our aim was to distinguish between temporal direction (i.e., future or past) and temporal distance (day, week, or year; see Table 1B). For example: *How often does the following statement apply: As I wake up, I think about the day ahead.*

A) Prior knowledge

When I wake up, …

Prior knowledge	**…I know…**	**…I want to establish…**
Place	...the place	…the place
Day	…the day	…the day
Time	…the time	…the time

B) Temporal orientation

As I wake up, I think about…

Direction	**Future**	**Past**

Distance (day)	…the day ahead	…the previous day
Distance (week)	…the week ahead	…the previous week
Distance (year)	…the year ahead	…the previous year

Table 1: Statements on A) prior knowledge and B) temporal orientation were presented to participants. Participants responded on a Likert scale from Always (3), Usually (2), Sometimes (1), to Never (0).

2.3. Analysis

2.3.1. Open recall responses

2.3.1.1. Thought characterisation

The purpose of thought characterisation is to capture the variety of unprompted thoughts and rank the most commonly occurring themes [25]. To identify common themes of penumbral thought content we used a blended approach between open and template coding [26,27] and an intercoder reliability procedure to develop a codebook [28]. Once themes had been identified, we used a co-occurrence analysis between the three identified themes and age, gender, and weekday. See Supplementary Materials 2 for full methodology, decision log, finalised codebook, and analysis. In line with the procedures in qualitative coding [29], no inferential statistics is used, but rather a focus is drawn to ranking between classes of response [25].

2.3.1.2. Thought context

To establish the context of penumbral thoughts each response was also rated on a number of dimensions previously identified in wakeful thought content

[9,19]. These include temporal orientation (past, present, future), protagonist (self or other), and valence of thought (positive, neutral, negative). As we were interested in the information that people seek to acquire when emerging from sleep, we also analysed sentence formulation (question or statement). Binomial tests with Clopper-Pearson 95% CI, controlled for multiple comparisons, were used to test for differences between reports across categories. To assess differences across age, gender, and weekdays we used chi-square tests across each dimension, also controlled for multiple comparisons.

2.3.2. Reflection responses

To show how often (DV) participants knew or sought to establish (IV1) thought about time, day, or place (IV2) when they first woke up, we used a 2x3 repeated measures ANOVA. Similarly, we used a 2x3 repeated measures ANOVA of day, week, year (temporal distance, IV1) by its temporal direction (past or future, IV2) to establish the temporal orientation of participants' firsts (DV). Next, we ran a 2x3x7 mixed design ANOVA, repeated the above two analyses adding in the factor of the day of the week (IV3), to measure consistency in any observed patterns across weekdays.

3. Results

3.1. Open responses

97.8% of participants reported thought content (811 of 829). The remaining 18 participants left the response box blank (n=11), mentioned that they had forgotten (n=6) or reported 'nothing' (n=1).

3.2 Thought characterisation

Three themes of penumbral thought content were identified: 1) reflection on present psychological or physical state (including transition from sleep to wakefulness), 2) temporal and/or spatial orientation, 3) establishing waking action (see Figure 1 for selective codes). Below we describe the themes and codes which elicited at least 3% of participants responses, in its ranked order.

3.2.1. Description of themes

A total of 1053 codes were awarded (range: 0–8 codes per response) to 807 responses (99.5% of all responses). See Figure 1 for a distribution of counts across themes. Due to imbalance in gender and age groups, comparisons are made across rows. Counts of codes in each theme group can be found in Supplementary Materials S3.

	Psychological and physical state					Temporal and spatial orientation				Waking action				Sum
	(Lack of) sleep or rest	Waking up or awoken	Discomfort, sick or ill	Dreams	Other	Place	Day	Time	Other	Immediate needs	To-do list & commitments	Technology	Other	
<25	55	19	8	9	21	6	2	56	1	38	107	13	7	342
26-38	56	30	11	9	21	18	19	71	1	57	143	11	20	467
38+	21	12	4	4	20	12	10	39	0	34	68	3	9	236
M	28	18	3	1	20	10	8	48	1	44	92	8	14	295
F	104	43	20	20	43	26	23	118	1	85	228	18	23	752
M	14	10	3	2	9	6	3	17	0	19	36	2	4	125
T	19	6	1	2	9	2	3	24	0	16	47	8	4	141
W	25	8	4	5	13	4	6	21	0	17	43	4	7	157
Th	22	10	5	5	9	5	2	28	0	18	43	1	5	153
F	15	9	2	3	8	7	6	28	0	15	54	3	6	156
S	19	7	2	1	5	4	10	18	1	26	46	5	6	150
Su	19	11	6	4	10	8	1	31	1	18	52	4	6	171
Sum	133	61	23	22	63	36	31	167	2	129	321	27	38	1053

Figure 1: Counts of codes based on free response statements to the question *"What did you think about when you first woke up*?" by demographic groups (age and gender) and by days of the week.

3.2.1.1. Reflection on psychological and physical state

For 1 out of 4 participants, their penumbral thought referred to their own psychological or physical state. Most of these referred to the transition from sleep to wakefulness. Of these participants, a quarter referred to their sleep or to still being asleep ('*I've slept too long*'), another quarter mentioned (still) being tired (and needing more sleep). Others described the waking up process ('*disoriented and tired'*) or specifically what they were awoken by (such as an alarm or an interruption *'oh no baby is crying'*). A few participants mentioned feelings of physical discomfort ('*headache', 'feel ill'*).

3.2.1.2. Temporal and/or spatial orientation

1 in 4 participants aimed to establish the time, day, or place when they first woke up. 1 in 5 aim to establish the time and, 1 in 10 participants note their exact penumbral thought to be '*What time is it?'.* Some others aimed to establish '*What day it is*' or how they expected to fill their time that day ('*what do I need to do today*'). Some participants referred to spatial orientation. Most

frequently they mentioned elements of change in their surroundings, such as the weather (‘*is it snowing?’, ‘what is the weather like?’*).

3.2.1.3. Establishing waking action

1 in 2 described thinking about the actions they needed to take that day. These included immediate bodily needs (*‘I need to eat’, ‘need the bathroom’*), but could also refer to longer timeframes of action. 1 in 3 participants referred to (items on) their ‘to-do list’ for the day, by noting this as a question (‘*what meetings do I have today?*’) or listing tasks for the day explicitly (*‘need to do my exercises’*). None of the participants explicitly described tasks further than a day ahead.

3.2.2. Consistency across age, gender, and weekday

To test for consistency of thought content, we segmented the data by the person characteristics. Co-occurrence analysis of the three emergent themes across three age categories (<25, 25-38 and 38+), gender, and weekday demonstrated high levels of consistency. Only two statistically significant associations were found. First, participants under the age of 25 were more likely to report physical and psychological state upon waking (OR: 1.40 (95% CI 1.00 - 1.95)). A qualitative inference suggests that this may be driven by fewer young participants describing being awoken (possibly due to lack of childcare responsibilities). Second, across weekdays, reports of time, day or place were more likely on Mondays than on other days (OR: 1.73 (95% CI 0.97 - 2.99)), and less likely on Sundays than on other days (OR: 0.50 (0.23 - 0.96)). See Table 2 for details.

	Physical and Psychological State	**Temporal and Spatial Orientation**	**Waking Action**
Age			

under 25	**1.40 (1.00 - 1.95)***	0.84 (0.52 - 1.33)	1.04 (0.73 - 1.47)
26 - 38	0.73 (0.52 - 1.02)	1.20 (0.76 - 1.95)	0.95 (0.67 - 1.35)
over 38	0.87 (0.60 - 1.26)	1.37 (0.85 - 2.17)	1.05 (0.71 - 1.52)
Gender			
Female	Reference		
Male	0.99 (0.69 - 1.40)	1.03 (0.63 - 1.63)	1.20 (0.83 - 1.71)
Weekday			
Monday	1.11 (0.69 - 1.76)	**1.73 (0.97 - 2.99)***	0.94 (0.56 - 1.53)
Tuesday	0.75 (0.45 - 1.21)	0.46 (0.19 - 0.99)	1.27 (0.79 - 2.01)
Wednesday	1.10 (0.70 - 1.71)	0.78 (0.39 - 1.47)	1.06 (0.66 - 1.68)
Thursday	1.34 (0.85 - 2.08)	1.27 (0.69 - 2.24)	0.85 (0.51 - 1.38)
Friday	0.86 (0.53 - 1.37)	1.37 (0.75 - 2.39)	0.85 (0.51 - 1.38)
Saturday	0.82 (0.50 - 1.31)	1.37 (0.75 - 2.39)	1.06 (0.65 - 1.69)
Sunday	1.09 (0.71 - 1.64)	**0.50 (0.23 - 0.96)***	0.99 (0.64 - 1.53)

Table 2: Co-occurrence between themes, age, gender, and weekday

presented in odds ratio, 95% confidence interval. *p < 0.05

3.3. Thought context

To characterise the context of penumbral thoughts, we categorised each response on four dimensions: (i) its temporal orientation (past, future), (ii) the protagonist or personal referent (self, other), (iii) its affective valence (positive, negative), and (iv) sentence formulation (statement, question). To avoid confusion between the participant-generated thought content and the above qualities of the thought, we will use the term ‘thought context’ for this group of features. To control for multiple comparisons, a Bonferroni adjusted p-value of 0.0125 was used for statistical inferences.

3.3.1. Distribution of responses across dimensions

See Figure 2 for the distribution of responses across dimensions. Due to imbalance in gender and age groups, comparisons are made across rows.

	Temporal Orientation		Protagonist		Valence		Sentence formulation	
	Past	Future	Self	Other	Positive	Negative	Question	Statement
<25	28	65	207	37	9	17	59	199
26-38	23	79	242	68	6	26	101	252
38+	13	42	125	37	10	10	64	134
M	14	52	161	41	7	11	65	160
F	49	133	410	100	18	42	159	422
M	6	22	75	19	1	8	26	79
T	8	29	75	27	1	5	22	88
W	10	22	86	17	4	7	37	79
Th	12	27	77	20	2	14	27	83
F	10	29	77	16	6	5	42	63
S	9	30	85	20	7	4	26	84
Su	9	27	100	23	4	10	43	97
Sum	64	186	575	142	25	53	223	573

Figure 2: Raw counts of observer ratings of free response statements to the question *“what did you think about when you first woke up*?” based on four dimensions: temporal orientation, the protagonist, valence, and sentence formulation, by demographic groups (age and gender) and by days of the week.

3.3.1.1. Dimension 1: Temporal orientation

Temporal orientation (past, future) was identifiable for 30.2% of the responses (N = 250). Other responses were excluded from further analysis. Of those given a temporal orientation, significantly more (74.4%; N=186) referred to future events (*'working today'* and *'I need to get up as expecting a delivery early'*), than events in the past (N=64; 25.6%;*'about the dream I just had' 'I messed up salary negotiation during a call with HR for a job i (sic) was interviewing for'*) [$p < 0.001$, $z = -7.65$, 95% CI = [68.5%, 79.7%]].

3.3.1.2. Dimension 2: Protagonist

More participants (80.2%; N = 575) expressed having a self-referred thought when they first woke up, than having an other-referred thought (19.8%; N = 142); [$p < 0.01$, $z = 16.13$, 95% CI = [77.1%, 83.1%]]. Individually centred statements included reflections on one's current state (*'am alive', 'im (sic) still tired'*), a plan for future activities (*'I'll go out for a walk', 'check my phone'),* or personal care needs (*'I need a wee.', 'I need a coffee')*. Other-centred thoughts referred to members of a social circle (friends, family, or pets on occasion). Qualitative inference indicated that other-centred thoughts were often paired with responsibilities, such as school preparation or other caring responsibilities ('*get kids ready for school', 'ringing and waking my boyfriend', 'how is my daughter'*). At times, participants mentioned having been awoken by someone or something in their household (*'oh no baby is crying'*).

3.3.1.3. Dimension 3: Valence

Explicit emotional valence of thought (negative, positive) could be attributed to only 9.4% (N = 78) of responses. Other responses did not express explicit valence, were interpreted as neutral ('*food*', '*Packaging some parcels'*), and thus excluded from this comparison. Negative statements (67.9%; N =53 *'About work. I have stressful deadlines today.'*) were twice as likely as positive statements (32.1%; N=25; '*"Yes!!!!!" - I always wake up like this.'*); $p < 0.001$, $z = 3.06$, 95% CI = [56.4%, 78.1%]. Statements of a negative valence most often referred to feelings of physical discomfort (*'can't breathe'*). Positive statements varied and referred to feelings of gratitude (*'Thank god it's Saturday'*), or general observations ('*That I had a good night's sleep', 'I'm (sic) so happy').*

3.3.1.4. Dimension 4: Sentence formulation

More (72.3%; N=586) penumbral thoughts were formulated as statements than as questions (27.7%; N = 225); [p < 0.001, z = 12.64, 95% CI = [69.0%, 75.3%]. Interestingly, the observed frequency of questions in this sample (N = 225, 27.7%) was significantly higher than the expected frequency based on analyses of everyday speech (5%)[23] [p < 0.001, z = 29.64, 95% CI = [24.7%, 31.0%]]. Common formulations include *'What are the kids doing?', 'Did I oversleep?'*. Unsurprisingly this code frequently co-occurs with establishing time or day '*What time is it?'*; c-coefficient = 0.442).

3.4. Consistency across demographics and weekday

Next, we examined the consistency in thought context across person characteristics and the samples for each day of the week. Controlling for multiple comparisons with a Bonferroni correction at a p-value threshold of 0.004, we found no differences were observed between any person characteristics or weekday across any of the dimensions (across age groups: (temporal orientation: [χ2 (2, *N* = 250) = 1.60, *p* = 0.449]; protagonist: [χ2 (2, *N* = 716) = 5.13, *p* = 0.077]; valence: [χ2 (2, *N* = 78) = 5.64, *p* = 0.060]; sentence formulation [χ2 (2, *N* = 809) = 5.27, *p* = 0.072]); between genders: (temporal orientation: [X^2 (1, *N* = 248) = 0.83, *p* = 0.361]; protagonist [X^2 (1, *N* = 712) = 0.04, *p* = 0.835]; valence:[X^2 (1, *N* = 78) = 0.50, *p* = 0.478]; sentence formulation [X^2 (1, *N* = 806) = 0.29, *p* = 0.588)]); across weekdays: (temporal orientation: [χ2(6, N = 811)= 8.165 , p = 0.226]; protagonist:[χ2(6, N = 811)= 4.139, p = 0.658]; sentence formulation: [χ2(6, N = 811)= 14.609, p = 0.024])). We conclude that there are high levels of consistency in thought context.

3.5. Reflection responses

Responses to the rating items are summarised in Figure 3.

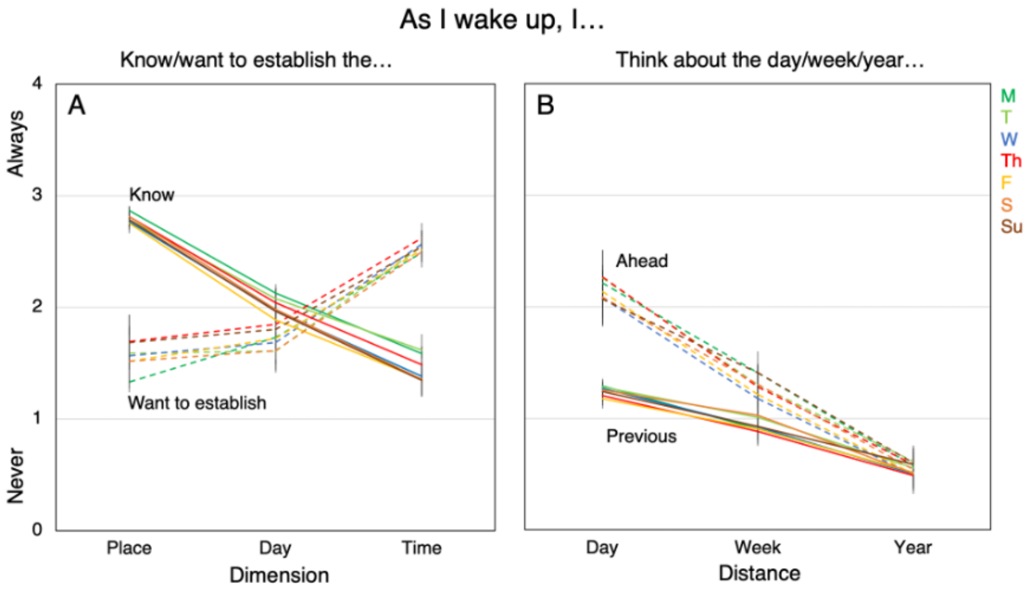

Figure 3: How often participants (**A**) know or want to establish the spatial (place) or two temporal (day and time) dimensions and (**B**) have thoughts about the week, day, or year ahead or behind, across seven independent samples (one for each weekday), when they first wake up. Error bars display 95% confidence intervals.

3.5.1. Knowing and establishing information

A 2x3 repeated measures ANOVA was performed of prior knowledge (know versus want to establish) by dimension (place, day, time), with knowing place (M = 2.80, SE = 0.02, 95% CI = [2.77, 2.83]), knowing day (M = 2.01 , SE = 0.02, 95% CI = [1.96, 2.06]), knowing time (M = 1.45, SE = 0.03, 95% CI = [1.39, 1.51]), wanting to establish place (M = 1.56, SE = 0.05, 95% CI = [1.47, 1.65]), wanting to establish day (M = 1.71, SE = 0.04, 95% CI = [1.64, 1.78]), and wanting to establish time (M = 2.54, SE = 0.03, 95% CI = [2.49, 2.59]). We observed a main effect of prior knowledge [$F(1, 821) = 19.90$, $p < 0.001$, η^2_p = 0.024, 95% CI = [0.007, 0.048]], and dimension [$F(2, 1642) = 86.60$, $p < 0.001$, η^2_p = 0.095, 95% CI = [0.070, 0.122]]. We also observe a significant interaction between dimension and knowledge [$F(2, 1642) = 985.90$, $p < 0.001$, η^2_p = 0.546, 95% CI = [0.516, 0.582]]. Post-hoc comparisons with a Bonferroni correction showed the interaction effect was driven by stark differences between spatial and temporal dimension in terms of prior knowledge and interest in establishing knowledge. There is a need for establishing the time, and a clear lack of knowing the time at the point of waking [pairwise comparison for establishing and knowing time: $t = 27.01$, $p < 0.001$, Cohen's $d = 1.385$, 95% CI = [1.277, 1.492].

However, there is a strong existing knowledge of place and a weaker inclination towards establishing it [$t = -24.6$, $p < 0.001$, Cohen's $d = -1.277$, 95% CI = [-1.375, -1.078]]. Lastly, there is a smaller gap between knowing and wanting to establish the day [$t = -6.91$, $p < 0.001$, Cohen's $d = -0.339$, 95% CI = [-0.476, -0.202]]. The general variation of time in an individual's waking up and the relative stability in the place help to contextualise these findings. See Supplementary Materials 4 for all pairwise comparisons.

To review the heterogeneity of this pattern across weekday, we ran a 2x3x7 mixed design ANOVA of repeated measures orientation of prior knowledge (knowing versus wanting to establish), and dimension of thought (place, day, time) and independent measure of weekday (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday). There was a significant main effect of dimension [$F(2,1628) = 6.59$, $p = 0.001$, $\eta^2_p = 0.008$, 95% CI = [0.001, 0.018]] but no significant main effect of prior knowledge [$F(1, 814) = 0.145$, $p = 0.703$, $\eta^2_p = 0.000$, 95% CI = [0.000, 0.006]]. Importantly, there was no significant main effect of weekday [$F(7,814) = 1.23$, $p = 0.285$, $\eta^2_p = 0.010$, 95% CI = [0.000, 0.019]] . There were also no significant interaction effects with weekday [dimension x weekday: $F(14, 1628) = 1.04$, $p = 0.409$, $\eta^2_p = 0.009$, 95% CI =[0.000, 0.010], prior knowledge x weekday: $F(7, 814) = 1.70$, $p = 0.105$, $\eta^2_p = 0.014$, 95% CI = [0.000, 0.026], dimension x prior knowledge x weekday: $F(14, 1628) = 0.437$, $p = 0.963$, $\eta^2_p = 0.004$, 95% CI = [0.000, 7.38e-4]]. This demonstrates that prior knowledge and dimension are consistent across weekdays (see Figure 3A).

3.5.2. Temporal orientation

A 2x3 repeated measures ANOVA of temporal orientation (future versus past) and temporal distance (day, week, year) [day ahead: $M = 2.16$, $SE = 0.03$, 95% CI = [2.11, 2.21], week ahead: $M = 1.30$, $SE = 0.23$, 95% CI = [1.25, 1.35], year ahead: M =0.56 , SE = 0.02, 95% CI =[0.51, 0.61], day before: M = 1.25, SE = 0.03, 95% CI = [1.20, 1.30], week before: M = 0.94, SE =0.02 , 95% CI = [0.94, 0.94], year before: M = 0.56 , SE = 0.02, 95% CI = [0.51, 0.61]] showed a significant main effect of temporal distance [F(2, 1640) = 1632, p < 0.001, η^2_p = 0.666, 95% CI = [0.643, 0.689]], a significant main effect of temporal orientation [F(1,820) = 447, p < 0.001, η^2_p = 0.353, 95% CI = [0.304, 0.399]] and a significant interaction effect for temporal distance and temporal orientation [F(2, 1640) = 391, p < 0.001; η^2_p = 0.306, 95% CI = [0.270, 0.339]]. A follow up analysis, using post-hoc comparisons using a Bonferroni correction revealed that the interaction was driven by an increased focus on the day ahead (relative to the day behind), with smaller differences between week ahead and week behind [t = 12.65, p = < 0.001, Cohen's d = 0.494, 95% CI = [0.356, 0.633]], and no differences between the year ahead and year behind [t = 1.69, p = 0.536, Cohen's d = -0.055, 95% CI = [-0.191, 0.081]].

Interestingly, these results also provide some insight into the mental representation of temporal distance and orientation. For example, post-hoc comparisons demonstrate no significant difference in the amount of time thought about the day before and week ahead [t = -1.40, p = 0.727, Cohen's d = -0.066, 95% CI = [-0.163, -0.030]]. This suggests that these two concepts may be psychologically similar, despite being chronologically very different (one day versus seven days). See Supplementary Materials 5 for details.

To analyse the heterogeneity of this pattern across the days of the week, we ran a 2x3x7 mixed measures ANOVA, of repeated measures orientation of thought (future versus past), and temporal distance of thought (day, week, year) and independent measure of weekday (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday). Results replicate a significant main effect of temporal distance [F(2, 1626) = 129.92, p < 0.001, η^2_p = 0.138, 95% CI = [0.108, 0.168]], a significant main effect of temporal orientation [F(1, 813) = 15.55, p < 0.001, η^2_p = 0.019, 95% CI = [0.005, 0.041]], and a significant interaction effect between temporal orientation and temporal distance [F(2, 1626) = 15.31, p < 0.001; η^2_p = 0.018, 95% CI = [0.007, 0.033]], but show no significant effect of weekday [F(7, 813) = 0 .98, p = 0.441, η^2_p = 0.008, 95% CI

=[0.00, 0.015]], and no significant interaction effects with weekday [temporal distance and weekday: $F(14, 1626) = 0.985$, $p = 0.466$, $\eta^2_p = 0.008$, 95% CI =[0.00, 0.016]]; temporal orientation x weekday: $F(7, 813) = 1.79$, $p = 0.085$, $\eta^2_p = 0.015$, 95% CI =[0.00, 0.023] ; temporal distance x temporal orientation x weekday: $F(14, 1626) = 1.473$, $p = 0.113$, $\eta^2_p = 0.013$, 95% CI =[0.00, 0.016]]. In sum, we demonstrate a high level of consistency in temporal orientation and distance of penumbral thoughts across the seven weekdays (see Figure 3B).

4. Discussion

In this paper we sought to understand penumbral thoughts—the contents of consciousness at the boundary between sleep and wakefulness. The combination of qualitative and quantitative data reveals a cohesive picture of thought content across age groups, genders, and weekdays. The homogeneity of responses across a broad participant sample suggests that certain cognitive priorities may be characteristic of regaining consciousness. First, we observe a much higher incidence of questions in reports of penumbral thoughts (27%) than expected based on language use elsewhere (5%) [30]. The apparent overrepresentation of questions suggests an orientation towards information seeking. Second, we identify the principal themes of penumbral thoughts—a mental or physical check-in, locating oneself in time, and previewing tasks for the day ahead. Third, we find that temporal location is less well known than spatial location upon waking, and that resolving time and day is a priority.

How do penumbral thoughts compare to other wakeful thoughts? There are some points of contact and some points of departure. Compared with previous studies, we see broadly similar patterns for affective valence [17,20], self-orientation [17,20,31–33], and temporal direction (past vs. future) [17,18]. On the other hand, penumbral thoughts seem to be especially focused on the short-term future, particularly the day ahead. Whereas D'Argembeau, Renaud & van der Linden found that only about 1 in 3 future-oriented thoughts pertain to the same day [18], we find that nearly all penumbral thoughts concern this timeframe. We also find that time is often the subject of penumbral thoughts, with 1 in 5 participants trying to establish the time as they wake up.

Indeed, the dominance of a small number of themes among penumbral thoughts—internal state, orientation in time, tasks for the day ahead—suggest that the first moments of wakefulness may be especially convergent. Dreams are highly diverse across individuals [15,16]. Wakeful thoughts are highly diverse across individuals [34–39]. In comparison, penumbral thoughts appear to be much more restricted.

As well as illuminating the nature of penumbral thoughts, our findings contribute to a growing psychological literature on the influence of the weekly cycle. It is well established that mood changes through the weekly cycle, both at the level of mental representations [23] and at the level of reported experience [24,40]. What is less clear is how these two levels may be related. Early retrieval of the day of the week suggests a path by which stereotypical weekday associations could set the tone for the rest of the day. At the same time, the uniformity of retrieval over the cycle suggests that differential associations for each day will land with similar force.

We note several possible limitations of our study. First, data collection took place during the COVID-19 lockdown period in the UK in November 2020. Given that some people reported difficulties keeping track of time during COVID-19 lockdowns [41], it is possible that our sample captures an unusual level of temporal disorientation. However, if lockdown was dominating participants' thoughts, we might expect it to be mentioned in their responses. In fact, such mentions were rare (two mention lockdown, two mention COVID-19). Nonetheless, we are aware that the government restrictions could have homogenised the set of experiences across individuals. Generalisability across data collection conditions could be estimated by repeating the study when lockdown restrictions are lifted.

A second limitation is that penumbral thoughts were solicited later in the day through recollection rather than immediately after they occurred. The delay between occurrence and reporting places a considerable burden on recall, with risk of introducing noise into the data. Importantly, the validity of such a method has been well-reported through the use of the day reconstruction method (DRM) [42] and the use of the present data collection method is widespread (e.g., [43–46]). A well-known limitation of the DRM is that delay can hinder recall performance [47]. This may apply more so when individuals rely on logical deductions or perhaps when sleep inertia applies, as could be the case in this study. Future studies could complement this methodology by adapting the sleep diary method to capture penumbral thoughts soon after they arise [48]. Such in-the-moment solicitation could then simultaneously serve to validate the use of DRM for penumbral thought elicitation. We situate this existing research as a first exploration of penumbral thoughts, laying theoretical groundwork for exciting future studies utilising a variety of methods.

Further, as specific question phrasing affects content of dream reports [49], another opportunity for future research is to elicit responses in early waking with different questions. For example, one could ask specifically about emotions, thoughts, and perception at the point of waking. Similarly, within-subject data on penumbral thoughts and daytime thoughts could be collected, further elucidating the differences between states but within an individual (and their specific context).

Future research could also integrate these self-reported findings with measures of neural activity to further characterise the relationship between the penumbral thoughts experienced and the neural correlates of these thoughts, especially in light of established patterns of activation within this sleep to wakefulness state transition [6]. Another interesting avenue for future research would be to examine penumbral thoughts when regaining consciousness in other situations, such as emerging from anaesthesia [50,51]. Such comparisons would allow us to test whether penumbral thoughts depend on the conditions in which consciousness was lost.

It is also important to note that many of the shared orientations and propensity towards the self in wakefulness thought are known to be affected by shared cultural cognitions (i.e., [52]) and particularly a culturally rooted understanding of self versus others [53]. An interesting future research pursuit would be to investigate the extent to which this applies to penumbral thoughts too.

For now, we offer a first insight into what people think about when they wake up. Across seven independent samples, we find that individuals are most likely to check in on their somatic or psychological state, focus on temporal orientation, and preview waking actions. We conclude that these themes reflect cognitive priorities as waking consciousness reboots.

5. Data availability statement

The datasets generated and/or analysed during the current study are available in the OSF repository, https://osf.io/ v3azp/.

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7. Author contributions

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Paper 2: Weakened weekdays: Lockdown disrupts the weekly cycle of risk tolerance

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Paper 2: In context

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This second paper takes another angle on understanding the day of the week effect through the lens of larger structural effects. This work examines a pre-established trait that fluctuates over the course of the week, namely risk, at different points of the COVID-19 lockdowns. The importance of the lockdowns for this study is that it provides a natural experiment to see what happens to the day of the week effect when the day itself ceases to have the same meaning and associations. As many recall, days blurred together during the lockdowns as the activities and behaviours that made each day distinct were removed. This allowed for an investigation to what extent the days of the week associations were needed for the day of the week effect.

The primary finding of this paper is the importance of meaningful day of the week associations for a day of the week effect. Study 1, which took place during an early lockdown, found that only those that reported a strong sense of the weekday showed day of the week effects. However, Study 2 showed that these associations themselves are not enough for the day of the week effect to hold in the same way—if the understanding of what each day means has eroded (such as occurs during repeated lockdowns), having a sense of the day of the week is not enough.

In sum, day of the week effects are something that cannot be attributed solely to individual cognition—rather, it seems that they take strongly from the structured activities in the world around us. Therefore, the temporal driver of heterogeneity acts in broad strokes, affecting everyone in stereotyped ways through the days of the week, bolstered via the structure of society. This helps further disentangle individual relationship to the day of the week effect.

1. Abstract

Risk tolerance decreases from Monday to Thursday and increases on Friday. Antecedents of this weekly risk cycle are difficult to investigate experimentally as manipulating the seven-day cycle is impractical. Here we used temporal disorientation during the UK COVID-19 lockdown to conduct a natural experiment. In two studies, we measured responses to risk in participants with either a strong or weak sense of weekday, after either a short or long period of disruption to their weekly routine by lockdown. In Study 1 (N = 864), the weekly risk cycle was consistent in risk attitude measures specifically to participants who reported a strong sense of weekday. In Study 2 (N = 829), the weekly risk cycle was abolished, even for participants who retained a strong sense of weekday. We propose that two factors sustain the weekly risk cycle. If the sense of weekday is lacking, then weekday will have little effect because the current day is not salient. If weekday associations decay, then weekday will have little effect because the current day is not meaningful. The weekly risk cycle is strong and consistent when (i) sense of weekday is robust and (ii) weekday associations are maintained.

2. Introduction

Does the day on which a decision is made affect the outcome of the decision? On its face, it seems unlikely. The day of the week is rarely a factor in decision making. However, weekdays have distinct profiles at the level of mental representation[1,2], are associated with different routines and activities[3], and can arouse contrasting emotional states[4–6].

Weekly fluctuations have been well documented in a variety of settings. Examples range from traffic flow[7] and energy consumption[8] to medical[9–11], economic[12], and political decisions[13]. For example, one study suggests that opting for a surgery later in the week can double the risk of complications[9]. Another study shows that the day on which national votes are held could determine their outcome[13]. As counterintuitive as it may seem, our adherence to the weekly cycle has unintended consequences in all sectors of society.

Why do weekly fluctuations in decisions outcomes occur, and why are they so widespread? At a higher level, insights from personality psychology can shed light on a speculative mechanism. Past work has shown that individuals behave in different ways, especially in manifestation of different personality traits, in different settings[14,15]. As such, each day of the week can be conceptualised as a different stereotyped ‘setting’, wherein the norms and expectations (i.e., one attends a pub in the UK on a Friday or Saturday at more than 4 times the rate as on a Monday[16]) dynamically shape the manifestations of different traits.

One possible explanation is that the weekly cycle affects a foundational cognitive process that feeds into thinking and behaviour more generally. We have previously proposed risk tolerance as a candidate process[13]. In a repeated-measures implementation of the Balloon Analogue Risk Task (BART[17]) that was counterbalanced for order effects, risk tolerance decreased from Monday to Thursday then increased on Friday. This same distinctive pattern was observed in UK polling data for high-stakes political decisions[13].

One of the difficulties in establishing a causal connection between the weekly cycle and a pattern of behaviour is the unrelenting nature of the cycle itself. From an experimental point of view, it would be informative to remove the weekly cycle and measure any resulting change in the behaviour of interest. For example, if the behavioural pattern were to disappear after the weekly cycle was suspended, that would suggest a causal role for the weekly cycle in maintaining the behaviour.

In practice, of course, we cannot suspend the weekly cycle. Instead, researchers have relied on minor perturbations to the weekly cycle, such as phase offsets caused by long weekends[1] or differences in cultural conventions[18].

The COVID-19 pandemic presented a unique opportunity to study a major disruption to the weekly cycle. Although the imposed lockdowns did not strictly suspend the weekly cycle, they loosened its grip on large parts of the population by placing millions of people on furlough and requiring others to stay at home. Many whose routines were disrupted reported losing track of what day it was or complained that all days began to feel the same—a phenomenon known as *Blursday* in the media[19].

In Study 1, we used this unique circumstance to examine the connection between reported salience of the weekly cycle (perception) and weekly fluctuations in risk tolerance (behaviour). Specifically, we compared risk measures for participants who reported a normal or strong sense of weekday (Normal/Strong SOW) and participants who reported a weak sense of weekday (Weak SOW). We predicted that the Normal/Strong group would show the same weekly risk cycle that we have seen elsewhere, with risk tolerance declining from Monday to Thursday then rebounding on Friday. However, we also predicted that this pattern would be attenuated in the Weak group, resulting in a flatter function for that group specifically. To explore the generality of these effects and their relation to different aspects of risk, we gathered from each participant several standard measures of risk that have been developed for different purposes. Regularities between these different measures should give us more confidence in the overall pattern and its scope.

The first study was conducted in May 2020, four weeks into the first UK lockdown since World War II. At this stage, disruption to weekly routines was considerable and widespread. Working from home had increased to 35.9%[20] and at its peak 29% of workers were furloughed[21]. In view of this disruption, it seemed likely that those affected would report a weaker sense of the weekday than they had before (Weak SOW), while people who were unaffected would report a sense of the weekday that was just as strong as normal (Normal/Strong SOW). Our main interest was whether a difference in SOW would impact the weekly risk cycle. Based on previous findings, we expected risk scores in the Strong SOW group to exhibit the following features: (i) systematic change through the week, rather than random fluctuation, (ii) decreasing, rather than increasing, risk tolerance from the start of the week, and (iii) inflection point on Thursday, such that risk tolerance on Friday is higher. Observing this very specific pattern in different risk measures should increase our confidence in the effect. If the weekly risk cycle depends on a clear idea of what day it is, then this pattern should be reduced or eliminated in the Weak SOW group, in a manner that is consistent across risk measures. We had no specific predictions concerning the weekend days but included them throughout for completeness.

The cycles we live by are laden with associations: Night is associated as darker than day, winter as colder than summer, Friday as preferable to Monday[1,22]. Yet the origins of these associations are very different. Diurnal and seasonal associations follow the clockwork of the solar system and are written into our biological inheritance[23,24].

In Study 2, we again examined the weekly risk cycle, this time during the second UK lockdown in November 2020. The design was similar to Study 1, using the same risk measures and the same comparison of Normal/Strong SOW versus Weak SOW groups. The most important difference was that Study 1 followed a period of stability in the weekly cycle (the decades preceding COVID-19 restrictions), during which we would expect normal weekday associations to have been continually reinforced. In contrast, Study 2 followed a period of severe disruption (the months of COVID-19 restrictions), during which we would expect normal weekday associations to be reinforced much less.

As with Study 1, we expected the weekly risk cycle to be absent in the Weak SOW group. Our main interest was in the Normal/Strong SOW group. If weekday associations are sustained via social structure, those associations should dissipate over prolonged disruption to those structures. In that situation, knowing what day it is should make no difference. A strong sense of weekday is meaningless if the weekdays have lost their meaning. It follows that a weekly risk cycle that is based on weekday associations should also dissipate, even in the Normal/Strong SOW group.

If normal social structure is not required to sustain weekday associations, or the weekly risk cycle does not depend on weekday associations, then the weekly risk cycle in the Normal/Strong SOW group should be as strong as it was in Study 1.

3. Methods

3.1. Materials and design (Study 1 & 2)

Each participant completed four risk assessments, reported on their sense of weekday, and provided answers to basic demographic questions. Specifically, both studies used four different risk assessments capturing different aspects of risk tolerance[25] that have been associated with different real-world behaviours: the Domain-Specific Risk Task (DOSPERT) questionnaire[26]; the German socioeconomic panel self-reported question (SOEP[27]); the incentive-compatible multiple lotteries gambling task (BEG[28,29]); and the performance-incentivised Balloon Analogue Risk Task (BART[17]). The BART and BEG are performance-incentivised tasks where participants had random chances of receiving the task pay-out in addition to their base pay. This diversity of risk measurements covers both actual risk-taking behaviour (BART, BEG) and general risk attitude (DOSPERT, SOEP). We believe that this spread of different risk measurements allows us to paint a more complete picture of an individual's risk attitude.

DOSPERT

Risk-taking has been shown to vary by domain[30,31]. The DOSPERT questionnaire asks participants to self-report the likelihood that they would participate in a certain risky activity (Likert scale from 1 to 7), with the activities purposefully spanning different domains: ethics, recreational, health & safety, social, and financial decisions. The DOSPERT subscales have demonstrated real-world validity in these separable domains (e.g.[32]). To arrive at a collective risk score as well as the five domain-specific risk scores, the average across the respective responses is calculated.

SOEP

The SOEP, originating from the German Socio-Economic Panel longitudinal study, asks participants to self-report their willingness to take risks using a 0-10 Likert scale[27]. Participants in our study were presented with both a general question, asking directly how prepared the participant was to take risks in general, as well as five specific questions duplicating the general wording, but asking regarding health, financial, career, driving, and leisure and sports risks. For its simplicity, the SOEP is used in many panel cohorts and has shown to be predictive of various behaviours[33,34].

BEG

The BEG is a multiple lotteries task, wherein participants select one gamble between six options[28,29]. Each gamble has two outcomes both with a 50% probability of occurring. Importantly, the expected value of each gamble increases but also presents a larger difference between the two outcomes (ranging from a certain pay-out of £28, to a gamble with a 50/50 chance of paying out £2 or £70). There was also an option presented to opt out and not participate in the gamble at all. The BEG is a common behavioural measure developed to assess risk preferences, and their applications to decision making and risk taking [28,29,35,36]. Across the studies, the participants had a 1 in 100 chance to be paid the outcome of their lottery choice.

BART

The BART measures risk taking through a virtual balloon-pumping task[17]. Participants are presented with a series of 20 balloons that they can inflate incrementally through clicking. The value of the balloon increases by a set amount (£0.01) per pump. However, each balloon will pop at a certain volume (based on a probability distribution unknown to the participants), bringing its value to zero. As such, a participant must balance increasing their pay-out from each balloon with the increasing risk of the balloon popping and losing the money for this particular balloon. For each participant, the *adjusted BART score* is calculated, as the average number of pumps for balloons that did not pop. The BART is a task developed in health psychology and shows to be most predictive of health risk behaviours such as smoking (e.g.[37]) or drinking (e.g.[38]). For the purpose of this study, the task was adapted for online use. For scalability, we also used a level of abstraction with respect to the stakes: rather than a direct pay-out of winnings, the participants had a 1 in 20 chance to be paid the winnings from the task. Based on the participants performance it was possible to earn a total bonus of up to GBP 81.80 across the two performance-incentivised tasks. While these tasks are designed to be incentive-compatible, we acknowledge that payment of tasks may not be enough to ensure true incentive compatibility[39–43].

Sense of weekday

In order to determine whether risk fluctuation may depend on subjective experiences of time, we separated participants by their self-reported *sense of weekday* (SOW). Each participant responded to the question “During lockdown, my sense of which day of the week we are on is...?” on a scale of much weaker than usual (1) weaker than usual (2) the same as usual (3) stronger than usual (4) much stronger than usual (5) by means of a manipulation check as to whether their experience of time had or had not shifted.

Demographic questions

Participants also reported on their age, gender, and employment.

3.2. Study 1

3.2.1. Participants and procedure

864 paid participants were recruited via Prolific Academic (www.prolific.co[44]) across 14 days from May 11 to May 24, 2020 (n = 122-128 per weekday; mean age = 32.9 years, age range = 18-77; 67.8% female; see Supplementary Materials Table A for a demographic breakdown by weekday). For their participation, the participants received a fixed payment of GBP 2.00 (Study 1) and GBP 3.00 (Study 2). Moreover, participants had the chance to be paid an additional bonus of up to GBP 81.80 based on two performance-incentivised tasks. Participants provided informed consent in line with the University Research Ethics Committee requirements (ethics approval number 07564) and were compensated in line with Prolific’s wage guidelines.

3.3. Study 2

3.3.1. Participants and procedure

829 paid participants were recruited via Prolific Academic across 14 consecutive days during a UK government lockdown between 16 November and 29 November 2020 (117-121 participants per day of week; mean age = 32.7 years, age range = 18-75; 71.9% female; see Supplementary Materials F for a detailed breakdown of participant demographics). Participants provided informed consent in line with the LSE Research Ethics Committee requirements (ethics approval number 07564) and were compensated in line with Prolific’s wage guidelines.

The procedure, materials and data analysis of Study 2 were identical to Study 1, bar one adjustment.

Similar to Study 1, each participant responded to the question “During this lockdown, my sense of which day of the week we are on is...?” on a scale of much weaker than usual (1) weaker than usual (2) the same as usual (3) stronger than usual (4) much stronger than usual (5). This differs from the question in Study 1 with the addition of the word “this”, to make sure it is clear which lockdown was being referred to.

4. Data Analysis

Using a linear regression model, the primary dependent variable for our analysis was a composite risk score, calculated in a three-step process. First, scores for each of the above risk measures were calculated by participant, as per the respective standard procedure[17,26–29]. Then, all individual scores across each risk measurement (and each subscale for the DOSPERT and SOEP) were converted into Z-scores. Third, the Z-scores were averaged across the four risk measures for each participant to obtain a single composite risk score. The choice of this methodology for computing the composite score builds upon the equal weight, both computationally and theoretically, of each risk measurement.

Subsequent analyses divided participants into two groups by sense of weekday (SOW). Therefore, each analysis was conducted once for those with a Normal/Strong SOW and once for those with a Weak SOW.

As independent variables we used the day of the week (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday). We categorise the sense of the weekday by splitting it into two groups: weak (Much weaker (1) or weak (2)) and strong (normal (3), strong (4) or much stronger (5)).

We additionally control for gender and age effects in the model which have been shown to be important predictors of risk tolerance. In particular, men have been found to be more risk tolerant than women[45–48] and age to be inversely related to risk tolerance[49–51]. In case of any imbalances in the sample, incidental effects of age and gender may appear and can be accounted for.

To check for consistency across the different risk measures, we repeat this analysis for each risk measure independently and report these findings in the Supplementary Materials.

5. Results

5.1. Study 1

Firstly, we note that there were no demographic differences between participants who self-reported a weak or strong SOW across the seven weekdays (see Supplementary Materials Table A). We note that we did not use weighting in the analysis to account for demographic variations.

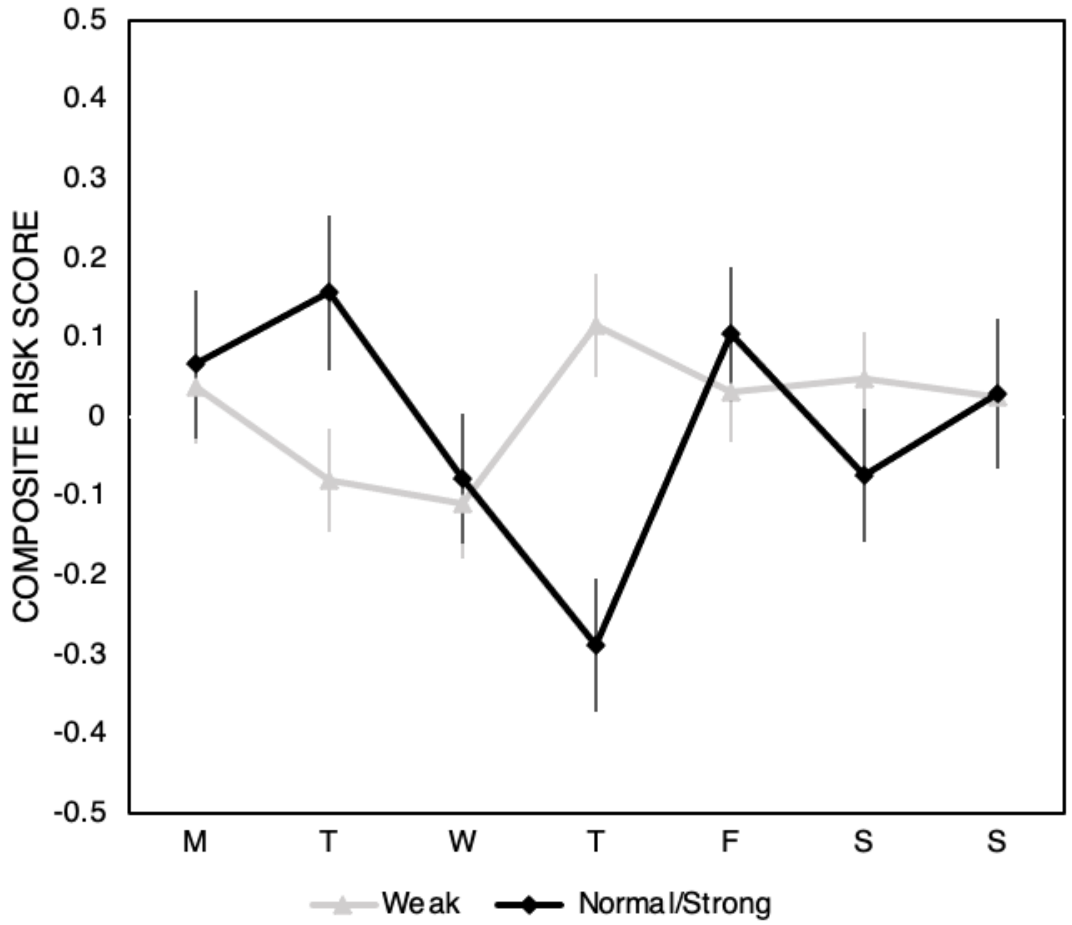

Figure 1: Composite risk score separated by participants with a Strong vs Weak sense of weekday plotted across the days of the week during the first lockdown. Error bars represent +/- SE.

Figure 1 shows the composite risk score by weekday separately for participants who report a strong SOW and those who report a weak SOW. Table 1 shows the associated values.

Sense	Day of the week	Mean	Standard Error	95% CI
Strong/Normal	Monday	0.066	0.093	[-0.116, 0.248]
	Tuesday	0.157	0.098	[-0.034, 0.349]

	Wednesday	-0.077	0.082	[-0.239, 0.084]
	Thursday	-0.288	0.084	[-0.454, -0.123]
	Friday	0.104	0.084	[-0.061, 0.269]
	Saturday	0.073	0.084	[-0.238, 0.092]
	Sunday	0.030	0.095	[-0.156, 0.216]
Weak	Monday	0.037	0.071	[-0.102, 0.176]
	Tuesday	-0.079	0.066	[-0.208, 0.049]
	Wednesday	-0.11	0.068	[-0.244, 0.023]
	Thursday	0.116	0.065	[-0.011, 0.243]
	Friday	0.032	0.063	[-0.092, 0.156]
	Saturday	0.048	0.059	[-0.067, 0.163]
	Sunday	0.260	0.063	[-0.097, 0.149]

Table 1: Composite risk score for Normal/Strong and Weak SOW across days of the week (mean, standard error, 95% CI).

A linear regression for those with a Normal/Strong SOW of weekday on composite risk score (adjusted $R^2 = 0.037$) reveals an effect of weekday (Effect size $\eta^2 = 0.058$, 95% CI [0.003, 0.103]) driven by Thursday – Monday (Estimate = -0.355, SE = 0.127, 95% CI [-0.604, -0.105] t = -2.802, p = 0.005). See Supplementary Materials Table B.1. for full reporting and Supplementary Material Table B.2. for post-hoc comparisons. Additionally, see and Supplementary Material Table B.3. – B.4. for full reporting and post-hoc comparisons of a model including additional demographic controls (age, gender).

A linear regression for those with a Weak SOW of weekday on composite risk score (adjusted $R^2 = 0.004$) reveals no main effect of weekday. See

Supplementary Materials Table B.5. for full reporting and Supplementary Material Table B.6. for post-hoc comparisons. Additionally, see and Supplementary Material Table B.7. – B.8. for full reporting and post-hoc comparisons of a model including additional demographic controls (age, gender).

The same analysis was performed for each risk measure separately, again dividing by sense of weekday into two groups (Normal/Strong SOW, Weak SOW). Analyses of both weekday only and of weekday, age, gender are both reported. See Supplementary Materials C for descriptives of each measure and Supplementary Materials Figure D and tables D.1. to D.32. for details of each independent analysis and Supplementary Materials Figure E and tables E.1. to E.8. for calculation of the composite risk score without the inclusion of BART. For the Normal/Strong SOW specifically, the Mon-Thursday dip was significant across both composite score variations (calculated with and without BART), as well as the SOEP and DOSPERT, but not the BEG or the BART.

5.2. Study 2

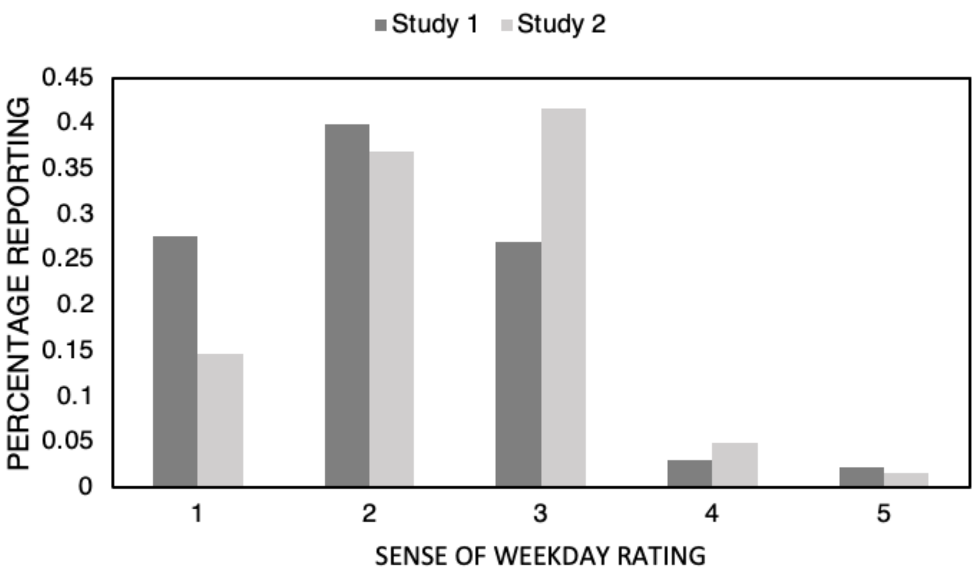

Figure 2: The distribution of participant scores for Study 1 and Study 2 for the question “How strong is your sense of weekday?” on a scale of 1 (much weaker) to 5 (much stronger).

Figure 2 shows the distribution of SOW for the two studies. To check whether the experience of the days of the week had shifted between the first and second lockdown, we compared Sense of Weekday (SOW) ratings obtained in Study 2 (lockdown 2) with those obtained in Study 1 (lockdown 1). An independent samples t-test ($t(1690) = -6.25$, $p < 0.001$; Cohen's $d = 0.332$) indicates that people reported a stronger sense of weekday on average in the second lockdown ($M = 2.420$, $SE = 0.0300$, Mode = 3) than in the first ($M = 2.123$, $SE = 0.032$, Mode = 2).

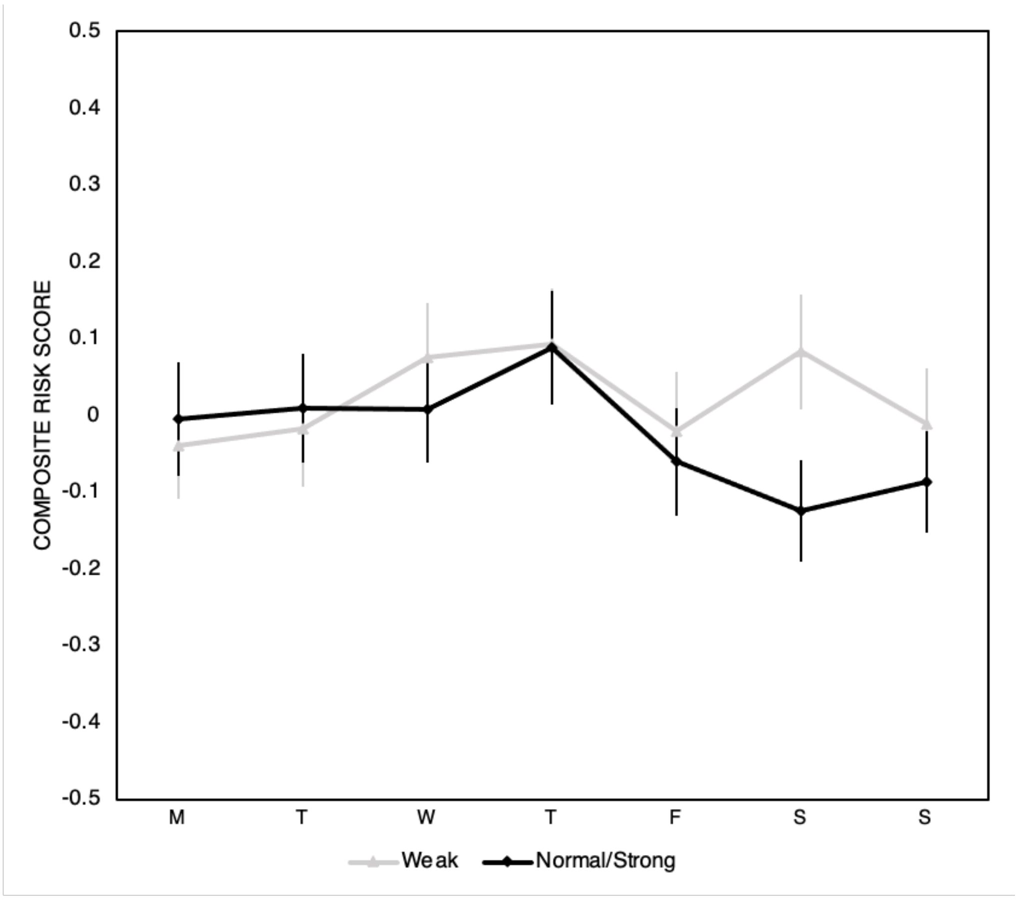

Figure 3: Composite risk score across weekdays separated by weak and strong sense of weekday. Error bars represent +/- SE.

Figure 3 shows the composite risk score separated by weekday for those who report a strong and those who report a weak SOW during the second lockdown. Table 2 shows the associated values.

Sense	Day of the week	Mean	Standard Error	95% CI
Strong/Normal	Monday	-0.004	0.074	[-0.149, 0.140]
	Tuesday	0.0103	0.071	[-0.130, 0.149]
	Wednesday	0.007	0.069	[-0.127, 0.142]
	Thursday	0.088	0.074	[-0.058, 0.234]
	Friday	-0.061	0.069	[-0.197, 0.076]
	Saturday	-0.125	0.066	[-0.255, 0.006]
	Sunday	-0.087	0.067	[-0.217, 0.044]
Weak	Monday	-0.039	0.068	[-0.173, 0.095]
	Tuesday	-0.018	0.073	[-0.161, 0.125]
	Wednesday	0.075	0.070	[-0.061, 0.212]
	Thursday	0.092	0.072	[-0.048, 0.233]
	Friday	-0.021	0.075	[-0.168, 0.127]
	Saturday	0.083	0.073	[-0.060, 0.225]
	Sunday	-0.011	0.071	[-0.150, 0.128]

Table 2: Composite risk score for Normal/Strong and Weak SOW across days of the week (mean, standard error, 95% CI).

A linear regression for those with a Normal/Strong SOW of weekday on composite risk score (adjusted R^2 = 6.884e-4) reveals no main effect of weekday. See Supplementary Materials Table G.1. for full reporting and Supplementary Material Table G.2. for post-hoc comparisons. Additionally, see and Supplementary Material Table G.3. – G.4. for full reporting and post-hoc comparisons of a model including additional demographic controls (age, gender).

A linear regression for those with a Weak SOW of weekday on composite risk score (adjusted R^2 = -0.005) reveals no main effect of weekday. See Supplementary Materials Table G.5. for full reporting and Supplementary Material Table G.6. for post-hoc comparisons. Additionally, see and Supplementary Material Table G.7. – G.8. for full reporting and post-hoc comparisons of a model including additional demographic controls (age, gender).

The analysis was repeated for each risk measure separately, again through separate analyses for those with Strong/Normal and Weak SOW (See Supplementary Material Figure H for descriptives, and Figure I and Tables I.1. to I.16 for details of analysis). As in Study 1, see Supplementary Material Figure J and tables J.1. to J.4. for comparison of the composite risk score as calculated with and without the inclusion of BART. Across all additional analyses, both for Normal/Strong and Weak SOW groups, there was no main effect of weekday.

6. Discussion

6.1. Study 1

This study makes a number of contributions. First and foremost, among those who reported a strong sense of weekday, we found a similar pattern of weekly fluctuations in risk tolerance to[13]. As with the original findings[13], risk tolerance began high in the beginning of the week, reached its lowest point on Thursday, and rebounded on Friday. The similarity of this pattern across studies is especially interesting given the differences between studies. The original study was conducted with a student sample in a laboratory setting, using a repeated measures design. The current study was conducted with a general population sample in an online setting, using a between-subjects design. Conservation of the basic pattern across these design changes suggests a high degree of generalisability.

Interestingly, the only measures that did not show the pattern is the BART and the BEG, the two tasks measuring actual risk taking (compared to self-reported, such as the DOSPERT and SOEP). At first sight, this may seem surprising, as the BART is the measure with which the pattern was originally observed. We explore further peculiarities of BART in the General Discussion (Section 6.3) that may have contributed to this finding. However, it is interesting to note that the effect of weekday fell cleanly along the split between tasks measuring actual risk taking and risk attitudes. We hypothesise that this discrepancy between the DOSPERT/SOEP and BART/BEG may be due in part to the relationships between the different types of measures and risk-taking behaviour: in a direct comparison, risk-taking questionnaires (in the present study, comparable to the SOEP and DOSPERT) have been shown to have a higher test-retest reliability and correlation with actual risk-taking behaviour than lottery-choice tasks (such as the BEG)[52]. The choice of risk task in experimental work has long been a point of interest[53], and we tentatively suggest that this difference in type of test may describe the present study's findings.

In another extension to previous work, we also collected data on weekend days. For the Strong SOW group, risk tolerance on Saturday and Sunday was similar to that on Monday, Tuesday and Friday, suggesting that the observed pattern is better characterised as a midweek dip than as peaks that bookend the working week. Given the human origins of the weekly cycle, we are inclined to attribute weekly fluctuations in risk tolerance to human causes, such as semantic or emotional associations with the days of the week. In the next study, we had the opportunity to examine the impact of COVID-19 restrictions over the longer term, when such associations may have atrophied.

6.2. Study 2

We found no evidence in Study 2 for the weekly cycle in risk tolerance seen in Study 1. Critically, the cycle was abolished even among people who retained a strong sense of weekday. We suggest that 30 weeks without normal reinforcement of weekday associations was enough to decouple mere knowledge of the current day from its usual ramifications.

6.3. General Discussion

In the current studies, we used the unique circumstance of the COVID-19 lockdown to examine connections between reported salience of the weekly cycle (perception) and weekly fluctuations in risk tolerance (behaviour). Our results corroborate the findings of previous studies: risk tolerance decreased from Monday to Thursday and increased on Friday. However, the current studies demonstrate this cycle using different measures of risk. They also identify conditions under which the weekly risk cycle emerges.

We begin by considering similarities between Study 1 and Study 2. In both studies, a portion of respondents reported that their sense of weekday was at least as strong as it had been before lockdown. Apparently, their sense of weekday was not perturbed by the onset (Study 1) or continuation (Study 2) of lockdown restrictions. There are at least two possible reasons for this resilience. The first appeals to situational factors[54]. For example, those reporting a strong sense of weekday might have continued their normal work pattern. The second appeals to dispositional factors. For example, the days of the week could be more salient to some people than to others. The latter suggests a more trait-like attribute, perhaps analogous to sense of direction. This analogy between sense of weekday and sense of direction seems potentially fruitful. A few studies have examined psychometric properties of sense of direction and identified clear personality correlates (e.g. [55]). Some aspects of previous findings suggest that sense of weekday could be amenable to similar analyses. For example, studies requiring participants to name the current day have shown broad distribution in performance[1,56]. As of yet however, no studies have taken an individual differences approach to the salience of the weekly cycle. One possible exception concerns studies of calendrical savants, who can rapidly report the weekday corresponding to a given date (e.g.[57]). Such individuals demonstrate that it is possible to be highly attuned to the days of the week. However, it is not clear whether this ability represents one extreme on a continuum of sensitivity or a qualitatively distinct skill.

We now turn to differences between Study 1 and Study 2. Even among participants who reported a strong sense of weekday, the weekly risk cycle was very different earlier during COVID-19 restrictions (Study 1) compared with later during the restrictions (Study 2). This finding shows that the weekly risk cycle is not reducible to sense of weekday and is dissociable from it. The absence of a weekly risk cycle in Weak SOW participants (Studies 1 & 2) suggests that a Strong SOW is *necessary* for the weekly risk cycle to occur. The absence of a weekly risk cycle in Strong SOW participants (Study 2 only) suggests that Strong SOW is not *sufficient*. Some other factor, present in Study 1 but not in Study 2, is also required for the weekly risk cycle to emerge. It is inevitable that the two studies differed in many ways that cannot be equated. For example, Study 1 was conducted in spring, whereas Study 2 was conducted in autumn; the participant samples contained different people. In view of such mismatches, we should be cautious in attributing divergent outcomes to any single cause. At the same time, part of the motivation behind this project was the temporal disorientation that people reported during COVID-19 restrictions, specifically concerning the days of the week[19,58,59]. Duration of disruption becomes key here. While participants in Study 1 had experienced only 4–5 weeks of disruption, participants in Study 2 had experienced 31–32 weeks of disruption. How might this factor be important? Our working hypothesis is that stereotypical weekday associations underpinning the weekly risk cycle require reinforcement. Normally, this reinforcement is supplied by the social environment—directly, as we adhere to weekly routines ourselves, and indirectly as we interact with others as they adhere to weekly routines. When this reinforcement is withdrawn (as during COVID-19 restrictions), weekday associations begin to decay suggesting a shift in what is understood as a 'normal' SOW, with association strength proportional to elapsed time. This is further supported by the larger proportion of individuals reporting a Normal/Strong SOW in Study 2, as we hypothesise the understanding of a 'normal' SOW shifted over the course of COVID-19 restrictions.

The upshot is that there are at least two ways in which the weekly risk cycle can fail. If sense of weekday is weak, then weekday will have little effect because the current day is not salient. This applies irrespective of weekday associations. If stereotypical weekday associations atrophy, then weekday will have little effect because the current day is not meaningful. This applies irrespective of sense of weekday. Figure 4 summarises our interpretation.

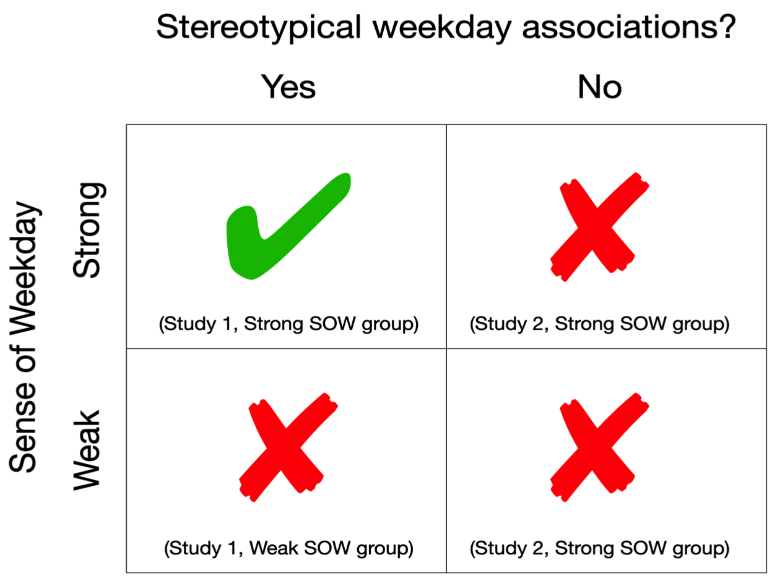

Figure 4: Factors affecting the weekly risk cycle. Rows refer to sense of weekday, which may be strong or weak. Columns refer to stereotypical weekday associations, which may or may not be maintained. Quadrants show the mapping of the current studies onto these factors. The weekly risk cycle occurs only when sense of weekday is strong and weekday associations are maintained (Top Left).

One further observation seems worth noting. In Study 2, there was no statistically significant effect of weekday in the Strong SOW group. In other words, risk scores were not statistically different from one day to the next. However, a separate question we can ask is: On which day of the week were risk scores most extreme? For the SOEP, the DOSPERT, and the BEG alike (but not the BART), the answer is Thursday. This observation is curious for two reasons. First, it seems improbable that the most extreme day should again be Thursday rather than some other day of the week. Second, for all three measures the deviation in Study 2 was in the opposite direction to the deviation in Study 1 (with Thursday being the most risk tolerant day rather than the most risk averse day). Again, the difference in Study 2 was not statistically significant.

A note on the different risk measures in this study. The first laboratory demonstration of a weekly risk cycle reported fluctuations in BART scores[13]. Our intention here was to use the same measure to examine the weekly risk cycle during lockdown. We also administered the DOSPERT, the SOEP, and the BEG to test whether the same weekly risk cycle was evident in other measures. As it turned out, the DOSPERT and the SOEP showed the weekly risk cycle. However, the BART and the BEG did not. How did we arrive at this puzzling outcome? The first noteworthy difference is that, by design, the DOSPERT and SOEP measure *risk attitudes*, while the BEG and the BART measure actual *risk taking* through use of tasks (gambles and balloon inflation, respectively).

Further, comparisons of BART designs provide some useful clues. [60,61] demonstrate that the sensitivity of the BART depends on reward structure. We made several changes to reward structure to accommodate online testing. For example, [13] involved a laboratory setting, larger rewards, and a more concrete representation of the stakes. In contrast, the current version involved an online setting, smaller rewards, and a more abstract representation of the stakes. We introduced these changes in an effort to make data collection more efficient. However, we believe that they may have blunted the sensitivity of the test. Separate analyses, unrelated to weekday effects, support this interpretation. For example, scores from the current implementation of the BART did not correlate with scores on other risk measures[47]. Nor did they detect well-established sex differences in risk taking[62]. Given these reservations, we recognise that there is a case for setting aside the current BART data: incorporating an insensitive measure into the combined risk score can only dilute the pattern of interest. We choose to include them here to avoid selective reporting, to reflect our uncertainty in the source of the discrepancy, and to underscore the insightfulness of [61] analysis. For the interested reader, we present combined risk scores that exclude the BART in Supplementary Materials. These alternative scores show the weekly risk cycle more emphatically (Study 1, Strong SOW), but otherwise support the same conclusions.

Despite the early stages of research in this area, there are already some clear predictions emerging from the work presented here. First, sense of weekday should reveal substantial individual differences, such that some people are more attuned to the weekly cycle than others. By analogy to sense of direction, we expect sense of weekday to be a trait-like attribute that generalises across different measures and is stable over time. Second, weekday associations should be malleable. This proposal could be tested by comparing weekday associations of people with unusual work patterns, for example, people who work weekends and take days off midweek (i.e., cross-sectional comparison). We expect that weekday associations in such groups will differ from stereotypical associations in systematic ways. Third, loss of weekday associations (or acquisition of new ones) should occur somewhere in a 4- to 30-week time window (the number of weeks between the two lockdown periods). A more precise time course could be established by studying transitions into or out of unusual weekly routines (i.e., longitudinal comparison as people retire, leave or enter a period of incarceration, start or leave work on an oil rig or cruise ship). Studying such transitions would also allow us to test directly for repulsion aftereffects when an entrained pattern ceases, namely whether suspension of an entrained weekly cycle, with its midweek dip in risk tolerance, might also induce a repulsion aftereffect, such that the midweek dip is temporarily reversed (i.e., a midweek boost in risk tolerance). Lastly, we believe there is scope to explore different stereotyped behavioural patterns associated with the day of the week beyond risk attitudes. Further explorations of a range of cognitive and individual traits fluctuating over days of the week could further add to this body of research.

For now, we show that the weekly cycle in risk tolerance generalises across several standard measures of risk. We identify two enabling conditions for the observed cycle: strong sense of weekday and stereotypical weekday associations. When both conditions were met, the weekly risk cycle was strong and consistent. Withdrawing either condition abolished the effect.

7. Competing interests

The authors declare no competing interests.

8. Author contributions

All authors developed the concept and designed the studies. MMG, RJ, and JGS funded the studies. BG conducted data collection and pre-processing for Study 1. VF conducted data collection and pre-processing for Study 2. VF conducted quantitative analysis for both studies. VF drafted the manuscript, with critical revisions from all authors. All authors approved the final version for submission.

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10. Data availability statement

The datasets generated and/or analysed during the current study are available in the OSF repository https://osf.io/h8rq9 .

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Paper 3: Does the day matter? No day of the week effect in an experiment on health information engagement

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Paper 3: In context

The third paper in this thesis shifts focus beyond the antecedents (paper 1) and contributing causes (paper 2) of the day of the week and focus to how the day of the week effect can have observable behavioural effects. Specifically, this paper looks within the framework of behavioural science, namely health information. The motivation for this paper is that, if the day of the week has a clear effect on engagement levels with health information, future information-based campaigns could build upon this information to reach individuals more effectively. This paper looks at if there is a day of the week effect on individual engagement with information on sedentary behaviour, measured through six different engagement metrics. Further, this paper adds a strong methodological contribution by randomly allocating individuals into participation on different days of the week to eliminate the confound of individuals self-sorting into days of the week to participate.

The main finding of this paper is the lack of the day of the week effect in engagement (along any of the six measurements). This study, with its strong methodology of randomly assigning individuals into participating on different days of the week, suggests that the day of the week effect is more nuanced in application than may have been previously thought. These findings of a null day of the week effect, along with the methodological innovation of random allocation, have important implications for behavioural science practitioners moving forward.

In sum, the day of the week effect is not found within engagement with health information engagement. While this adds a degree of liberty in research design (i.e., the day of the week effect is not always a strong confound), it also adds to the increased complexity of understanding and applying an understanding the day of the week effect.

Abstract

Does the day on which participants receive information matter? Correlational and cross-sectional research suggests that different days of the week can amplify different attitudes and beliefs, which may result in different choices. The present large pre-registered experiment is the first to experimentally test for different levels of engagement with health information. After screening 3,000 online participants, 2,138 respondents in the UK who did less than 150 minutes of exercise per week were randomly allocated into one of seven consecutive days of the week to participate in our study. We measured engagement with educational material relating to sedentary behaviour using cognitive and behavioural outcomes, and preferences around physical activity. While preference to engage in physical activity varied over the course of the week, there was no significant differences in levels of engagement with health information, as measured by cognitive outcomes such as performance on sorting and knowledge, and behavioural outcomes such as engagement with a link and amount of time spent engaging with stimuli.

1. Introduction

Days of the week are important markers of time, deeply engrained in human behaviour (Henkin, 2018). The notion of a preferred day of the week for messaging, broadly construed, is empirically supported and widely accepted within marketing and advertising (Bleier & Eisenbeiss, 2015; Heflin & Haygood, 1985; Huang et al., 2021; Spasojevic et al., 2015; Villanova et al., 2021). For instance, fine tuning the temporal element of advertising can improve consumer engagement (Bleier & Eisenbeiss, 2015; Heflin & Haygood, 1985; Huang et al., 2021; Spasojevic et al., 2015; Villanova et al., 2021). These results have important practical applications: an online search of non-academic platforms results in countless web resources guiding advertisers and social media users alike on when the best day of the week and time to post for maximum engagement is (Geyser, 2019; Glover, 2023; Oladipo, 2023); this extends to when is the best time to post studies on research sites (*When Are Prolific Participants Most Active?*, 2023; *When Is the Best Time to Send a Survey?*, n.d.). While findings vary, Tuesday has, for example, been proposed as the best day to post on Instagram (Geyser, 2019; Glover, 2023). However, these findings are, to the best of our knowledge, based on correlational evidence and base conclusions on number of 'hits' (whatever the metric given the message sender's aim) on different days and times.

Both advertising and behavioural science share a common aim to change behaviours. For instance, behavioural science messaging has been applied in a variety of domains, from encouraging healthier behaviours (Marteau et al., 2011) to promoting pro-environmental behaviours (Byerly et al., 2018). Yet, behavioural science has been slower to embrace the idea of testing when, if any, is the *right time* to message. Further, this has not been explored experimentally: the above understandings of when is the 'right' time are based around correlational evidence. For the purposes of this paper, the understanding of the 'right' time will centre around when it is most likely to capture the attention of the recipient and engaged with, rather than ignored. Further discussion of the concept of engagement can be found in the Methods section.

The under-explored concept of temporality within behavioural science is an opportunity for investigation. This concept has both theoretical and applied impacts for the field. Theoretically, understanding differential response rates to messaging would contribute to the ongoing 'heterogeneity revolution' (Bryan et al., 2021) within behavioural science by further informing how individuals differ systematically across days of the week. In a research setting, understanding these differences would impact how behavioural science research is conducted. Researchers would be compelled to take into consideration the day when undertaking research, whether through expressly focusing on (or excluding) a particular day from data collection or having to ensure an even distribution of responses across days of the week. In this setting, a misrepresentation of day of the week differences could erroneously lead to misattributions of association to experimental conditions. In applied settings, understanding temporal fluctuations of engagement with information could also serve to increase the effectiveness of messaging interventions.

The temporal dimension of behavioural science information communication has been rarely investigated. Many prominent studies centring around information dissemination for behaviour change do not typically report the time and day of the week when messaging was sent, as well as if and when the message was engaged with in the desired way, such as if itw as opened (Milkman et al., 2022; Park et al., 2015; Patel et al., 2023; Stockwell et al., 2012).

There is the possibility that the lack of consideration given to when information is sent is contributing to the high heterogeneity of participant responses, and thus of their reported effects (Bryan et al., 2021; Szaszi et al., 2022). The motivation for further investigation into timing for the field of behavioural science is clear: there is no way to *not* make a choice regarding timing if one is sharing information—the information will be sent at a certain time on a certain day, whether or not the senders have deliberately selected these parameters.

The day of the week structures much of how individuals spend their time (Kennedy-Moore et al., 1992). There is correlational evidence that different days of the week come with different mental representations (Ellis et al., 2015; Pecjak, 1970), different emotional states (Helliwell & Wang, 2014; Mishne & De Rijke, 2006; Stone et al., 2012; Tsai, 2019) and different attitudes (Fedrigo et al., 2023; Sanders & Jenkins, 2016). The behavioural and affective synchrony around the day of the week has been reported to create knock-on effects on decision making and behaviour across a variety of domains from energy consumption (Singh & Yassine, 2018), to economic choices (Gibbons & Hess, 1981), from medical decisions (Aylin et al., 2013; Brådvik & Berglund, 2003; Ellis et al., 2022), to political outcomes (Sanders & Jenkins, 2016).

Despite these reported differences in individual and large-scale behaviour related to different days of the week, the mechanisms of these effects are neither clear nor certain across different individuals and samples (Gnambs, 2021). To the best of our knowledge, all work within the field has been cross-sectional rather than experimental; thus, there have not been examinations explicitly into differences across days of the week Further, the effect itself has been brought into doubt, raising the question of unobservable characteristics causing participants to non-randomly sort into different days of the week when taking part in a study (Tumen & Zeydanli, 2014). This concern is only strengthened by some of the methods used to collect data in behavioural science: convenience sampling, which allow participants to take part in a study on a day or time that suits them; or secondary data analysis, which often obfuscates information about the day when the original data were solicitated or collected. As such, there is an opportunity to complement the current evidence with experimental methods to test for day of the week effects on how people respond to messages.

The present study is motivated by the intersection of day of the week effect and the lack of experimental studies on differences across days of the week in engagement with health information. Motivated by the suggestion that the day of the week could have tangible effects on individual behaviour and decision-making, this work aims to experimentally test whether and how the day of the week could impact an individual's engagement with information. By introducing randomization into the allocation of individuals into the seven days of the week, we seek to improve methodologically upon existing evidence, and to directly address the issue of "non-random sorting on unobservables" potentially impacting non-experimental studies (Tumen & Zeydanli, 2014). We aim to explore how the day of the week could potentially drive different levels of engagement with a message.

2. Methods

This study's design and analyses were pre-registered (https://osf.io/8uhs5/) and approved via University Ethics approval (number 144834).

2.1. Participant recruitment

Participants were recruited via Prolific in a two-step procedure to ensure random allocation to different days.

The first step of recruitment, hereafter referred to as the screener stage, involved a short survey to query individual interest in participating in a main survey (n = 3,000 participants) on July 21, 2023. Eligibility for this stage used

Prolific's inbuilt filters, limiting the survey to those who exercised under 150 minutes per week and were residing in the UK. Participants in this screener survey were informed that they would be invited to the main survey on one day of the coming week and asked to participate in the main survey on the day the invitation was received. After participants were provided with general information on the main survey, they were asked whether they would be interested in participating through a yes or no question. Participants were informed that compensation for this screener stage was not dependent on their response with respect to interest in the main survey. Median participation time was 42 seconds and participants were compensated in line with Prolific's wage guidelines. 97.37% (2,921 of 3,000 responses) confirmed interest in participation in the main survey.

All participants who expressed interest were asked to partake in the main survey. Using a between-subjects design, interested participants were randomly allocated into seven groups (numbered 1-7), to allocate the day of participation in the main survey. Participants were invited on one randomly allocated day to participate in the survey. If they did not participate on the day on which they were invited, they lost access to the survey and were not invited to participate on subsequent days.

The main survey was posted on seven consecutive days (Monday to Sunday) at the same time every day (6 AM) between July 24-30, 2023. When the survey was posted on the Prolific platform, participants received an email invitation to participate in the main survey. The survey was made unavailable at the same time every day (9:40 PM), regardless of whether all invited participants had taken the survey. Survey content remained identical in each posting and all participants provided informed consent. Through this process, out of 2,921 invited participants, 2,205 participants completed the survey (with a total of 2,138 participants passing attention checks). Participants were compensated in line with Prolific's wage requirements.

2.2. Materials and procedure

The context of our experiment is one of the most prevalent domains in behavioural science: health information, in this case to encourage physical activity and to discourage sedentary lifestyles (for a review, see (Williamson et al., 2020)). Currently, the recommendations for adults are at least 150 minutes of moderate-intensity physical activity a week (NHS, 2021). The health impacts of insufficient physical activity on individual health are well-documented, with increased risk of cardiovascular diseases, diabetes, cancer, and an increased risk of death (World Health Organization, 2022). Additionally, physical activity carries significant mental and physical benefits. Yet 1 in 4 adults globally do not meet the recommended levels (World Health Organization, 2022). This motivates the choice of the specific content of messaging in our study. The information utilized in this study is structured as a 'System 2 nudge', focusing on providing information and statistics to individuals (Sunstein, 2016).

2.2.1. Dependent variables: engagement

We utilized three different sets of dependent variables to measure participant engagement with information on physical activity.

Here, we measure engagement by looking at how our participants interface with different tasks and information sources. This measurement helps create a point-in-time estimate by using several quantifiable aspects of how the participant interfaces with a task to create a multi-faceted characterization of overall individual level of engagement. Firstly, we consider the amount of time spent on a task. As there is no requirement inherent in the activity to spend a certain amount of time on a survey, we consider a longer time spent on a task to suggest a deeper engagement with it. Secondly, we consider performance on tasks as a proxy for the effort the participant exerted on the task, as a higher score can be understood as a proxy for higher effort. Together, these tasks help build out a profile of the participant as they completed the tasks: Did they take their time, or rush through? Were the answers carefully considered, or randomly clicked through? Through measuring engagement across three different tasks as above, we are able to gain a deeper understanding into how an individual completed our tasks.

The first set was via presenting a link to the United Kingdom's National Health Service (NHS) page on sedentary behaviour. The webpage, designed for the general public, was informational with some suggestions on how to improve levels of physical fitness while outlining the issues that sedentary behaviour could pose for health. Participants were invited to click on the NHS link [https://www.nhs.uk/live-well/exercise/exercise-guidelines/why-sitting-too-much-is-bad-for-us/] with the following language:

"We would like to provide you with some information on sedentary behaviour that we believe may be helpful to you from the NHS. If you would like to learn more about NHS recommendations Click here*. This link will open in a separate window. Please return to the survey whenever you are ready."*

To ensure that we measured genuine engagement with the information, the note was added to ensure participants understood that clicking on the link was optional and would not affect their progress within the study. The survey recorded, but did not display to participants, a binary metric of whether the link was clicked and how long participants spent on this survey page.

The second set was through a sorting quiz. Participants were presented with 12 physical activities and asked to classify each as either gentle, moderate, or vigorous physical activity. Activities contained in this quiz were evenly divided between gentle, moderate, and vigorous physical exertion. Information contained in this quiz did not overlap with information displayed on the previous page's NHS link. Participants were informed that their performance on this quiz would not affect the compensation for the study. The survey recorded how long participants spent on this page but did not display a timer to participants. Once participants had completed the quiz and clicked to finalize their responses, they were able to see a 'scored' version of the quiz showing which ones and how many they answered correctly. They were not able to revise their responses at this stage.

The third set was through a knowledge quiz, similar in format to the previous form (sorting quiz). Participants were presented with 10 questions covering various aspects of physical activity and sedentary behaviour. As with the second form, participants were informed that their performance on this quiz would not affect their compensation for the overall survey. The survey recorded how long participants spent on this page but did not display a timer to participants. After completing the quiz and finalizing their responses, participants were able to see a ‘scored’ version of the quiz showing which ones and how many they answered correctly. They were not able to revise their responses at this stage.

2.2.2. Dependent variables: preferred day for physical activity

The last set of dependent variables focused around when participants would want to participate in two types of physical activity: a one-time charity walk, and a repeated fitness regimen (Couch-to-5k). The format and the phrasing of the questions were identical; however, they were repeated twice (first for the one-time charity walk, then for the repeated fitness regimen).

Participants first read a short description of the event and were asked what day of the week they would like to participate on, assuming no prior scheduling conflicts; and then what time of the day they would like to participate at (segmented into early morning, mid-morning, early afternoon, late afternoon, evening). For the one-time charity walk, the above questions corresponded to when they would like to participate in this one-time event. For the repeated fitness regimen, they were asked on what day and then what time of that day they would like to start this regimen.

The motivation behind capturing the preferred day of the week for participating in physical exercise (both one-time and repeated) was that individual engagement with health behaviours has been found to vary significantly with day of the week (Dai et al., 2014). For example, online searches relating to stopping smoking have been found to peak on Mondays (Ayers et al., 2014), at a volume larger than Tuesday to Sunday combined. As such, the view of Monday as a preferred day to engage in health-seeking behaviours would suggest that engagement in physical activity could be hypothesized to follow a similar pattern, peaking on Monday.

2.2.3. Control variables: busyness

To better understand, and control for, the day of the week dynamics within the sample, we also queried participants on how they would rate their busyness on each day of a typical week, looking at the last weeks. Participants scored their relative busyness on a Likert scale from “extremely calm” to “extremely busy”.

2.2.4. Exploratory analyses: other personality and cognitive measures

To further characterize the day of the week effect on other personality and cognitive measures, we added in three further measures. Firstly, we utilized the Ten Item Personality Index (TIPI) (Gosling et al., 2003) to see whether there were marked differences in personality manifestation across the days of the week. While exploratory and seemingly contrary to certain conceptualizations of personality as stable (Bergner, 2020), this enquiry follows the conceptualization of personality as changeable in its manifestation across different situations (Fleeson, 2001). Secondly, we utilized the SOEP risk attitude question (Wagner et al., 2007) to explore whether risk attitudes varied over the days of the week. Lastly, experienced affect on that day was also queried; participants were asked whether they experienced enjoyment, happiness, worry, sadness, stress, and anger that day, in line with how these were queried in (Stone et al., 2012), a previous exploration of day of the week effect on affect. Questions were used and presented as they were in the original studies above.

3. Results

For participant characteristics, see Supplementary Materials S1.

3.1. Main analysis

Following the pre-registered analysis plan (see sections 2.2.1. and 2.2.2. in Methods), we sought to determine whether there was an effect on the day of the week the survey was taken on engagement and preferred day for physical activity. As discussed above (section 2.2.1), engagement is defined through three sets of dependent variables: for the NHS link, whether it was clicked and how much time was spent on the page; for the two quizzes (sorting quiz and knowledge quiz), number of questions correct, and time spent on the page. As discussed above (section 2.2.2), preferred physical activity is defined through two dependent variables: preferred day of the week for a one-time charity walk, and for a repeated fitness regimen (Couch-to-5k).

3.1.1. NHS Link- Click

Of all participants, 639 clicked on the link (29.89% of total respondents, SE = 0.0099).

A logistic regression was used due to the binary nature of the outcome variable, with 0 representing the link not being clicked and 1 representing the link being clicked. The dependent variable was whether or not the link was clicked.

A logistic regression model (McFadden's R^2 = 0.002) of weekday showed no significant effect of weekday on whether or not the link was clicked across all weekday comparisons (Tuesday – Monday: Estimate = -0.016, SE = 0.172, 95% CI [-0.353, 0.321], Z = -0.093, p = 0.926; Wednesday – Monday: Estimate = -0.013, SE = 0.171, 95% CI [-0.347, 0.322], Z = -0.074, p = 0.941; Thursday – Monday: Estimate = 0.039, SE = 0.173, 95% CI [-0.299, 0.377], Z = 0.227, p = 0.821; Friday – Monday : Estimate = -0.239, SE = 0.181, 95% CI [0.594, 0.115], Z = -1.323, p = 0.186; Saturday – Monday: Estimate = -0.246, SE = 0.184, 95% CI [-0.606, 0.114], Z = -1.339, p = 0.181; Sunday – Monday: Estimate = 0.061, SE = 0.175, 95% CI [-0.282, 0.404], Z = 0.346, p = 0.729).

A further logistic regression model (McFadden's R^2 = 0.008) of weekday, age, number of children at home, and gender on whether or not the link was clicked revealed again no significant main effects of weekday, and additionally no significant effect of number of children at home. However, there were significant effects of gender such that males clicked less often than females (male – female; Estimate = -0.234, SE = 0.099, 95% CI [-0.428, -0.041], Z = -2.370, p = 0.018) and of age such that older individuals clicked more than younger ones (Estimate = 0.007, SE = 0.005, 95% CI [1.320e-4, 0.014)], Z = 1.997, p = 0.046) on the binary outcome of whether or not the link was clicked. For full reporting, please see Table S2.

3.1.2. NHS Link- Time

Across all participants, the average time spent on the NHS page was 34.696 seconds (SE = 1.205).

A linear regression was used with the dependent variable of amount of time spent on the NHS page.

A linear regression model ($R^2 = 0.004$) of weekday showed no significant effect of weekday on time spent on the NHS page across all weekday comparisons (Tuesday – Monday: Estimate = -0.245, SE = 4.415, 95% CI [-8.904, 8.414], t = -0.055, p = 0.956; Wednesday – Monday: Estimate = 3.259, SE = 4.415, 95% CI [-5.342, 11.860], t = 0.743, p = 0.458; Thursday – Monday: Estimate = 0.486, SE = 4.457, 95% CI [-8.255, 9.226], t = 0.109, p = 0.913; Friday – Monday : Estimate = -6.134, SE = 4.533, 95% CI [-15.024, 2.757], t = -1.353, p = 0.176; Saturday – Monday: Estimate = -5.040, SE = 4.592, 95% CI [-14.046, 3.966], t =-1.097, p = 0.273; Sunday – Monday: Estimate = 4.141, SE = 4.533, 95% CI [-4.749, 13.032], t = 0.914, p = 0.361).

A further linear regression was used, with the outcome variable being amount of time spent on the page. A linear regression model ($R^2 = 0.008$) of weekday, age, number of children at home, and gender revealed no significant main effects of weekday, number of children in the home, or gender, but a significant effect of age such that older individuals spent more time on the page (Estimate = 0.234, SE = 0.091, 95% CI [0.056, 0.412], t = 2.581, p = 0.010, Effect size η^2= 0.002, 95% CI [0.000, 0.007]) on the amount of time spent on the NHS webpage. For full reporting, please see Table S3.

3.1.3. Sorting quiz- Score

A linear regression was used with the dependent variable of the score on the sorting quiz.

A linear regression of weekday (R^2 = 0.001) showed no significant effect of weekday on the score on the sorting quiz (Tuesday – Monday: Estimate = -0.148, SE = 0.128, 95% CI [-0.399, 0.103], t = -1.157, p = 0.247; Wednesday – Monday: Estimate = -0.144, SE = 0.127, 95% CI [-0.394, 0.105], t = -1.134, p = 0.257; Thursday – Monday: Estimate = -0.149, SE = 0.129, 95% CI [-0.403, 0.104], t = -1.156, p = 0.248; Friday – Monday : Estimate = -0.034, SE = 0.131, 95% CI [-0.291, 0.224], t = -0.256, p = 0.798; Saturday – Monday: Estimate = -0.043, SE = 0.133, 95% CI [-0.304, 0.218], t = -0.321, p = 0.749; Sunday – Monday: Estimate = -0.113, SE = 0.131, 95% CI [-0.370, 0.145], t = -0.857, p = 0.391).

A linear regression model (R^2 = 0.016) of weekday, age, number of children at home, and gender revealed again no significant main effects of weekday, and no effect of gender, or of number of children present in the home on the score on the sorting quiz. However, there was a significant effect of age such that older individuals scored worse than younger ones (Estimate = -0.014, SE = 0.003, 95% CI [-0.019, -0.008], t = - 5.179, p <.001, Effect size η^2 = 0.012, 95% CI [0.005, 0.023]) on the score on the sorting quiz. For full reporting, please see Table S4.

3.1.4. Sorting quiz- Time

A linear regression was used, with the dependent variable of the amount of time spent on a sorting quiz.

A linear regression of weekday (R^2 = 0.003) showed no significant effect of weekday on the amount of time spent on the sorting quiz (Tuesday – Monday: Estimate = 3.561, SE = 5.559, 95% CI [-7.340, 14.461], t = 0.641, p = 0.522; Wednesday – Monday: Estimate = 1.116, SE = 5.521, 95% CI [-9.712, 11.943], t = 0.202, p = 0.840; Thursday – Monday: Estimate = -7.906, SE = 5.611, 95% CI [-18.909, 3.098], t = -1.409, p = 0.159; Friday – Monday : Estimate = -4.078, SE = 5.707, 95% CI [-15.270, 7.114], t = -0.715, p = 0.475; Saturday – Monday: Estimate = -2.085, SE = 5.781, 95% CI [-13.422, 9.253], t = -0.361, p = 0.718; Sunday – Monday: Estimate = -4.429, SE = 5.707, 95% CI [-15.621, 6.763], t = -0.776, p = 0.438).

A further linear regression model (R^2 = 0.010) of weekday, age, number of children at home, and gender revealed no significant main effects of weekday, but an effect of age (Estimate = 0.384, SE = 0.114, 95% CI [0.160, 0.608], t = 3.365, p < .001, Effect size η^2= 0.005, 95% CI [9.234e-4, 0.013])) on the amount of time spent on the sorting quiz, such that older individuals spent longer. Additionally, there was no significant effect of weekday, gender, or of number of children present in the home. For full reporting, please see Table S5.

3.1.5. Knowledge quiz- Score

A linear regression was used, with the dependent variable of the score on the knowledge quiz.

A linear regression of weekday (R^2 = 0.003) showed no significant effect of weekday on the score on the knowledge quiz (Tuesday – Monday: Estimate = -0.181, SE = 0.111, 95% CI [-0.399, 0.036], t = -1.634, p = 0.102; Wednesday – Monday: Estimate = -0.040, SE = 0.110, 95% CI [-0.256, 0.176], t = -0.363, p = 0.717; Thursday – Monday: Estimate = -0.011, SE = 0.112, 95% CI [-0.230, 0.209], t = -0.094, p = 0.925; Friday – Monday : Estimate = -0.159, SE = 0.114, 95% CI [-0.382, 0.065], t = -1.392, p = 0.164; Saturday – Monday: Estimate = 0.003, SE = 0.115, 95% CI [-0.223, 0.229], t = 0.026, p = 0.979; Sunday – Monday: Estimate = -0.042, SE = 0.114, 95% CI [-0.265, 0.182], t = -0.367, p = 0.714).

A further linear regression model (R^2 = 0.013) of weekday, age, number of children at home, and gender revealed again no significant main effects of weekday or gender, but an effect of age such that older individuals score worse than younger ones (Estimate = -0.007, SE = 0.002, 95% CI [-0.011, -0.002], t = -3.025, p = 0.003, Effect size η^2= 0.004, 95% CI [5.207e-4, 0.011])) and number of children in the home such that those with more children in the home score worse than those with fewer or none (Estimate = -0.089, SE = 0.033, 95% CI [-0.153, -0.025], t = -2.724, p = 0.007, Effect size η^2= 0.003, 95% CI [2.631e-4, 0.010])) on the score on the knowledge quiz. For full reporting, please see Table S6.

3.1.6. Knowledge quiz- Time

A linear regression was used, with the dependent variable of the amount of time on the knowledge quiz.

A linear regression of weekday (R^2 = 0.003) showed no significant effect of weekday on amount of time spent on the knowledge quiz (Tuesday – Monday: Estimate = 2.955, SE = 6.723, 95% CI [-10.228, 16.139], t = 0.440, p = 0.660; Wednesday – Monday: Estimate = -3.256, SE = 6.678, 95% CI [-16.351, 9.840], t = -0.488, p = 0.626; Thursday – Monday: Estimate = -11.064, SE = 6.786, 95% CI [-24.372, 2.244], t = -1.630, p = 0.103; Friday – Monday : Estimate = -0.164, SE = 6.902, 95% CI [-13.700, 13.372], t = -0.024, p = 0.981; Saturday – Monday: Estimate = 3.796, SE = 6.992, 95% CI [-9.916, 17.508], t = 0.543, p = 0.587; Sunday – Monday: Estimate = -0.696, SE = 6.902, 95% CI [-14.232, 12.840], t = -0.101, p = 0.920).

A further linear regression model (R^2 = 0.012) of weekday, age, number of children at home, and gender revealed no significant main effects of weekday, but an effect of age (Estimate = 0.520, SE = 0.138, 95% CI [0.250, 0.791], t = 3.772, p <.001, Effect size η^2= 0.007, 95% CI [0.002, 0.015])) on the amount of time spent on the knowledge quiz, such that older individuals spent longer. Further, there was no effect of weekday, gender, or of number of children present in the home. For full reporting, please see Table S7.

3.1.7. One shot – preferred participation day

To see if there was a difference in what day people said they wanted to participate in a charity walk, a Chi square goodness of fit test was used. There was a significant difference in preferred days [$\chi^2(6, N = 2134) = 1296.197$, p <.001) such that Saturday was the favourite day to participate.

To examine if there was a difference in preferred day based on what day participants answered the survey, a contingency table was used. There was no significant day of the week effect on preferred day [$\chi^2(36, N = 2134) = 46.611$, p = 0.111, Cramer's V = 0.060).

For full reporting, please see table S8.

3.1.8. Repeated– preferred participation day

To see if there was a difference in what day people said they wanted to begin an exercise regime, a Chi square goodness of fit test was used. There was a significant difference in preferred days [$\chi^2(6, N = 2127) = 2607.590$, p = <.001), such that Monday was the preferred day to begin.

To examine if there was a difference in preferred day based on what day participants answered the survey, a contingency table was used. There was no significant day of the week effect on preferred day [$\chi^2(36, N = 2127) = 38.511$, p = 0.357).

For full reporting, please see table S9.

3.2. Exploratory analyses

Following the pre-registered exploratory analyses plan (see section 2.2.2 – 2.2.4. in Methods), we sought to investigate further day of week effects.

3.2.1. SOEP

To see whether there was a difference in risk attitude across days of the week, measured via SOEP, a risk attitude question querying “Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?” with response on a 0-10 Likert scale, a linear regression was used, with the outcome variable being the score on the SOEP.

A linear regression model ($R^2 = 0.008$) of weekday revealed a significant effect of day of the week driven by Sunday—Monday (Estimate = -0.457, SE = 0.208, 95% CI [-0.866, -0.048)], t = -2.193, p = 0.028), such that Sunday was significantly less risk averse than Monday.

A further linear regression model ($R^2 = 0.065$) of weekday, age, number of children at home, and gender revealed a significant effect of day of the week driven by Saturday—Monday (Estimate = -0.438, SE = 0.206, 95% CI [-0.842, -0.026)], t = -2.126, p = 0.034) and Sunday—Monday (Estimate = -0.424, SE =

0.203, 95% CI [-0.822, -0.026)], t = -2.089, p = 0.037), such that Saturday and Sunday were both significantly more risk averse days than Monday. Additionally, there was a significant effect of age wherein older individuals were less risk-taking than younger ones (Estimate = -0.029, SE = 0.004, 95% CI [-0.037, -0.021], t = -7.024, p < .001, Effect size η^2= 0.022, 95% CI [0.011, 0.036]), number of children in the home (Estimate = 0.135, SE = 0.058, 95% CI [0.021, 0.250], t = 2.317, p = 0.021, Effect size η^2= 0.002, 95% CI [3.999e-6, 0.008]), such that those with more children in the home were more risk-seeking, and gender (male—female, (Estimate = 0.919, SE = 0.111, 95% CI [0.701, 1.137], t = 8.667, p < .001, Effect size η^2= 0.031, 95% CI [0.017, 0.045]), such that males were more risk-taking than females.

For full reporting, please see table S10.

3.2.2. Busyness on different days of the week

To see whether different days were ranked differently in terms of busyness, a one-way ANOVA was run. There was a significant difference in busyness rating given to each of the days of the week (F(6,6647) = 262.6, p<.001).

The Games-Howell Post-hoc Test revealed that this difference was driven by Saturday (Mean = 2.06, SE = 0.03) and Sunday (Mean = 1.642, SE = 0.03) having significantly lower busyness ratings than Monday to Friday across all pairwise comparisons between days of the week (p<.001).

For full reporting and all pairwise comparisons, please see table S11.

3.2.3. TIPI

To see whether there was a difference across the five different sub-measures of the TIPI across days of the week, a linear regression was used with the outcome variable being the score of each sub-measure.

The only sub-measure that revealed day of the week effects was TIPI – Extroversion. A linear regression model (R^2 = 0.005) of weekday revealed a significant effect of day of the week driven by Wednesday—Monday (Estimate

= 0.278, SE = 0.118, 95% CI [0.046, 0.511)], t = 2.350, p = 0.019), such that Wednesday was significantly extroverted than Monday.

The other four sub-measures of TIPI showed no effects of the day of the week. For full reporting across all TIPI sub-measures, please see table S12.

Affect

To see whether there was a difference across the seven different sub-measures of affect across the days of the week used by (Stone et al., 2012), a binomial logistic regression was used with the outcome variable being the answer to the question (yes or no).

For each sub-measure, the primary analysis (a linear regression of weekday on the sub-measure) is presented below. For further analyses including the addition of demographic controls and for full reporting, please see table S13. The different sub-measures are presented next.

3.2.5.1. Enjoyment

A logistic regression model (McFadden's R^2 = 0.003) of weekday showed a significant effect of weekday on individuals responses to a question if they had experienced joy, driven by a significant weekend effect (Saturday – Monday: Estimate = 0.417, SE = 0.167, Z = 2.505, p = 0.012; Sunday – Monday: Estimate = 0.413, SE = 0.163, Z = 2.514, p = 0.012), such that weekends had more people saying they had experienced enjoyment.

3.2.5.2. Happiness

A logistic regression model (McFadden's R^2 = 0.012) of weekday showed a significant effect of weekday on individual responses to a question if they had experienced happiness, driven by Sunday (Sunday – Monday: Estimate = 0.374, SE = 0.173, Z = 2.169, p = 0.030).

3.2.5.3. Worry

A logistic regression model (McFadden's $R^2 = 0.012$) of weekday showed no significant effect of weekday on individual responses to a question if they had experienced worry.

3.2.5.4. Sadness

A logistic regression model (McFadden's $R^2 = 0.004$) of weekday showed a significant effect of weekday on individual responses to a question if they had experienced sadness, driven by Sunday (Sunday – Monday: Estimate = -0.492, SE = 0.197, Z = -2.497, p = 0.013), such that fewer individuals experienced sadness on Sundays.

3.2.5.5. Stress

A logistic regression model (McFadden's $R^2 = 0.004$) of weekday showed a significant effect of weekday on individual responses to a question if they had experienced stress, driven by Sunday (Sunday – Monday: Estimate = -0.412, SE = 0.168, Z = -2.449, p = 0.014), such that fewer individuals experienced stress on Sundays.

3.2.5.6. Anger

A logistic regression model (McFadden's $R^2 = 0.003$) of weekday showed no significant effect of weekday on individual responses to a question if they had experienced anger.

4. Discussion

The present work innovatively contributes to the literature on weekday effects by introducing a rigorous randomization procedure to better understand differences across days of the week in engagement with health information.

This study makes a crucial methodological contribution by experimentally allocating participants across the seven days of the week to participate in the study. Further, this study keeps track of a range of actual participant engagements, not just when information was presented (but perhaps not read).

These key features of our study complement and qualify the evidence previously gathered employing different non-experimental methods, relying upon secondary data with no or little information about the day when the original data were collected, or on studies where participants could self-select onto participation timeslots. We know of no other study that has addressed this self-selection bias issue with respect to engagement with information. This has allowed us to achieve a between-subjects randomized study design to rigorously examine what effect, if any, day of the week has on participant engagement levels with health information.

Contrary to the literature that points to day-of-the-week effects through correlational or cross-sectional data collection methods (Stone et al., 2012), our experimental study does not find such an effect on any of our dependent variables: we find no statistically significant differences across days of the week across six total outcome variables for engagement.

Our study also successfully replicates a number of existing findings. First, it substantially echoes in an implicit within-subjects design the fresh start effect originally documented by (Dai et al., 2014) using a within-subjects design, wherein more people wanted to start a repeated exercise regime on a Monday. This is especially noteworthy as this result is robust to the day of the week on which participants took the study and is therefore not due to the distance between the day in which the preference is expressed and the day preferred. Second, it replicates previous findings that males are more risk-taking than females using the SOEP measurement (Byrnes et al., 1999; Fisher & Yao, 2017). Third, it confirms that better mood is experienced on weekends (Stone et al., 2012).

We find no statistically significant differences across the seven days of the week in any of our dependent variables. It is important to further note that engagement with clicking on the NHS link did not suffer from a floor or ceiling effect, with 29.89% of participants choosing to explore the page. As such, this measure maintains its ability to discriminate different levels of engagement between participants. It is also worth noting that the differences across the seven weekdays in all our five dependent variables are not statistically significant even before correcting for multiple hypotheses testing, an appropriate correction given the multiple dependent variables.

The discussion of the role of heterogeneity in behavioural science is gaining a lot of attention, with the rightful acknowledgement from researchers that not all individuals will react to stimuli in the same way (Bryan et al., 2021; Cikara et al., 2022; Hallsworth, 2023; Hecht et al., 2019; Mertens et al., 2022; Szaszi et al., 2022; Tipton et al., 2023). The lack of a day of the week effect in the present study highlights the complexity of understanding drivers of heterogeneity in behavioural science research: while the day of the week had previously been positioned as a potential cause of heterogeneity, we do not find that it is so in our present context. Day of the week is an ingrained important framework (Henkin, 2018) around which discussion and understanding of individual trait and behaviour fluctuations and rhythms have been scaffolded. The day of the week indeed can affect risk taking measure, mood, and preferences for starting behaviours. However, we find that day of the week does not actually affect engagement with health information.

While in our study we employ a broad and diverse set of dependent variables to measure cognition and proxies for the relevant outcome behaviour, we also openly acknowledge that our findings may not necessarily generalize to other behavioural outcomes, settings, domains, or interventions. In particular, whether information dissemination to specifically target long-term changes in physical activity in naturally occurring settings would or would not show distinctive patterns for effectiveness across different weekdays remains to be tested and understood.

This result adds a degree of freedom on the researcher’s side, as it suggests that data collection on outcomes with relation to attention and engagement with a message do not need to consider the day on which data were collected as a potential confounder. While the content of this study strictly refers to engagement with health information, further work could generalize and scale-up these findings beyond this domain.

This work leaves open the interesting question of what relationship we *do* exactly have to the day of the week. As a 'synthetic' concept based in neither biology nor astronomy, and studied by historians, it has introduced a regimented way that many use to structure their time. Both in a one-time charity walk and in beginning a repeated exercise regimen, participants report overwhelming favourite days to engage in these activities. Despite finding that weekdays are reported as roughly the same level of busyness by participants in the present study, our data show Monday is the preferred day to engage in a repeated behaviour, while Thursday lags considerably behind. This finding mirrors the "fresh start effect" (Dai et al., 2014), showing that individuals do, in some way, differentiate between days of the week when it comes to beginning new behaviours.

In conclusion, we believe this study represents an important step forward in understanding the causal effect of the day of the week on behaviour. The role of the day of the week on individuals needs a more nuanced understanding, one that will unfortunately not permit sweeping statements on different days leading to a uniform set of different behaviours across domains. Rather, we should ask—what makes a Tuesday a Tuesday? And for whom does this apply and in what way? How can we look beyond the day of the week to understand what other lurking factors are fluctuating behind the scenes, be it stress, free time, perceived autonomy, etc., that influence how we engage with information? For now, this work suggests a cautious and nuanced approach to characterizations of day-to-day heterogeneity and its effects on behaviour.

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6. Data Availability

Pre-registration and full data are available at https://osf.io/8uhs5/.

7. Author contributions

Conceptualization: VF, MMG, BF, JGS

Methodology: VF, MMG

Validation: VF

Formal analysis: VF

Investigation: VF

Data curation: VF

Writing – original draft: VF

Writing – review & editing: VF, MMG, BF, JGS

Supervision: MMG, BF

Project administration: MMG

Funding acquisition: MMG, BF

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Paper 4: Replication and extension of the affect gap: robust to day of the week effects

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Paper 4: in context

The fourth paper in this thesis expands the understanding of the day of the week effect into an established decision-making pattern, the affect gap. The affect gap refers to how decisions that are rich in affect often invoke different decision-making strategies than those who affect-poor, often leading to a preference reversal between parallel questions that vary only in affect level. The motivation behind this is that different decision-making strategies tend to be related to individual's underlying affect. Given the fluctuation of affect based on day of the week, it would be natural to test whether the affect gap also fluctuates based on the day of the week.

This chapter adds a new depth to the understanding of the day of the week effect. This work replicates the established affect gap and the established fluctuation in affect over the days of the week but does not find an effect of the day of the week on the affect gap. Further, it replicates the different decision-making strategies under affect-rich and affect-poor conditions. This paper contributes significantly through a large-scale replication of the affect gap (across seven days), as well as by replicating the differences in affect across the days of the week. These findings add to the existing evidence for both the day of the week effect and the affect gap (of which the authors are not aware of any published replications).

This replication and extension help advance the understanding of how the day of the week, as a driver of temporal heterogeneity, can affect established decision-making patterns (like the difference between affect-rich and affect-poor decisions). By showing that affect does indeed change over the course of the week, but the affect gap is not affected, this suggests that, broadly, there may be certain core tenets of how individuals navigate decision-making that are robust to the small-scale changes that take place (such as affect over the course of the week). While out of the scope of the present paper, this begins to open the conversation of what aspects of individual cognition the day of the week effect does change. The robustness of the affect gap suggests that differential processing (in terms of different decision-making strategies) of affect-rich versus affect-poor questions is not easily affected by intra-individual heterogeneity.

Abstract

The day of the week has been shown to change an individual's expression of cognitive and personality traits, especially affect, but its impact on consequential judgments and decisions, with varying level of affect present, has not yet been fully explored. Our large pre-registered study tests how the day of the week affects the so-called "affect gap". The affect gap is the within-subject differential judgement between affect-rich and affect-poor versions of equivalent scenarios that often leads to preference reversals (Pachur et al., 2014). Our study replicates this seminal study across 7 consecutive days of the week and extends it to a contemporary and important context: vaccine decisions. 2,138 UK participants were randomly allocated into participating on one of seven consecutive days, and asked to make 26 choices, across thirteen affect-rich (medical vaccines) and affect-poor (monetary lottery) options, calibrated to have matched willingness-to-pay (WTP). We find consistent evidence for preference reversals between affect-rich and affect-poor questions and no day of the week effect on the presence of the affect gap. However, we do find individual affect impacted by the day of the week effect. This suggests that the difference in judgement between affect-rich and affect-poor decisions is robust to the day of the week effect and the associated changes in individual affect. Theoretical and practical implications are discussed.

1. Introduction

Affect plays an important role in everyday decision-making, from individual understanding of risk in communications to making everyday choices. Different decisions have varying levels of affect attached to them, for example, situations of medical decisions (often seen as affect-rich) versus filling out tax forms (often seen as affect-poor). When making a decision, affect may overpower strictly rational and cognitively-driven assessments of the choice and sway ultimate decision-making, as postulated, for example, by the risk-as-feelings theory (Loewenstein et al., 2001) or the affect infusion model (Forgas, 1995). Overall, there is an understanding of affect as an important driver in decision making (Lerner et al., 2015).

The way in which affect modifies decision-making can very clearly be seen when equivalent decisions, with differing levels of affect, are directly compared. This has given rise to the finding of the 'affect gap', or the difference in decisions made in affect-rich versus affect-poor settings. These affect-rich and affect-poor decisions are often evaluated differently by decision-makers, often leading to preference reversals between two equivalent questions (Pachur et al., 2014). In a seminal paper using within-subjects design, Pachur et al. (2014) investigate different decision-making strategies between affect-rich and affect-poor scenarios. The questions were formulated to be equivalent by soliciting individual willingness-to-pay (WTP) to avoid certain side effects and then presenting this information in two ways. First, in the affect-rich situation, participants were asked to choose between a certain percentage (for example, 10%) chance of one side effect (for example, depression) versus another percentage chance (for example, 30%) of another side effect (for example, itching). In the parallel affect-poor question, participants were asked whether they would choose a 10% chance of losing the monetary amount allocated to their WTP for depression versus a 30% chance of losing the monetary amount allocated to their WTP for itching. Pachur et al. (2014) find that individuals use a more compensatory strategy and consider both outcomes and probability when assessing affect-poor decisions (e.g., maximising expected value [EV], such as EVmax decision-makers), whereas in affect-rich decisions, individuals use simpler strategies that neglect probabilities and compare outcomes (e.g., choosing the 'least worst' choice, such as mini-max decision-makers). This suggests that decision makers use different heuristics in contexts that are affect-rich versus affect-poor.

For the purposes of the present research, there will be a focus on EVmax versus mini-max as the potential heuristics individuals could use. While the study of heuristics is wide-reaching and encompasses many different information strategies (Gigerenzer & Gaissmaier, 2011), the selection has been based upon previous work showing those engaging in affect-rich decisions to be more likely to display probability neglect (as discussed in Pachur, 2014, see also McGraw, Todorov & Kunreuther, 2010), pointing towards a mini-max strategy. Conversely, if a decision-maker were to not neglect the probabilities, the strategy of maximizing the expected value (EVmax), would likely come into play; EVmax rests upon a simplification of expected utility theory (Schoemaker, 1982) that has served as the backbone of much decision-making research. As such, the two heuristics highlighted focus on either the probability neglect (mini-max), or a simple model of incorporating probability (EVmax). While there are countless other models for decision making that have been investigated (for an example investigation see Camerer, 1989), the current research will focus on the above two.

Understanding this effect and what strategies individuals use in different types of decisions is important to help create more effective communications. For example, the implications of the affect gap are especially salient in risk communications, where it would be important to emphasise probabilities in high-affect situations to help decision-makers avoid neglecting probabilities and only deciding based on what the outcomes are. Pachur et al. (2014) have shown this to be relevant in the context of considering choice of drugs (in relation to their medical side effects). The affect stirred by the question and topic itself could change the decision-making heuristic used and could be likely to lead to suboptimal decision-making. Here we extend existing affect gap work to the context of people's vaccinations choices. Vaccination decisions, especially for new vaccines (such as during the COVID-19 pandemic) are a similar high-affect situation. As such, the present study investigates vaccine side effects as a choice setting: under which settings do people ignore probability more or less in such an important decision as vaccination? Concretely, do people look more of the severity of the vaccine side effect, and ignore the probability when the vaccine decisions are presented in an affect-poor rather than affect-rich manner?

An individual’s underlying affect can have important effects on what decisions are made. An important distinction is the incidental affect (such as an individual’s mood going into a decision) and integral affect (that is, affect directly related to the decision at hand, such as of vaccine side effects, or medicine side effects as studied and measured by Pachur et al. (2014)), both of which have been shown to affect decision-making (Västfjäll et al., 2016).

Further, incidental affect, as well as the valence of the affect, has been shown to change an individual’s decision-making or information processing strategy (Bless et al., 1996; Fredrickson, 2004; Schwarz et al., 1991; Schwarz & Clore, 1996). For example, both negative mood (Schwarz & Clore, 1996) and positive mood (Fredrickson, 2004) have been shown to relate to more compensatory strategies. An example of incidental affect’s impact on decision-making was described by Johnson & Tversky (1983) where the authors create incidental affect in participants (either negative or positive) and find that positive incidental affect decreased the judgement of the likelihood of risky events, despite being unrelated. The present study presents a novel contribution of investigation of both incidental and integral affect.

One factor that has been shown to affect incidental affect is the day of the week (termed the ‘day of the week effect’). The day of the week is omnipresent in all decisions made. While a seemingly innocuous feature of a decision, individual decision-makers are all subject to the same ‘context’ of the day of the week. Broadly, the day of the week serves as a unifying societal organisation that dictates many individual behaviours, activities, and time allocations (Kennedy-Moore et al., 1992). Following the terminology introduced above, each day of the week can be thought of as a population-wide ‘functional equivalency class’, introducing its own set of trait pressures, resultant behaviours, and affect. Therefore, synchronised societal activity of days of the week introduces in and of itself different influences into decisions.

The day of the week is a unique rhythm as it often plays a dominant role in structuring life but is not linked to any existing celestial rhythms and has been extant for thousands of years (Copeland, 1939). Despite this, the days of the week are extremely salient and individuals have strong associations for different days of the week and different affect is manifested on different days, such as the weekend having more positive affect (Stone et al., 2012). Broadly, the day of the week has been shown to affect incidental affect across several studies (Elgoff et al., 1995, Ryan et al., 2010, Tsai, 2018), especially in regard to weekends having a more positive affect than weekdays. These studies are largely correlational or analyses of secondary data and do not utilise random assignment for allocating participants into particular days to take part.

The day of the week has a notable effect on many unexpected domains in everything from medical decisions (Aylin et al., 2013; Brådvik & Berglund, 2003; Ellis et al., 2022) to energy consumption (Singh & Yassine, 2018). However, the exact mechanism and traits of the so-called ‘day of the week effect’ is poorly understood and has been questioned as an emergent property of experimental design creating a “non-random sorting on unobservables” (Tumen & Zeydanli, 2014)—as such, it is difficult to predict how different facets of decisions are affected.

This day of the week effect on incidental affect sets up an opportunity to further understand the affect gap and its relationship to incidental affect. The mechanism of the affect gap builds on the integral affect, namely the affective properties of the task as a mechanism for bringing about different heuristics in the participant’s decision. However, it remains to be understood what relationship incidental affect plays in this process. If an individual were faced with both affect-rich and affect-poor questions, would their use of different decision-making heuristics be swayed by their existing incidental affect? For example, if an individual is happier (incidental affect) on a particular day, it could be hypothesized that the affect of the task (integral affect) would impact them less (or perhaps more!), leading to different choices than someone less happy—much in line with Johnson & Tversky (1983), Schwarz & Clore (1996) and Fredrickson (2004), where an individual’s incidental affect was found to affect decision-making. The present research then seeks to explore the relationship between integral affect and incidental affect in relation to the manifestation of the affect gap.

The present research and analyses (pre-registered at https://aspredicted.org/6QF_QG2) therefore rests on three main aims. First, we seek to replicate the finding of the affect gap by demonstrating preference reversals between affect-rich and affect-poor decisions. Secondly, we seek to understand the decision-making strategy used in affect-rich versus affect-poor decisions to see how they vary. We predict that preference reversals will occur, as affect-poor questions will rely more on a calculation of expected value of the two options, whereas affect-rich questions will disregard probabilities and choose the most attractive ('least worst') option. Thirdly, we seek to replicate the affect gap over the days of the week to understand whether there is a day of the week effect on the presence or strength of the affect gap. This line of inquiry seeks to understand the role of incidental affect on the affect gap, as the days of the week have been shown to have differences in incidental affect as outlined above.

Therefore, we seek to investigate the interplay between the day of the week effect and the affect gap. The difference in affect, decision-making, and general behaviour across different days of the week is documented, but what is unclear is how these small-scale fluctuations to an individual's incidental affect can affect established decision-making patterns. It is plausible that the affect gap, a difference in information search, may fluctuate in strength across the days of the week, if shifts in individual affect affects the strength of this affect gap. However, it is also possible that this affect gap is enduring and while the underlying individual affect traits may fluctuate, an affect-poor decision will always be understood differently from an affect-rich decision. Focusing on the above characterisation of a more compensatory decision-making strategy being prompted by either a negative (Schwarz & Clore, 1996) or a positive (Fredrickson, 2004) affect, we seek to investigate whether the affect gap is attenuated during days with more negative affect, or amplified during those days, respectively. Overall, the present paper seeks to better understand and characterise the intersection between the day of the week effect and the affect gap.

2. Methods

2.1. Participant recruitment

The study was approved by the University Research Ethics committee (approval number 136961) and all participants provided informed consent. Participants were recruited via the Prolific platform sharing the method and data collection of paper 3 of this thesis (in preparation for publication).

Recruitment followed a two-step method to ensure participants were not able to self-select into participating on a certain day of the week.

The first step was a screening survey where participants indicated their interest in participating in a future survey (n = 3,000 responses) in July 2023. Respondents were informed that they would be invited to participate in a follow-up survey on a random day the following week and would be asked to participate on the day the invitation was received. Once participants had received the above general information on the follow-up survey, they were asked through a yes or no response if they were interested in participating in the follow-up survey. It was explicitly stated that compensation for the present survey would not depend on an individual response. 97.37% (2,921 of 3,000 responses) confirmed interest in participation in the main survey.

Participants who expressed interest in the above screening survey were invited to participate in the main survey. Prior to the commencement of the main survey, individuals were randomised into seven groups denoting which day of the week they would be invited to participate in the main survey. The main survey was posted on seven consecutive days (Monday to Sunday) between 24 and 30 July 2023. The survey was posted and taken down at the same time every day. From the screener survey, 29,21 participants were invited to the main survey and 2,205 participants completed the main survey. Of those, 2,138 participants passed attention checks. For more information on participant demographics, please see Supplementary Materials S1.

2.2. Materials and procedure

The study analyses are pre-registered at [redacted prior to publication]. For measurement of the affect gap, the present study replicated the methods of (Pachur et al., 2014). The affect gap refers to the difference in choices between commensurate choices phrased in either affect-rich or affect-poor framing.

The first set of questions were broadly ‘willingness to pay’ (WTP) questions. They listed 12 side effects of a vaccine and asked participants how much money, in GBP, they would be willing to pay to avoid experiencing this side effect. There were no restrictions set on what amounts participants entered.

Subsequent questions fell broadly into two categories: affect-poor and affect-rich choices (presented randomly in line with Pachur et al., 2014). In the affect-poor choices, participants were asked to choose between two monetary loss gambles (example, 70% chance of losing £10 or 20% chance of losing £20). In the affect-rich choices, participants were asked between two side effects of a vaccine (note, the original study stated a medication) with different probabilities of occurring.

The survey structure was set up to pipe in responses from the first set of willingness to pay questions into the rest of the survey. As such, each affect-rich question would have a 'paired' affect-poor question. For example, a question asking participants to choose between 70% probability of depression and 20% probability of itching, would then be twinned with an affect-poor question that would ask 70% probability of losing the amount the participant said they would pay to avoid depression and a 20% probability of losing the amount the participant said they would pay to avoid itching.

The structure allowed for a direct within-subject comparison of participant decisions between parallel questions, where the monetary value matched the WTP each participant ascribed to the side effects. This allowed for the examination of preference reversals by seeing how many times an individual switched their preferred choice between parallel questions (i.e., the affect-poor and affect-rich version of the same question). The affect gap then refers to this *difference* in participant decisions between the affect-poor and affect-rich versions of the question.

Lastly, we also queried incidental affect replicating measures used in previous research of day of the week effect (Stone et al., 2012) through six different sub-measures (sadness, anger, stress, worry, enjoyment, happiness). Each of the sub-measures was measured by asking participants if they had experienced a particular emotion that day, and respondents answered yes or no. Of note, this measure is an extension to the methods of Pahcur et al. (2014) who did not measure incidental affect.

3. Results

3.1. Preference reversals

To understand whether the type of scenario (affect-rich vs. affect-poor) changed the choices people made, we calculated a proportion of preference reversal score. As our decisions are matched for willingness to pay, we calculate this by counting the number of reversals out of the total number (N= 27,794) of decisions (or 13 decisions for each of the 2,138 participants). On average, collapsing across days of the week, individuals had preference reversals in 33.97% of cases (mean = 0.3397, standard error = 0.0042). For comparison, Pachur et al. (2014) found preference reversal to occur at the following rates in their studies: Study 1, 46.4% (SD = 24.5); Study 2, 36.7%(SD = 15.4); Study 3, 42.6% (SD = 17.5).

To examine the effect of the day of the week on the proportion of preference reversals (i.e., when the choices between paired affective and non-affective questions were different), a non-parametric Kruskal-Wallis test was conducted with the percentage of preference reversals as the dependent variable. There was no significant effect of the day of the week on percentage of preference reversals ($\chi^2(6) = 2.300$, $p = 0.890$).

3.2. Day of the week effect on heuristic and integral affect

For each decision made by a participant, we determined whether this decision aligned with an expected value maximisation heuristic (EVmax) or the prioritising less harmful outcomes ignoring probabilities heuristic (mini-max). Each participant made 13 decisions in each condition (for a total of 26 decisions). Importantly, depending on the WTP inputted by the participant in the first part, there were occasions where the EV of the two options were equal and/or there was no ‘worst’ choice (i.e., both choices were equally ‘bad’, so minimax ascribes equal value to both; alternatively, the expected value is equal for both choices). As such, it cannot be said in these situations if the participant choice is aligned with either heuristic, as the heuristic in question ascribes an equal value to both. There was a total of 14.68 % of decisions that fell into this category and were therefore excluded from ‘counting’ towards a choice that used that heuristic. To clarify further with an example, if one of the participant’s

13 questions in the Affective category had an expected value of 15 for each option, the participant's choice would not be counted as aligning with EVmax, as both options have the same expected value. As such, the total number of questions when considering the overall percentage of choices that aligned with EVmax would be 13 total – 1 excluded = 12 remaining.

Next, we looked at for each person, what percent of decisions they made that aligned with EVmax or mini-max heuristic, again excluding the cases where a heuristic ascribed equal value to both options. As such, the total number of 'valid' decisions differs by individual, as there were different numbers of questions per heuristic that had to be discarded per participant. Therefore, the amounts are presented in percentages, with the note that the total number varies. Note that these percentages may total over 100% as sometimes the option that aligned with the EVmax heuristic and the option that aligned with mini-max are the same, therefore it is impossible to then discern which heuristic was used. To elaborate further: If in a question, option B is both the option with the highest EV and the 'least-worst' option, and the participant chose B, this decision would be counted both as a case where EVmax was used and where mini-max was used. As such, the percentages where EVmax was used and where mini-max were used could total over 100%.

When making decisions presented in an affect-poor manner, decision makers used an EVmax compensatory strategy 84.62% of the time and a non-compensatory mini-max strategy 49.43% of the time. When making decisions presented in an affect-rich manner, decision makers used an EVmax compensatory strategy in 64.83% of the time and used a non-compensatory mini-max strategy in 49.99% of the time. Of all valid affect-rich decisions, 64.83% used EVmax and 49.99% used mini-max. Of all valid affect-poor decisions, 84.62% used EVmax and 49.43% used mini-max.

We subsequently investigated the main, within-participant effects of category of decision (affect-rich or affect-poor) and heuristic (EVmax or mini-max) and the between-participant effects of day of the week.

A repeated measures ANOVA with repeated measures factors of heuristic (mini-max; EV) by category of decision (affect-rich; affect poor) with day of the week as a between-subject factor revealed several significant effects. First, there was a significant effect of heuristic ($F(1) = 1645.073$, $p < .001$). Post-hoc comparison of mini-max to EV revealed a mean difference of -0.216 ($t(1832) = -40.559$, $p_{tukey} < .001$), suggesting that individuals used EV more than mini-max collapsing across both affect-rich and affect poor decisions.

Further, there was a significant effect of category of decision ($F(1) = 177.115$, $p < .001$). Post-hoc comparison of affect-poor to affect rich revealed a significant mean difference of 0.063 ($t(1832) = 13.308$, $p_{tukey} < .001$), suggesting that individuals in affect-poor decisions made decisions aligned with any decision-making heuristic (either EVmax or mini-max) more than those in affect-rich decisions, who aligned their choices less with either decision-making heuristic (i.e., did not follow EVmax or mini-max). Finally, there was no significant between-participant effect of day of the week ($F(6) = 0.891$, $p = .501$).

There was also a significant interaction between heuristic and category of decision ($F(1) = 770.480$, $p < .001$). Post-hoc comparisons revealed that all comparisons between the four categories (affect-rich using EVmax, affect-rich using mini-max, affect-poor using EVmax, affect-poor using mini-max) were significant at the $p_{tukey} < .001$ level, suggesting the percentage of individuals relying upon each heuristic in each category of decision was significantly different. Importantly, mini-max was used more in affect-rich than in affect poor situations. However, it is important to note that the small absolute difference in proportion (49.99% versus 49.43% in affect-rich versus affect-poor, respectively) suggests a small effect size. Additionally, EV was used more in affect-poor than affect-rich situations. This mirrors findings in Pachur et al. (2014). See Supplementary Materials S2 for full reporting.

Finally, there was no significant interaction between heuristic, category of decision, (or even heuristic * category of decision) and day of the week (heuristic * day of week: $F(6) = 0.562$, $p = .761$; category * day of week: $F(6) = 0.403$, $p = .877$; heuristic * category * day of week = $F(6) = 1.143$, $p = .334$).

This suggests there was no impact on day of the week for the type of strategy individuals used in decision-making.

3.3. Incidental affect changes over the week

A composite measure of incidental affect (hereafter 'composite incidental affect score') was made by adding up the scores for each of the six affect sub-measures (1 for yes, 0 for no) and reverse scoring those of negative affect (worry, sadness, stress, anger) and standard scoring for positive affect (enjoyment, happiness).

A linear regression model of weekday only (no other predictor variables) (R^2 = 0.005) showed no significant effect of weekday on the composite incidental affect score.

Next, we looked at the effect of weekday versus weekend (creating a dummy variable for 0 = weekday and 1 = weekend) on the composite incidental affect score. A linear regression model of weekend or weekday showed a significant effect (Weekend – Weekday: Estimate = 0.285, t = 3.148, p = 0.002), suggesting that the composite incidental affect score was higher on weekends (Saturday and Sunday) than weekdays (Monday to Friday).

3.4. Preference reversals, heuristics, and incidental affect

An exploratory analysis looked at whether there was a correlation between the percentage of preference reversals and the composite incidental affect score, an extension to the original design of Pachur et al. (2014) as the original design did not measure incidental affect. Further, the percentage of decisions that used mini-max or EVmax for each category of decision (affect-poor or affect rich) are included. There was no significant correlation with the composite incidental affect score, heuristic use, and preference reversals. See Supplementary S3 for a full report.

4. Discussion

This exploration of the day of the week effect within the established predictable difference in decision-making of the affect gap allows for a sharpened understanding of both phenomena. Through a randomization of participants into different days of participation, we conduct a large-scale replication of the affect gap finding across seven different days and show that it is robust to any day of the week effects, despite finding that incidental affective differences do exist between days of the week with weekends being generally more positive than the rest of the week. We show different heuristics at play (EVmax versus mini-max) used in different types of decisions (affect-rich versus affect poor) with preference reversals present within individuals between the two types of decisions, replicating the findings of Pachur et al., (2014) in a closely related domain (yet one that is distinct—medication side effects versus the present vaccine side effects). This reinforces the finding of the decreased sensitivity to presented probabilities in affect-rich decisions. Overall, this work replicates the finding of the affect gap (Pachur et al. (2014). Further, this work echoes the work found in (Stone et al., (2012) that affect is higher on the weekends than weekdays, although not detecting any change in affect over the day of the week with the existing measure used. Lastly, our work shows that there is no detectable correlation between the utilized incidental affect measure and preference reversals or heuristic used in decisions. This can suggest that the affect gap relates more directly to integral affect, although further work would be needed to fully investigate this link.

First, this finding offers an important theoretical contribution by deepening the characterization of the affect gap and understanding in regard to theories of affect's role in decision making. By showing that the affect gap perseveres no matter what day of the week a participant makes these choices, this seven-sample, large-scale replication further cements the phenomenon as something intrinsic to human decision-making and how affect-rich and affect-poor stimuli are processed. While day of the week effects can impact many individual cognitive processes and incidental affect (and we do indeed find differences in affect across the days of the week), the differential processing between affect-rich and affect-poor stimuli perseveres. This extends the original investigation of Pachur et al. (2014) by controlling for incidental affect in the investigation of questions with different integral affect. This replication of the affect gap with the tightly controlled temporal element suggests a much deeper level of weighting of affect, beyond what can be impacted by outside influences and incidental affect, that yields these different decision-making heuristics and the affect gap effect.

One possible hypothesis rests in the very nature of the affect gap, especially when compared to the characteristics of other cognitive traits for which the day of the week has been found (for example, risk, Fedrigo et al., (2023)). This suggests that the processing of affect-rich and affect-poor scenarios, and any differences therein, may be robust to large-level changes in affect that an individual may experience (for example, across weekdays). The individual's 'starting affect' therefore may have limited importance. One way to conceptualise this is through the often-cited concepts of state and trait. The day of the week may impart different states upon an individual, but the affect gap (and the extent to which it affects an individual) is a trait of such decisions.

This work has important implications for how information is communicated in affect-rich versus affect-poor scenarios, as the tendency to neglect information on probabilities seems inherent to situations high in integral affect. For example, affect-rich communications have significant impacts for public health policy and programs, such as individuals choosing whether to vaccinate when presented with a number of affect-rich side effects. As such, policymakers can choose how information is framed (affect-rich or affect-poor), the present work suggesting that an affect-poor frame may support decision makers in making better choices. Further, this work suggests that the incidental affect experienced by the decision maker (something out of control of policymakers) plays less of a role in the information search and heuristic used by decision-makers. This follows the research line of "boosting" (Hertwig & Grüne-Yanoff, 2017), wherein the aim is to empower decision makers to make informed decisions, rather than pushing towards a singular choice as many behavioural science nudges traditionally do. Taken together, this presents a strong set of suggestions for how high-risk, high-impact decisions can be framed to support decision makers.

Another important contribution of this work is to help to further understand the role of individual heterogeneity in behavioural science (Bryan et al., 2021). Individual heterogeneity helps illuminate why responses to different behavioural interventions often vary significantly across individuals. However, this unified manifestation of the affect gap suggests that the bounds of individual heterogeneity are to be explored on a case-by-case basis. For example, when is the effect size of individual heterogeneity large enough to completely nullify a purported effect of an intervention, and when is it less consequential (such as for the affect gap)? By further understanding drivers of heterogeneity and their interplay with established affective states, behavioural interventions—and in this particular case, risk communications—can be more effectively designed and implemented.

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6. Data Availability

Pre-registration available at https://aspredicted.org/6QF_QG2

7. Contributions

Conceptualization: VF, CH, MMG, BF

Methodology: VF, CH, MMG

Investigation: VF

Data curation: VF, CH

Writing – original draft: VF

Writing – review & editing: VF, CH, BF, MMG

Supervision: MMG, BF

Project administration: MMG

Funding acquisition: MMG, BF

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General Discussion

This thesis set out to tackle a broad overarching question—what relationship does time and the temporal dimension have to the heterogeneity expressed between and within individuals?

The initial introductory literature review tackled topics such as what really is behavioural science, the question of heterogeneity in behavioural science, the dynamic nature of personality, behavioural science in health, and weekday fluctuations. This served to set the stage for the central research themes that would run through the rest of the thesis, focusing on temporal heterogeneity through the day of the week effect.

The first paper examined the antecedents of these day of the week effects by focusing on what thoughts individuals had upon waking. This paper found that the thoughts over the days of the week were very uniform, suggesting a focus on what was to come up that day for the individual and what their own to-do list was.

The second paper looked at some of the causes of the day of the week effect, using the government lockdowns during the pandemic to address both the role of individual and societal understanding of weekdays in fluctuations in risk aversion. This paper found that both a societal setting that gave meaning to the days of the week as well as an individual understanding of days of the week in order to show day of the week effects.

The third paper then looked into the manifestations of the day of the week effect in engagement levels with health information, using an innovative methodology to randomly assign participants into days of the week to participate (removing the issue of self-sorting). This paper found no effect of the day of the week, introducing a level of nuance into understandings of what the day of the week effect may be.

The fourth paper then looked at whether there was a day of the week effect within an established pattern within judgment and decision-making (namely, the affect gap showing different decision-making and processes during affect-rich versus affect-poor choices). This also found no day of the week effect, suggesting limits to which realms the day of the week effect can have an effect.

Overall, this work presents a cohesive view of temporal drivers of heterogeneity, focusing on the antecedents, potential causes, manifestations, and extensions of application. The conclusion of this thesis will seek to contextualize this work further by presenting the contributions, the promise, and the limitations, implications, and outlook for this work looking forward.

Contributions

The work presented herein it spans multiple research threads and cannot be subsumed by one field of behavioural science. Further, one of the primary contributions (especially within the third and fourth papers presented) is methodological, which raises the question: where does this work fit in and how does it contribute? After all, the value of this research, apart from any intrinsic value determined by its conceptualization and rigor, primarily lies in how it can help to advance understanding of what behavioural science (broadly) wants to do and *can* do.

The core idea of this work is the concept of heterogeneity, and how it can be primarily within individuals (as well as between). The very nature of attempting to measure heterogeneity and isolate drivers is how many confounds are within the system and how challenging it is to isolate any one candidate influence. The work presented here seeks to isolate (as much as possible) and understand the influence of time, primarily the days of the week, as a driver of heterogeneity.

However, I argue that the primary contribution of this thesis extends beyond the concrete findings of each paper that help elucidate the inner mechanisms of the day of the week effects. I argue that this work makes significant strides in three primary areas: 1) understanding of temporal fluctuations, 2) methodological contributions, and 3) high-level understandings of heterogeneity.

First, the surface-level contribution of this work, spanning across all papers, can be pithily summarized: the day of the week effect is shaped by our surroundings and affects some facets of individual decision-making. This in and of itself is a novel characterization of an effect that, to this point, has presented itself with various levels of definition—where the effect came from, how strong it was, and how it manifested, as in the early stages of characterization. The present work sharpens the understanding of this effect significantly, cautioning us for when it should be treated with caution and when it can be understood and handled accordingly. Spanning across four papers, the current understanding is the following: the day of the week effect can be said to not form upon waking, but rather be an emergent effect of what a particular day means to the individual, what is to be done, combined with how external societal patterns give meaning and structure to the days. The day of the week effect, however, may be diminished when using random assignment for experimental participation (discussed more in the next contribution). This suggests that there is a degree of uncharacterized sorting that takes place between individuals between the days that may either fully comprise or strengthen an existing day of the week effect in studies that use a between-subject design, without random assignment, to show differences across days of the week. Importantly, this does not apply to research that observes behaviours over time without a selection or recruitment component. Lastly, the day of the week effect was not shown to impact an established decision-making pattern (the affect gap), which further puts into question when and how it impacts individuals. Overall, this characterization on multiple levels leads to a more complete understanding of the day of the week that can help guide future investigations.

Second, regarding methodology, the present work refines existing practices within the study of temporal heterogeneity. In short, this work, primarily the third and fourth papers, seeks to assess and address the issue of individuals self-selecting their participation into studies, as far as the day of the week upon which to participate, at their convenience. By working to uncouple the individual's participation from any individual behavioural patterns, it is possible to gain a sharpened (that is, less confounded by unobserved characteristics) understanding of the temporal effect on heterogeneity. Methodologically, there seems to be very little argument for why this *does not* help to characterize the day of the week effects and therefore should not become common practice for such an investigation. While this may seem like a strong statement, it is anchored in existing norms and practices in social sciences more generally: random assignment is one of the existing tools to limit the effect of confounds. As such, the practice to randomly assign individuals to different days of the week, if one starts with the assumption that the days can be in a sense 'treatment groups', follows clearly from existing best practices. This leads to the suggestion that the random assignment should then become common practice.

Third, regarding a more abstracted understanding of heterogeneity, this work seeks to refine the understanding of a dimension along which heterogeneity is evident, the temporal dimension. We understand time and setting as abstractly important features in determining our own comportment, but the work herein drives us to question what time is actually serving as a proxy for. The first and second papers begin to suggest that the heterogeneity based on day of the week is built upon a delicate balance of individual perceptions, individual activities, and external or societal patterns. However, the different ways in which these factors contribute is not entirely clear. As such, the heterogeneity observed becomes presents itself as an emergent factor of both individual and societal patterns, where the contributions of each theoretical component are not yet clear. This leads to an understanding of temporal heterogeneity which, in theory is clear to understand—different times and time cycles can lead to different individual manifestations of traits and behaviours. However, the mechanisms and components (what is sufficient or necessary?) is not yet resolved. When discussing a circadian rhythm, time can be thought of as a proxy for the hormone levels that fluctuate like clockwork within a 24-hour cycle. When considering other, longer cycles like the week, the answer becomes less obvious.

The work herein argues that we have yet to gain enough of an understanding of this day of the week effect, both on an individual and societal level, to reliably call upon it. Individually, the open question remains on what individual traits, if any, are amplified on different days that create these differences between days of the week. If these previously characterized day of the week effects disappear when individuals are not allowed to self-select into different days to participate in research, then what actually *is*, if anything, changing between individuals on different days of the week? As such, the evidence (contributed by the second paper) suggests that there are larger societal drivers behind the observed changes in individual behaviour. However, characterizing exactly what goes into these social dimensions is something that is unfortunately beyond the scope of the current work.

Summarizing the above contributions, this allows for a renewed understanding of what temporal heterogeneity means and how it should be addressed. The first paper solidifies that temporal heterogeneity is not something that is present immediately, rather, first thoughts are incredibly uniform, and the differences form over the course of the day. The second paper suggests that these differences require both individual tuning to the days of the week as well as a social structure that keeps these notions intact. The third paper finds that these individual fluctuations are not present when random assignment into participation takes place, suggesting that there is an internal process (unobserved characteristics motivating self-sorting) that drives these different manifestations across the days of the week in between-subject studies that recruit, without random assignment, into different days of the week. The fourth paper considers these changes in the light of an established decision-making pattern, finding that again, there are no changes present—suggesting that the effect of the day of the week may not permeate into certain established patterns. Together, this sets the groundwork for future studies into what heterogeneity means, where it originates, and how it manifests.

Limitations

The present research seeks to understand how the structure of time influences individual displays of heterogeneity. However, there are three limitations to the research that are important in interpretation and implications for future work.

The first limitation may not be thought of as a limitation per se, but as a word of caution when interpreting the work included in this thesis (and similar). In short, many of the measured dependent variables serve as the best possible proxy for 'real-world' behaviours but cannot be taken as direct substitutes. Specifically, within the context of the present work, the link between observed behaviour and underlying personality trait levels is stated as a primary conceptual construct upon which this line of research is built (as set out in the introduction). While this is an established connection within the field of personality psychology, it is important to note that this means that the measured variables may be conceptually 'one step away' from the true underlying variable of interest (such as a risk measurement versus actual risk-taking behaviour). This does not devalue the findings within this work, as the changes in the measured dependent variables add important information to understanding heterogeneity. However, the direct applicability of this work to larger naturalistic phenomena, especially when looking at behaviour, should be treated with caution.

As an important introductory note, it is crucial to note that the gap between true phenomena of interest and measured variables is one that is not unique to the present work nor unique within behavioural science. Whether due to limitations in feasibility, resources, or time, measuring something more accessible in lieu of a complex naturalistic behaviour is a frequent tactic within the field. I would go so far as to argue that this is not a true problem or limitation as long as interpretations are kept within the bounds of what is reasonable given the design. This issue is described subsequently within the context of the second and third papers.

In the context of the second paper, the dependent variable measured over the course of the study is risk attitude. However, while risk attitude fluctuations due to the day of the week effect is important when considering temporal drivers of heterogeneity, the important implication of risk attitude is how it influences behaviour. As such, the interpretation of this work can lay the groundwork for speculation on behavioural impacts but cannot be used to definitively characterize them. This does not diminish the impact of the work, as understanding fluctuations in risk attitudes is arguably a 'pre-step' to understanding fluctuations in risk behaviour (as attitudes are antecedents to behaviours). As such, these understandings still add an important part of the puzzle to manifestations of temporal heterogeneity, but interpretations should be restrained by the scope of what is actually measured.

This concept can be similarly extrapolated to the content of the third paper, which looks at engagement with health information in relation to the day of the week effect. While the measures for engagement for this paper were carefully crafted to capture as many angles as possible (time spent on measures, scoring, engagement with links), it is exactly that in the long term—measures of engagement and behaviour in a smaller scale. The findings here are important as they can inform experimental design and response to information in a controlled environment, but larger implications on behaviour over the course of the week are not possible. As such, the limitation of this work is also its strength—by understanding engagement levels across days of the week, we can begin to puzzle together the factors that contribute to behaviour.

Taken together, this first limitation is not something that needs to be 'solved', per-se, as measuring what is conceptually the next-best dependent variable (for example, lab measurements of risk attitude versus risky behaviour in the real world) is the backbone of much of experimental work. The reason this aspect of the research is highlighted is that it is important to interpret findings in light of what was actually done and measured. Of course, in a perfect world, measuring real-world behaviour would be ideal, but then loss of control over confounds would be incurred, and often field experiments are not immediately feasible. The value of experimental work, as such, is not diminished at all—applications and implications can be speculated upon, but there is always more work to be done to bring measured variables closer to the true behaviour of interest.

A second limitation of this work is the primary view of time cycles, namely, the seven-day week. Using a seven-day week has significant strengths in that it examines an omnipresent unified societal and social schedule that is imposed upon individuals. It is expressed in every avenue, from schedules to behaviours to store openings. However, this focus on the day of the week rests on a number of assumptions that are very hard to disentangle within the present set of experimental designs. Simply put, different individuals have different conceptions of what a Tuesday is, and a great degree of that is shaped by microenvironments that are difficult to characterize.

More concretely, it is useful to consider the thought exercise of comparing an individual living in a rural environment versus one living in an urban area. What gives that individual a sense of day of the week? Perhaps it is the schedule of a routine 9-5, Monday-Friday desk job in an urban setting, but what about the variable schedule of someone working on a farm, or someone working as part of the gig economy? Perhaps it is the schedule of the children in school, but what about a family without children, or a couple with opposing shift work? While these examples are purposefully selected to show a range of possibilities, they do speak to an integral truth—individual schedules may synchronize *within* small microcosms (such as individuals with similar lifestyles and rhythms), but it is unclear how these microcosms may sync *between* themselves.

The issue of “what makes a Tuesday, a Tuesday?” could be further investigated by embracing the many different factors that day of the week is currently used as a proxy by. Mixed-methods research could be used to take a deep dive into the days and schedules of a range of individuals, from the farm worker to the gig economy worker mentioned above, to understand what truly gives individuals their steer for what the day of the week looks like. This thesis touches upon the idea of unobservable characteristics driving day of the week effect several times, but this limitation could begin to be addressed by taking a deep dive into what makes a Tuesday, a Tuesday for a wide variety of individuals to drill down further into what is driving this linked to the day of the week temporal heterogeneity.

Thirdly, this research relies repeatedly on a participant sample gathered from Prolific who are living in the UK. This presents a two-pronged problem in the sense that the participant pool is both poorly diversified and poorly specified.

Regarding poorly diversified, the fact that those who are participating from the UK on Prolific is not a representative sample of the human experience is an obvious argument that does not require much elaboration. This work should be understood to limited to a profoundly WEIRD (western, educated, industrialized, rich, democratic) sample from a single region—as such, it cannot generalize broadly. This becomes even more so the case when the understanding of the days of the week is built upon one specific to such a population; the days of the week have different connotations and associations in different areas of the world and among different populations. This ties back to the discussion of heterogeneity—claims when investigating heterogeneity with the population at hand is, by many metrics, homogenous, should be made cautiously This work should be repeated with a broader sample in different populations to create a more universal understanding of what is driving temporal heterogeneity, across different populations with different perceptions of days and activities.

Regarding this population being poorly specified, as the measures of what makes each day unique are not yet clear (as discussed previously), it is then also hard to measure how much the day of respondents on Prolific mirrors or diverges from an average Tuesday. It is important to consider how representative, even with the narrow population of individuals living in the UK, a Prolific online sample is. How much do their days align with the days of the 'average' UK individual? This is of course difficult to concretely answer as the metrics at hand only reflect basic demographic information when the nuance is likely much more complex than that and we can only begin to guess. For example, perhaps the day characteristics (and how we would assess its difference between a Prolific respondent and an 'average' UK inhabitant)—how much urgency is in their day to day? What is asked of them each day? How much of that requires interaction with immediate close individuals, or with society at large? As these questions cannot be answered, this limitation can only be raised as something to keep in mind when interpreting both the results included in this thesis and broader work on the topic.

As such, research on heterogeneity in general requires making a set of (simplifying) assumptions. While we look at heterogeneity looking for a particular explanatory factor (in the context of this thesis, temporal cycles), it is difficult to have a complete view of the number of confounds present in the sample. While randomization techniques (such as those used in the third and fourth papers) help to ward against some confounds, it is important to keep this larger concept in mind when looking into heterogeneity. What factors are being measured? What factors are being controlled for? What oversights may exist? While cautious experimental design is a strong start, the challenge in measuring true drivers of heterogeneity is a difficult aspect of this line of research.

Future studies and directions

The research contained in this thesis shows just a first step towards untangling the question of individual heterogeneity and its role within behavioural science broadly. The structure of this thesis has represented a progression in a sense, from the first paper seeking the antecedents of the day of the week effect to the final two papers that look for its manifestations in a variety of domains. Especially in light of the limitations discussed previously, there are a two main lines of additional investigations that can be suggested to help continue the work of this thesis.

First and foremost, the nature of the day of the week effect and its role in driving temporal heterogeneity is not entirely understood, and this thesis itself presents mixed results in that regard. As such, the exploration should begin with better understanding where and how the days of the week shape behaviour.

The above is relatively narrow in scope, as it focuses solely on one particular manifestation of how time, and cycles of time, shape individual cognition and manifestation of personality traits. However, this understanding can be broadened in future work to explore the role of the day of the week. For example, the day of the week is in a sense used as a proxy for coordinated societal actions, but as seen in the limitations, that is perhaps an oversimplification. As such, the investigation could continue into what makes days of the week what they have come to mean. For example, would a Tuesday hold the same meaning among different groups whose experience of the week is further from the ‘typical’ modern, westernized conceptualization? For example, if living in regions of the world where the so-called ‘weekend’ is different, or working a fixed, Sunday-Thursday schedule? While these questions may seem on the surface mundane, it would help to get to an integral question the present research has not been able to definitively answer—is it our own actions, the actions of others, or both, that help shape what a day means to us?

Secondly and more broadly, the current characterization of the day of the week effect only begins to scratch the surface into what parts of individual behaviour and predisposition are changeable by this amorphous society/individual interaction of the weekdays. Further work, both to further characterize the extent and the mechanism of these temporal drivers of heterogeneity, should continue to explore where and how this day of the week effect is found. The third paper suggested that it is not present for engagement with health information, but what if it is extended to other types of information, or to measured change in behaviour? Further, the fourth paper shows a common pattern within information search and decision-making does not manifest any day of the week effect—what types, if any of the established decision-making patterns are susceptible changes due to the day of the week effect? Is it driven by underlying changes in more primary traits (such as risk or affect) or is it an emerging feature, a result of a symphony of changes that yield different decision-making effects?

As such, the further directions for this line of work can be understood to fall into two broad categories: first, what do the days of the week serve as a rough proxy for? Namely, when we investigate the day of the week effect, what effect are we truly looking at (social, personal, an interplay)? Second, what parts of the individual (both states or traits and behaviours) are susceptible to change? How do evidenced patterns of decision-making hold up against these fluctuations, if any? By understanding these dimensions of the day of the week effect, it will be possible to better characterize individual heterogeneity, both out of individual interest and for the improvement of behavioural science interventions.

Answering the above questions will require an interdisciplinary investigation. As mentioned in the introduction, behavioural science will have to acknowledge its strengths and weaknesses—while being incredibly interdisciplinary, it often comes from an angle of changing behaviour first without understanding the full ensemble of individual and societal influences that lead to a behaviour. As such, it is likely that the balance between individual systems (from the biological to the behavioural) and larger systems (societal) cannot be fully understood if the lens is through strictly behaviour change only, rather than behaviour *characterization*. Focusing on heterogeneity, it is now an unavoidable acknowledgement within the discussion of behavioural science that individuals are different and there are both individual and social or societal drivers to this. To create better behaviour change methods (the goal of much of behavioural science), one must understand the ways in which the population differs both within and between individuals. An approach harmonizing different levels of scholarship is likely a strong direction. Biological drivers of behaviour, whether characterized through hormonal analyses or through understanding different neural activation patterns, would help to characterize *why* some differences exist even if they cannot be fully articulated by the person at play. Economists' analyses of behaviour can help to further elucidate mechanisms of how decisions are made, what are the main drivers, and where people differ. These analyses can further be enhanced by physiological measurements, helping to marry the ideas and proposed mechanisms of biological and economic views of decision-making. Additionally, large-scale investigations driven by sociologists would help to inform what role our society plays in shaping this temporal heterogeneity and heterogeneity overall. The above is purposefully painted in broad strokes as it is important to understand how many directions behavioural science can, and arguably *must* expand, to continue to build (in parallel) understandings of and modifications for behaviour.

Implications for practitioners

How then, does the present work inform behavioural science work (both in academia and outside of it) moving forward? Given the general push for an acknowledgement of heterogeneity and refinement of methods, the slightly mixed bag of results presented herein does not immediately present a clear path forward. This section will therefore outline three key implications and associated, actionable recommendations for practitioners moving forward.

Firstly, there are implications that must be considered for experimental design. A primary question is of course how much time and its cycles must be considered within the design of studies, as the present work highlights the risk that the day(s) upon which data is collected inadvertently changes the findings. The extent to which this must now be taken into account is not immediately clear, as findings from the second paper recommend caution, while findings from the third and fourth papers suggest a more nuanced approach. As such, the outlook and methods can be interpreted in a multitude of ways.

On one hand, there seems to be evidence for individuals, when allowed to self-select into participation days and when couched within the societal structure, indeed exhibiting differences in traits (broadly construed). On the other hand, it seems that distance from a societal structure and random participation assignment into days of the week may wash out these effects. Or perhaps the interpretation should be held at the level of the measure of interest—perhaps for more base-level traits such as risk attitude, the day of the week matters more, but for more emergent and nuanced behaviours (that are a compounding of other traits) such as reaction to information, there is less of a day of the week effect?

For the practitioner, the above leaves more questions open than answered. As such, experimental design should proceed with caution and awareness. For example, considering one's risk attitude: a single point collection for measuring one's risk attitude, regardless of the day of the week, is unlikely to create a robust picture of an individual's trait. Where possible, experimental design should consider to what extent it is feasible to distribute data collection across days (and indeed both within and between participants, depending on the research question at hand). This would help to diffuse some of the concerns presented by the discussions of temporal heterogeneity—by focusing on a dependent variable of interest sampled at multiple points (where possible), it becomes harder to create elaborate hypotheses based upon what are underlying fluctuations and cycles of heterogeneity.

Secondly, another important recommendation is to consider when participants participate (or indeed, when measurements are taken) as a variable that should be controlled for, especially when it is not randomly assigned by the experimenter. If an individual participates in a study on a day of their choosing (especially when assuming a data collection that spans several days), it is important to consider what that choice of participation says about the individual. What traits and predispositions are this day of participation a proxy for—more leisure time, a changed risk attitude, listlessness, something else? The unfortunate response of course is that it is impossible for a researcher to keep in mind the many different causes present within the participant that could lead to the choice to participate. However, by understanding the day of participation as something that may shape the outcomes of the work, it is possible to maintain control over its influence in experimental design.

Thirdly, and perhaps in seeming opposition to the above, perhaps the day of the week effect does not need to create such a methodological and structural headache for researchers. Namely, it seems that while the day of the week may be a handy proxy of a driver of temporal heterogeneity in some domains, perhaps its effect remains limited. For example, the third paper demonstrates a clear nullification of the effect, even when there could have been a theoretical explanation for how the effect could hold. As such, it seems that one must not necessarily worry about the validity of individual studies and measurements if the day of the week was taken casually—for example, within the domain of engagement with health information, or when examining existing decision-making patterns (fourth paper) there was no effect found, and it is unlikely that this is the only domain with such a lack of effect. Therefore, perhaps one possible explanation is that the existing link between complex behaviours and these more base-level traits that do fluctuate is too abstracted to draw solid causal conclusions regarding the effects of temporal heterogeneity.

Conclusion

This research follows in a research stream of understanding why and how our ‘tools’ within behavioural science work, especially when considering how individuals differ both from each other and within themselves from day to day. The underlying assumptions of this field, briefly covered in the introductory chapter, often assume a homogenous response to a stimulus in heterogeneous populations—an obvious issue from the start.

This work sought to untangle one dimension of heterogeneity, the temporal one, to understand how time and all of the meaning, dispositions, and behaviours it creates can create synchronized (and ideally predictable) fluctuations within individual behaviours. The first and second papers found that much of these fluctuations are individually and socially informed and driven, while the third and fourth papers raised questions about if and when/where these fluctuations can be found. It is perhaps inherent to the nature of the line of inquiry itself, as heterogeneity in a system as complicated as our social world has a multitude of drivers that cannot always be cleanly understood or dissociated by experimental methods. Taken together, this works suggests that temporal drivers of heterogeneity are much more nuanced than was once assumed. Rather than seeing a day of the week as a broad stroke that affects everyone in the same way, this thesis has contributed nuance and caution to the interpretation. Individuals indeed are affected by the day and the setting around them, but the extent and mechanism remain unknown.

This thesis presents a complex set of recommendations that are not always clear—perhaps then the takeaway is to control as much as possible (random allocation where possible, samples taken over multiple days), but to acknowledge that temporal heterogeneity is more complicated than we are fully able to appreciate. Changes in individuals due to time cycles are likely the culmination of a multitude of different influences that we are unable to fully capture—from the banal time spent to the moods of others, traffic, obligations, expectations, and the outlook for the future (or the feelings of the past). As such, when we view the idea of the ‘day of the week effect’, it is exactly that—a proxy wherein we attempt to box together all the above into a neatly packaged label, a black box of “Tuesday” and all the elements therein. However, as we cannot fully understand what goes into this box at this stage, it becomes difficult to use this concept in a reliable and predictive way, especially as individuals have unique demands on their time and dynamics to their days (a retiree versus a white collar 9-5 versus a student versus a parent) that we have yet to fully measure. This of course leaves the door open to other exciting work, as a full exploration into what makes a Tuesday a Tuesday for individuals would likely begin to shed light on this phenomenon—however, this is unfortunately out of the scope of the present work. As such, this thesis likely joins many others in recommendations that can be light-heartedly summarized as “well, it’s complicated”.

Supplementary Materials

Paper 1

S1: Demographics by weekday

Day of Week	N	% Male	Average Age	Age range
Monday	118	29.66	33.73	18-66
Tuesday	117	25.64	32.61	18-66
Wednesday	120	32.50	31.65	18-63
Thursday	117	23.08	33.34	18-67
Friday	118	24.58	33.69	18-75
Saturday	118	27.97	32.53	18-75
Sunday	121	33.06	31.62	18-65

S2: Full methodology of thematic analysis, decision log and codebook

To identify common themes of penumbral thought content we used a blended approach between open and template coding [1,2]. It is important to note that several codes (temporal content, protagonist, valence, sentence formulation) were templates, whereas the others emerged through open coding. The codes and process were refined through an intercoder reliability procedure [3]. A random 10% of items were coded independently by authors JGS and VF. Once completed, coders discussed emerging codes, and areas of divergence until they reached agreement (see the decision log, Stage 1 below). This yielded a first intercoder rating (Krippendorf's alpha = 0.855). Following this process, themes originating from the open coding were further distilled to axial codes and resulted in selective codes [4,5].

Next, all items were coded by author VF. To establish a final interrater agreement, score 10% of coded items were randomly selected and coded by author JGS independently. Coders discussed differences in interpretation and agreements were logged (see the decision log, Stage 2 below; Krippendorf's alpha = 0.954). The coded data was then adjusted in line with the decision log by author VF. Finally, some codes were collapsed into selective codes to simplify the data (see Supplementary Material 3 for the finalised codebook).

In line with the procedures in qualitative coding, no inferential statistics is used, but rather a focus is drawn to ranking between classes of response [6]. This is in line with reporting standards for qualitative research as "cannot be usefully quantified given the nature, composition and size of the sample group, and ultimately the epistemological aim of the methodology" [7]. We do review co-occurrence between the three identified themes for each demographic characteristics of age and gender and across the seven weekdays. Sub-themes could not be analysed due to a minimum count of 20 items per cell. As we had an imbalance in the sample for age and gender, we compared the number of reported accounts for each theme, relative to the number of reports on other themes (by row), controlling for the number of participants in each demographic cell (columns). Where there were more than two cells per comparison, counts were compared with the average count across the others within the same characteristic (age, gender, or weekday), for example: under 25 years old, versus average of 25-38 and over 38 for age.

Decision Log for qualitative coding exercise

STAGE 1 (initial coding of 10% of items by authors VF and JGS and discussion of emerging codes)

- Simple statements of "food" or similar (coffee, breakfast, etc.) are expressions of desires that are not temporally anchored (i.e., thought is not referring to time frame)

- "I need to ___" or similar is a statement of intent or a tentative plan, so it refers to something in the unspecified future, regardless of coder interpretation of when the event would logically take place.

- Statements of “food” or similar (coffee, breakfast, etc.) are referring to self-based thoughts unless otherwise explicitly mentioned

- “I’m still tired” or similar is a past unspecified occurrence, as it is something that was true in the past and is now continuing.

- “Time to get the children ready” or similar is about other, as it is a social action with “other” beneficiary

- “What time/day/etc is it” is temporal>other, as it is clearly a time anchored inquiry but cannot be said to be either future or past necessarily

- Any statement that explicitly refers to time but is not clearly related to future/past (i.e. “Why am I awake (it was 3am)” is coded as temporal>other, because it is anchored into time but not in relation to future/past

- Statements that are left blank or say “nothing” or “I can’t remember” are left completely blank

- References to being late are treated as future unspecified, as they refer to an individual thinking of an event that is yet to happen

- Statements of illness or physical discomfort are treated as negative valence

STAGE 2 (coding of an additional 10% of data by VF & JGS, further discussion and collapsing of codes as necessary)

- Statements of action that don't specify any time frame (i.e., "ringing my boyfriend") are no time reference, as we cannot suppose they are future

- to do list is things you either do or don't have to do, so "i have to work" and "i don't have to work" both apply

- "what things I have to do today" is establishing a to-do list, not establishing time

Final codebook and dimension categorisation

	N1 code	N2 code	N3 code	N4 code
Thought characterisation	**Thoughts about feelings of states**	**(lack of) sleep or rest** *Example: "I wish i (sic) slept more hours"*		
		Dreams *Example: "…that was a weird dream"*		
		Discomfort/sick/ill *Example: "I'm aching"*		
		Waking up or being awoken	Alarm clock, alarm or noise *Example: "I need to turn my alarm off"*	
			Being awake *Example: "I don't want to be awake yet."*	
			Being woken up *Example: "why have the cats both woken me up earlier than usual?"*	
		Spatial orientation (inc. weather) *Example: "omg, what a bad weather"*		

	Spatial or temporal orientation	**Temporal orientation (day)**	What day is it *Example: "What day is it"*	
			How many days are left	
			Known day *Example: "ps5 is out today"*	
		Temporal orientation (time)	What time is it *Example: "What time is it?"*	
			Known time *Example: "Why am I awake (it was 3am)"*	
			How much time is left/lateness *Example: "Oh god I am late for work"*	
	Waking action	**Immediate needs (water, food, bathroom)**	**Attending to bodily needs**	Drinking *Example: "having a drink"*
				Eating *Example: "food"*

				Medication *Example: "Taking my medication for my chronic disease"*
			Getting up	Showering *Example: "Need to get a shower"*
				Bathroom *Example: "That I needed the bathroom"*
				Toilet *Example: "I need to go to the toilet"*
				Getting out of bed *Example: "Better get*

<table>
<tr><td rowspan="5"></td><td rowspan="5"></td><td rowspan="2"></td><td rowspan="2"></td><td>out of bed at some point”</td></tr>
<tr><td>Getting ready or dressed

Example: “I need to get ready for work”</td></tr>
<tr><td colspan="3">Looking at technology (phone or email)

Example: “Check my phone.”</td></tr>
<tr><td rowspan="2">To-do list for the day</td><td colspan="2">Establishing ‘to do list’ of the day

Example: “What I have to do in the day”</td></tr>
<tr><td>Commitment to…</td><td>Self (work/ chores/tasks)

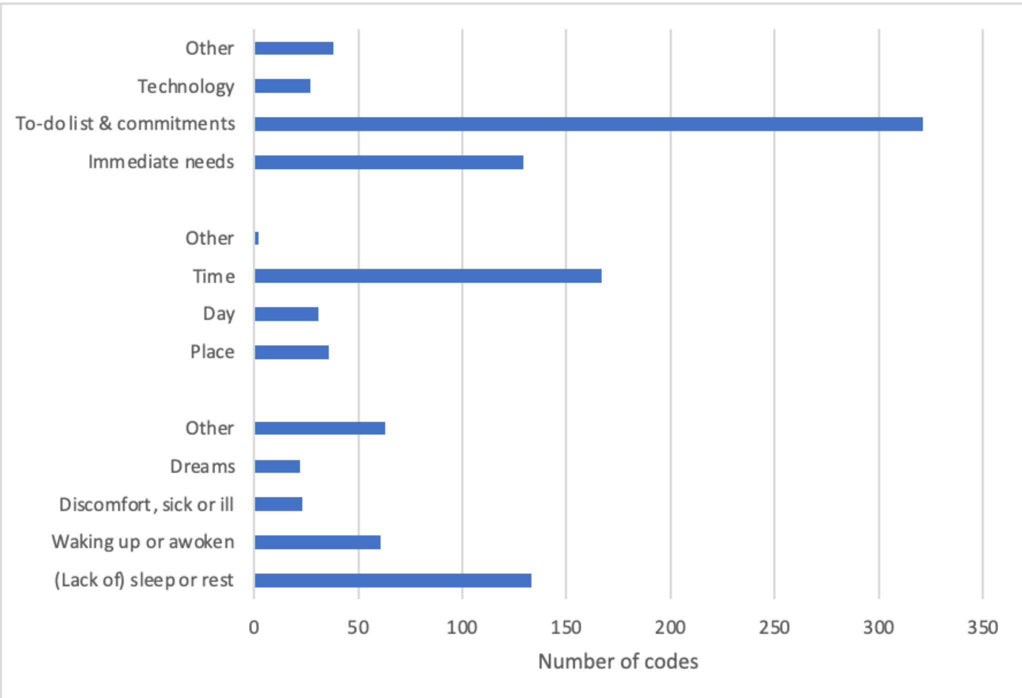
Example: “About my chores for the day”</td></tr>
</table>

				Other (work/ chores/tasks) *Example: “Get kids ready for school”*
Thought context	**Dimension**	**Categories**		
	Temporal window **(“when am I?”)**	**Thought is not referring to a timeframe**		
		Thought refers to past	Day *Example: “Remembering something upsetting that happened to me yesterday.”*	
			Week	
			Unspecified *Example: “something about the dream I was having, related to work”*	
		Thought refers to future	Day *Example: “work for the day”*	
			Week	

			Example: "About a hospital appointment next week."
			Unspecified *Example: "how much work I needed to do"*
	Question vs. statement	**Question** *Example: "what shall I wear?"*	
		Statement *Example: "it's dark"*	
	Valence of statement	**Positive** *Example: "glad im (sic) here"*	
		Negative *Example: "felt frustration and mild despair"*	
		Neutral *Example: "To check my phone"*	
	Protagonis t	**Self** *Example: "I'm tired"*	
		Other	Partner

			Example: "Ringing and waking up my boyfriend"
			Family/children/friends *Example: "go and get my son"*
			iPhone/PS5/email/electronics *Example: "I wonder if I'm going to have a lot of emails in my inbox"*

S3: Numbers of reports in different code groups



S3: Pairwise comparisons for prior knowledge and dimension

	Establish Place	Establish Day	Establish Time	Know Place	Know Day	Know Time
Establish Place		-0.157*	-0.984**	-1.242**	-0.446**	0.112
Establish Day	0.157*		-0.827**	-1.085**	-0.290**	0.269**
Establish Time	0.984**	0.827**		-0.258**	0.538**	1.096**
Know Place	1.242**	1.085**	0.258**		0.796**	0.796**
Know Day	0.446**	0.290**	-0.538**	-0.796**		0.558**
Know Time	-0.112	0.269**	-1.096**	-1.354	-0.558**	

4073 ***Note: boxes contain the mean difference between the values. *p < 0.05***
4074 ***level, **p < 0.001 level using Bonferroni correction.***

4075 **S4: Pairwise comparisons for temporal orientation and temporal distance**

	Day Ahead	Week Ahead	Year Ahead	Day Before	Week Before	Year Before
Day Ahead		0.864**	1.596**	0.907**	1.216**	1.630**
Week Ahead	-0.864**		0.732**	0.044	0.352*	0.766**
Year Ahead	-1.596**	-0.732**		-0.689**	-0.380**	0.034
Day Before	-0.907**	-0.044	-1.596**		0.308**	0.722**
Week Before	-1.216**	-0.352**	0.380**	-0.308**		0.414**

Year Before	-1.630**	-0.766**	-0.034	-0.722**	-0.414**	

*Note: boxes contain the mean difference between the values. *p < 0.05 level, **p < 0.001 level*

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Paper 2

Study 1:

***Supplementary Table A:** Demographic breakdown by weekday and Sense of Week (SOW) in Study 1. Chi-square test was used to determine any deviations in observed frequencies of males in strong [$\chi 2(6, N = 172) = 4.28$, $p = 0.64$)] and weak [$\chi 2(6, N = 106) = 6.99$, $p = 0.32$)] groups. A t-test was used to determine whether there were significant variations in ages between the strong/normal and weak groups and was found to be non-significant [$t(12) = -0.90$, $p = 0.39$]. There were significantly more males in the Normal/Strong SOW group than in the Weak SOW group significant [$t(517.9) = -2.446$, $p = 0.015$].

Sense of weekday	**Day of the Week**	**N**	**% Male**	**Average Age (σ_M)**
Strong, Normal	*Monday*	41	41.46	32.93 (1.53)
	Tuesday	43	30.23	33.58 (1.77)
	Wednesday	47	32.61	35.66 (1.75)
	Thursday	37	24.32	34.43 (2.15)
	Friday	36	52.78	32.08 (1.78)
	Saturday	34	44.11	31.76 (1.60)
	Sunday	39	43.59	32.74 (1.79)
Weak	*Monday*	81	34.57	34.04 (1.30)
	Tuesday	80	25.93	33.86 (1.46)

Wednesday	76	27.63	32.55 (1.28)
Thursday	84	19.27	32.59 (1.42)
Friday	86	34.88	31.21 (1.37)
Saturday	94	31.91	33.21 (1.38)
Sunday	83	46.66	31.60 (11.46)

***Supplementary Table B.1.:** Results of generalized linear model for Z-scored composite risk score for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.009	0.034	-0.058	0.076	0	266	0.264	0.792
Tue - Mon	0.092	0.123	-0.151	0.335	0.162	266	0.746	0.456
Wed - Mon	-0.143	0.12	-0.379	0.093	-0.251	266	-1.192	0.234
Thu – Mon**	-0.355	0.127	-0.604	-0.105	-0.623	266	-2.802	0.005
Fri - Mon	0.036	0.128	-0.215	0.287	0.063	266	0.283	0.777
Sat - Mon	-0.141	0.131	-0.398	0.116	-0.248	266	-1.082	0.28
Sun - Mon	-0.037	0.125	-0.283	0.209	-0.065	266	-0.295	0.768

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table B.2.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Normal/Strong SOW of weekday only.

Weekday		**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**

Fri	-	Sat	0.177	0.135	1.318	266	0.189	1
Fri	-	Sun	0.073	0.129	0.565	266	0.572	1
Mon	-	Fri	-0.036	0.128	-0.283	266	0.777	1
Mon	-	Sat	0.141	0.131	1.082	266	0.28	1
Mon	-	Sun	0.037	0.125	0.295	266	0.768	1
Mon	-	Wed	0.143	0.12	1.192	266	0.234	1
Mon	-	Thu	0.355	0.127	2.802	266	0.005	0.115
Mon	-	Tue	-0.092	0.123	-0.746	266	0.456	1
Sat	-	Sun	-0.104	0.132	-0.791	266	0.43	1
Wed	-	Fri	-0.179	0.124	-1.441	266	0.151	1
Wed	-	Sat	-0.002	0.127	-0.013	266	0.99	1
Wed	-	Sun	-0.106	0.122	-0.873	266	0.384	1
Wed	-	Thu	0.212	0.123	1.718	266	0.087	1
Thu	-	Fri	-0.391	0.131	-2.99	266	0.003	0.064
Thu	-	Sat	-0.214	0.134	-1.597	266	0.112	1
Thu	-	Sun	-0.318	0.128	-2.481	266	0.014	0.288
Tue	-	Fri	0.056	0.128	0.439	266	0.661	1
Tue	-	Sat	0.233	0.131	1.787	266	0.075	1
Tue	-	Sun	0.129	0.125	1.032	266	0.303	1
Tue	-	Wed	0.235	0.12	1.959	266	0.051	1
Tue	-	Thu*	0.447	0.127	3.529	266	< .001	0.01

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table B.3.:** Results of generalized linear model for Z-scored composite risk score for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.034	0.034	-0.033	0.101	0.000	264	0.994	0.321
Male – Female**	0.223	0.069	0.086	0.359	0.391	264	3.215	0.001
Age*	-0.008	0.003	-0.014	-0.002	-0.151	264	-2.575	0.011
Tue - Mon	0.121	0.121	-0.117	0.358	0.212	264	1.000	0.318
Wed -Mon	-0.102	0.117	-0.333	0.129	-0.179	264	-0.867	0.387
Thu – Mon*	-0.305	0.124	-0.550	-0.060	-0.536	264	-2.456	0.015
Fri - Mon	-0.003	0.125	-0.249	0.242	-0.006	264	-0.026	0.979
Sat - Mon	-0.154	0.127	-0.405	0.097	-0.271	264	-1.211	0.227
Sun - Mon	-0.043	0.122	-0.283	0.197	-0.076	264	-0.353	0.724

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table B.4.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.151	0.132	1.149	264	0.252	1
Fri	-	Sun	0.040	0.126	0.315	264	0.753	1
Mon	-	Fri	0.003	0.125	0.026	264	0.979	1

Mon	-	Sat	0.154	0.128	1.211	264	0.227	1
Mon	-	Sun	0.043	0.122	0.353	264	0.724	1
Mon	-	Wed	0.102	0.118	0.867	264	0.387	1
Mon	-	Thu	0.305	0.124	2.456	264	0.015	0.309
Mon	-	Tue	-0.121	0.121	-1.000	264	0.318	1
Sat	-	Sun	-0.111	0.129	-0.864	264	0.389	1
Wed	-	Fri	-0.099	0.123	-0.802	264	0.423	1
Wed	-	Sat	0.052	0.125	0.419	264	0.675	1
Wed	-	Sun	-0.059	0.119	-0.494	264	0.622	1
Wed	-	Thu	0.203	0.121	1.686	264	0.093	1
Thu	-	Fri	-0.302	0.130	-2.329	264	0.021	0.433
Thu	-	Sat	-0.151	0.131	-1.147	264	0.252	1
Thu	-	Sun	-0.262	0.126	-2.082	264	0.038	0.805
Tue	-	Fri	0.124	0.126	0.986	264	0.325	1
Tue	-	Sat	0.275	0.128	2.151	264	0.032	0.681
Tue	-	Sun	0.164	0.122	1.339	264	0.182	1
Tue	-	Wed	0.222	0.117	1.899	264	0.059	1
Tue	-	Thu*	0.426	0.124	3.442	264	< .001	0.014

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table B.5.:** Results of generalized linear model for Z-scored composite risk score for those with a Weak SOW of weekday only.

	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	-7.397e−4	0.024	-0.049	0.047	0	574	-0.03	0.976
Tue - Mon	-0.116	0.093	-0.299	0.067	-0.197	574	-1.248	0.212
Wed - Mon	-0.148	0.094	-0.333	0.037	-0.251	574	-1.567	0.118
Thu - Mon	0.079	0.092	-0.102	0.26	0.133	574	0.856	0.392
Fri - Mon	-0.006	0.091	-0.186	0.174	-0.01	574	-0.064	0.949
Sat - Mon	0.011	0.09	-0.165	0.187	0.019	574	0.123	0.902
Sun - Mon	-0.012	0.093	-0.193	0.17	-0.02	574	-0.126	0.9

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table B.6.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Weak SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.017	0.088	-0.192	574	0.848	1
Fri	-	Sun	0.006	0.091	0.064	574	0.949	1
Mon	-	Fri	0.006	0.091	0.064	574	0.949	1
Mon	-	Sat	-0.011	0.09	-0.123	574	0.902	1
Mon	-	Sun	0.012	0.093	0.126	574	0.9	1
Mon	-	Wed	0.148	0.094	1.567	574	0.118	1
Mon	-	Thu	-0.079	0.092	-0.856	574	0.392	1
Mon	-	Tue	0.116	0.093	1.248	574	0.212	1
Sat	-	Sun	0.023	0.089	0.254	574	0.8	1
Wed	-	Fri	-0.142	0.093	-1.532	574	0.126	1
Wed	-	Sat	-0.159	0.091	-1.745	574	0.082	1

Wed	-	Sun	-0.136	0.094	-1.453	574	0.147	1
Wed	-	Thu	-0.227	0.093	-2.43	574	0.015	0.323
Thu	-	Fri	0.085	0.09	0.936	574	0.35	1
Thu	-	Sat	0.068	0.089	0.764	574	0.445	1
Thu	-	Sun	0.09	0.091	0.988	574	0.323	1
Tue	-	Fri	-0.11	0.091	-1.207	574	0.228	1
Tue	-	Sat	-0.127	0.09	-1.417	574	0.157	1
Tue	-	Sun	-0.105	0.093	-1.13	574	0.259	1
Tue	-	Wed	0.032	0.094	0.335	574	0.738	1
Tue	-	Thu	-0.195	0.092	-2.119	574	0.035	0.725

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table B.7.:** Results of generalized linear model for Z-scored composite risk score for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.078	0.025	0.029	0.127	0.000	571	3.124	0.002
Male – Female***	0.380	0.050	0.282	0.479	0.643	571	7.582	< .001
Age***	-0.011	0.002	-0.014	-0.007	-0.233	571	-6.035	< .001
Tue - Mon	-0.086	0.087	-0.256	0.084	-0.146	571	-0.993	0.321
Wed - Mon	-0.137	0.088	-0.309	0.035	-0.232	571	-1.564	0.118
Thu - Mon	0.125	0.086	-0.044	0.294	0.211	571	1.449	0.148
Fri - Mon	-0.037	0.085	-0.204	0.130	-0.063	571	-0.439	0.661
Sat - Mon	0.013	0.083	-0.151	0.177	0.022	571	0.154	0.878

Sun - Mon	-0.026	0.086	-0.195	0.143	-0.044	571	-0.301	0.764

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table B.8.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Weak SOW of weekday, age, and gender.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.050	0.082	-0.612	571	0.541	1
Fri	-	Sun	-0.011	0.084	-0.136	571	0.892	1
Mon	-	Fri	0.037	0.085	0.439	571	0.661	1
Mon	-	Sat	-0.013	0.083	-0.154	571	0.878	1
Mon	-	Sun	0.026	0.086	0.301	571	0.764	1
Mon	-	Wed	0.137	0.088	1.564	571	0.118	1
Mon	-	Thu	-0.125	0.086	-1.449	571	0.148	1
Mon	-	Tue	0.086	0.087	0.993	571	0.321	1
Sat	-	Sun	0.039	0.083	0.467	571	0.641	1
Wed	-	Fri	-0.100	0.086	-1.157	571	0.248	1
Wed	-	Sat	-0.150	0.085	-1.772	571	0.077	1
Wed	-	Sun	-0.111	0.087	-1.277	571	0.202	1
Wed	-	Thu	-0.262	0.087	-3.011	571	0.003	0.057
Thu	-	Fri	0.162	0.085	1.916	571	0.056	1
Thu	-	Sat	0.112	0.083	1.350	571	0.178	1

Thu	-	Sun	0.151	0.085	1.763	571	0.078	1
Tue	-	Fri	-0.049	0.085	-0.571	571	0.569	1
Tue	-	Sat	-0.099	0.083	-1.184	571	0.237	1
Tue	-	Sun	-0.060	0.086	-0.698	571	0.486	1
Tue	-	Wed	0.051	0.088	0.584	571	0.559	1
Tue	-	Thu	-0.211	0.086	-2.455	571	0.014	0.302

4141 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4142

4143 **Supplementary Material Table C:** Individual risk measurement descriptives
4144 by weekday and Sense of Week (SOW) in Study 1.

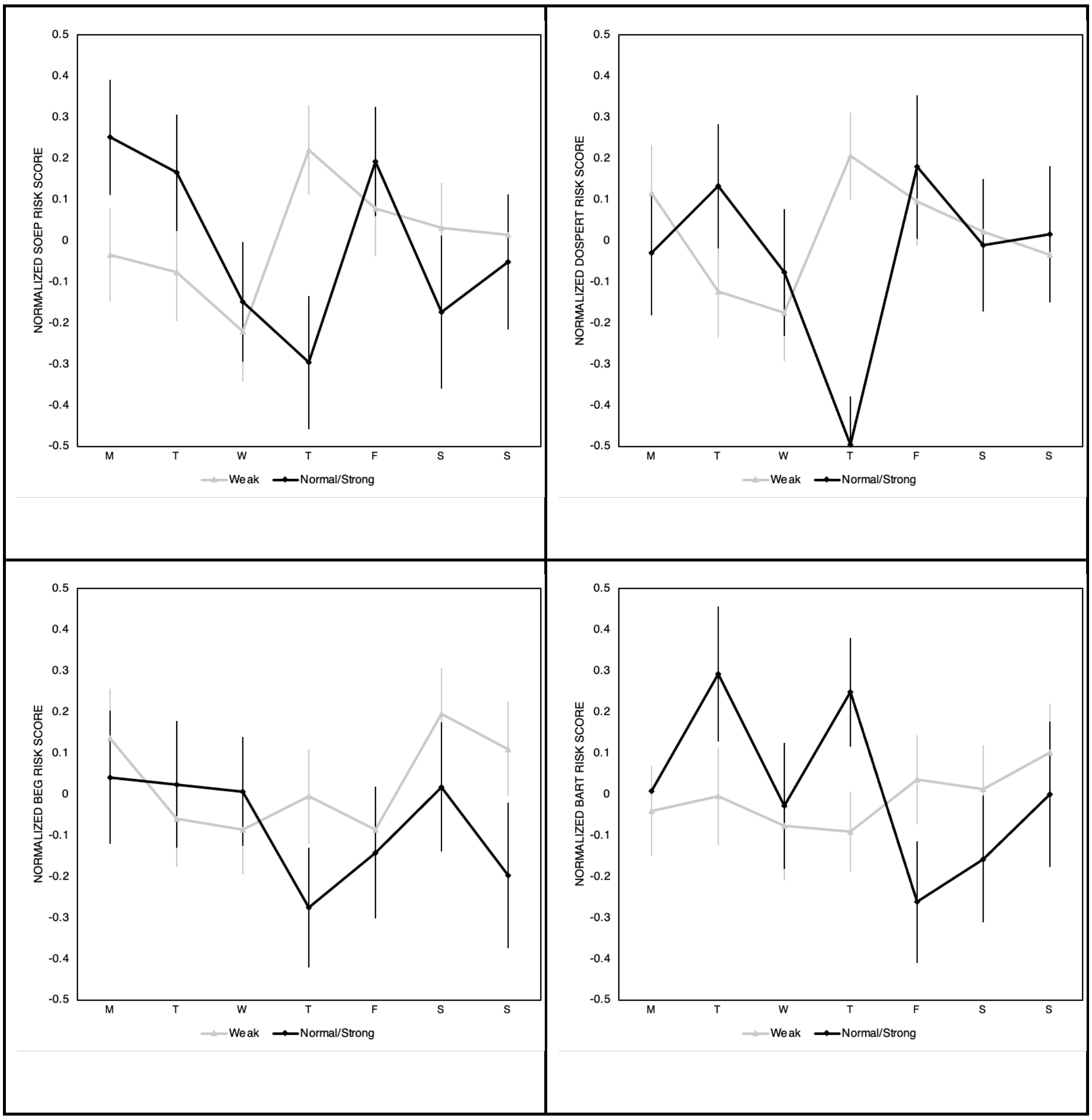
			N	**Mean**	**σ_M**
SOEP	**Strong, Normal**	*Monday*	41	0.251	0.14
		Tuesday	42	0.165	0.141
		Wednesday	47	-0.149	0.145
		Thursday	37	-0.296	0.162
		Friday	38	0.192	0.133
		Saturday	34	-0.174	0.186
		Sunday	39	-0.0519	0.164
	Weak	*Monday*	81	-0.0338	0.112

		Tuesday	80	-0.0767	0.118
		Wednesday	76	-0.221	0.12
		Thursday	84	0.22	0.107
		Friday	86	0.0773	0.113
		Saturday	94	0.0313	0.107
		Sunday	83	0.0132	0.0958
DOSPERT	**Strong, Normal**	*Monday*	41	-0.0301	0.152
		Tuesday	43	0.132	0.151
		Wednesday	47	-0.0772	0.154
		Thursday	37	-0.495	0.117
		Friday	38	0.179	0.174
		Saturday	34	-0.0112	0.161
		Sunday	39	0.015	0.166
	Weak	*Monday*	81	0.115	0.116
		Tuesday	80	-0.123	0.112
		Wednesday	76	-0.175	0.116

		Thursday	84	0.206	0.104
		Friday	86	0.0952	0.106
		Saturday	94	0.0224	0.105
		Sunday	83	-0.0351	0.112
BEG	**Strong, Normal**	*Monday*	41	0.0407	0.162
		Tuesday	43	0.0233	0.154
		Wednesday	46	0.00678	0.132
		Thursday	37	-0.275	0.145
		Friday	36	-0.142	0.16
		Saturday	33	0.0175	0.157
		Sunday	39	-0.197	0.177
	Weak	*Monday*	80	0.136	0.119
		Tuesday	80	-0.0597	0.115
		Wednesday	76	-0.0865	0.108
		Thursday	84	-0.00556	0.113
		Friday	86	0.195	0.1

		Saturday	93	0.195	0.109
		Sunday	82	0.11	0.114
BART	**Strong, Normal**	*Monday*	41	0.00711	0.131
		Tuesday	43	0.292	0.164
		Wednesday	47	-0.0278	0.153
		Thursday	37	0.248	0.132
		Friday	38	-0.262	0.148
		Saturday	34	-0.158	0.154
		Sunday	39	0.000184	0.177
	Weak	*Monday*	81	-0.041	0.108
		Tuesday	80	-0.00473	0.117
		Wednesday	76	-0.0762	0.132
		Thursday	84	-0.0909	0.0951
		Friday	86	0.0356	0.107
		Saturday	94	0.0125	0.104
		Sunday	83	0.101	0.117

Supplementary Material Figure D: The mean scores for each of the four main risk measurements across participants, separated out between a weak (rating of 1 or 2 on a scale of 1 to 5) versus normal or weak (rating of 3, 4, or 5 on the same scale) sense of the week, in Study 1, all normalized using z-scoring. A) SOEP General, B) DOSPERT General, C) BEG, D) Normalized BART scores, scored as per Lejuez et al. (2002) methodology. Error bars represent +/- SE.



***Supplementary Table D.1.:** Results of generalized linear model for Z-scored SOEP for those with a Normal/Strong SOW of weekday only.

		95% Confidence Interval	

Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	-0.004	0.06	-0.122	0.113	0	271	-0.069	0.945
Tue - Mon	-0.089	0.217	-0.517	0.339	-0.089	271	-0.409	0.683
Wed - Mon	-0.412	0.212	-0.828	0.005	-0.412	271	-1.944	0.053
Thu - Mon*	-0.563	0.225	-1.005	-0.121	-0.563	271	-2.505	0.013
Fri - Mon	-0.061	0.223	-0.5	0.378	-0.061	271	-0.273	0.785
Sat - Mon	-0.437	0.23	-0.889	0.015	-0.437	271	-1.902	0.058
Sun - Mon	-0.312	0.222	-0.748	0.125	-0.312	271	-1.407	0.161

***Supplementary Materials Table D.2.:** Results of post-hoc comparisons for Z-scored SOEP risk score for those with a Normal/Strong SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	0.376	0.234	1.608	271	0.109	1
Fri	-	Sun	0.251	0.226	1.11	271	0.268	1
Mon	-	Fri	0.061	0.223	0.273	271	0.785	1
Mon	-	Sat	0.437	0.23	1.902	271	0.058	1
Mon	-	Sun	0.312	0.222	1.407	271	0.161	1
Mon	-	Wed	0.412	0.212	1.944	271	0.053	1
Mon	-	Thu	0.563	0.225	2.505	271	0.013	0.269
Mon	-	Tue	0.089	0.217	0.409	271	0.683	1
Sat	-	Sun	-0.125	0.232	-0.539	271	0.59	1
Wed	-	Fri	-0.351	0.216	-1.622	271	0.106	1
Wed	-	Sat	0.025	0.223	0.114	271	0.91	1

Wed	-	Sun	-0.1	0.215	-0.466	271	0.642	1
Wed	-	Thu	0.151	0.218	0.694	271	0.488	1
Thu	-	Fri	-0.502	0.229	-2.193	271	0.029	0.612
Thu	-	Sat	-0.126	0.235	-0.535	271	0.593	1
Thu	-	Sun	-0.251	0.227	-1.104	271	0.27	1
Tue	-	Fri	-0.028	0.222	-0.126	271	0.9	1
Tue	-	Sat	0.348	0.228	1.523	271	0.129	1
Tue	-	Sun	0.223	0.22	1.011	271	0.313	1
Tue	-	Wed	0.323	0.21	1.534	271	0.126	1
Tue	-	Thu	0.474	0.223	2.122	271	0.035	0.73

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.3.:** Results of generalized linear model for Z-scored SOEP for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.04	0.06	-0.079	0.158	0	269	0.663	0.508
Male - Female	0.387	0.122	0.146	0.627	0.387	269	3.168	0.002
Tue - Mon	-0.041	0.214	-0.462	0.379	-0.041	269	-0.193	0.847
Wed - Mon	-0.355	0.208	-0.765	0.055	-0.355	269	-1.704	0.089
Thu – Mon*	-0.481	0.221	-0.917	-0.045	-0.481	269	-2.173	0.031
Fri - Mon	-0.103	0.219	-0.534	0.329	-0.103	269	-0.469	0.64
Sat – Mon*	-0.459	0.225	-0.903	-0.015	-0.459	269	-2.037	0.043
Sun - Mon	-0.322	0.217	-0.749	0.106	-0.322	269	-1.481	0.14

Age	-0.01	0.005	-0.021	1.56E-04	-0.114	269	-1.939	0.054

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.4.:** Results of post-hoc comparisons for Z-scored SOEP risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.356	0.229	1.554	269	0.121	1
Fri	-	Sun	0.219	0.222	0.989	269	0.324	1
Mon	-	Fri	0.103	0.219	0.469	269	0.64	1
Mon	-	Sat	0.459	0.225	2.037	269	0.043	0.896
Mon	-	Sun	0.322	0.217	1.481	269	0.14	1
Mon	-	Wed	0.355	0.208	1.704	269	0.089	1
Mon	-	Thu	0.481	0.221	2.173	269	0.031	0.644
Mon	-	Tue	0.041	0.214	0.193	269	0.847	1
Sat	-	Sun	-0.137	0.228	-0.602	269	0.547	1
Wed	-	Fri	-0.252	0.214	-1.181	269	0.239	1
Wed	-	Sat	0.104	0.22	0.473	269	0.637	1
Wed	-	Sun	-0.033	0.211	-0.157	269	0.875	1
Wed	-	Thu	0.126	0.214	0.59	269	0.556	1
Thu	-	Fri	-0.378	0.227	-1.668	269	0.097	1
Thu	-	Sat	-0.022	0.233	-0.095	269	0.924	1
Thu	-	Sun	-0.159	0.224	-0.71	269	0.478	1

Tue	-	Fri	0.061	0.219	0.281	269	0.779	1
Tue	-	Sat	0.418	0.225	1.858	269	0.064	1
Tue	-	Sun	0.281	0.217	1.295	269	0.196	1
Tue	-	Wed	0.314	0.207	1.52	269	0.13	1
Tue	-	Thu	0.44	0.219	2.007	269	0.046	0.96

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.5.:** Results of generalized linear model for Z-scored SOEP for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.004	0.041	-0.086	0.077	0	577	-0.108	0.914
Tue - Mon	-0.042	0.157	-0.351	0.266	-0.042	577	-0.27	0.787
Wed - Mon	-0.185	0.159	-0.498	0.128	-0.185	577	-1.161	0.246
Thu - Mon	0.251	0.155	-0.054	0.556	0.251	577	1.615	0.107
Fri - Mon	0.11	0.154	-0.194	0.413	0.11	577	0.711	0.477
Sat - Mon	0.064	0.151	-0.233	0.361	0.064	577	0.426	0.671
Sun - Mon	0.047	0.156	-0.259	0.353	0.047	577	0.299	0.765

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.6.:** Results of post-hoc comparisons for Z-scored SOEP risk score for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**P**	**$p_{bonferroni}$**
Fri	-	Sat	0.045	0.149	0.306	577	0.76	1

Fri	-	Sun	0.063	0.154	0.412	577	0.68	1
Mon	-	Fri	-0.11	0.154	-0.711	577	0.477	1
Mon	-	Sat	-0.064	0.151	-0.426	577	0.671	1
Mon	-	Sun	-0.047	0.156	-0.299	577	0.765	1
Mon	-	Wed	0.185	0.159	1.161	577	0.246	1
Mon	-	Thu	-0.251	0.155	-1.615	577	0.107	1
Mon	-	Tue	0.042	0.157	0.27	577	0.787	1
Sat	-	Sun	0.018	0.15	0.119	577	0.906	1
Wed	-	Fri	-0.295	0.157	-1.877	577	0.061	1
Wed	-	Sat	-0.249	0.154	-1.62	577	0.106	1
Wed	-	Sun	-0.231	0.158	-1.461	577	0.144	1
Wed	-	Thu	-0.436	0.158	-2.76	577	0.006	0.125
Thu	-	Fri	0.141	0.153	0.922	577	0.357	1
Thu	-	Sat	0.187	0.15	1.246	577	0.213	1
Thu	-	Sun	0.204	0.154	1.324	577	0.186	1
Tue	-	Fri	-0.152	0.155	-0.983	577	0.326	1
Tue	-	Sat	-0.107	0.152	-0.704	577	0.482	1
Tue	-	Sun	-0.089	0.156	-0.569	577	0.569	1
Tue	-	Wed	0.142	0.16	0.891	577	0.373	1
Tue	-	Thu	-0.293	0.156	-1.883	577	0.06	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.7.:** Results of generalized linear model for Z-scored SOEP for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.102	0.043	0.017	0.187	0	574	2.355	0.019
Male – Female***	0.518	0.087	0.347	0.688	0.518	574	5.966	< .001
Age***	-0.016	0.003	-0.022	-0.01	-0.205	574	-5.199	< .001
Tue - Mon	-0.002	0.15	-0.297	0.292	-0.002	574	-0.015	0.988
Wed - Mon	-0.173	0.152	-0.471	0.125	-0.173	574	-1.14	0.255
Thu – Mon*	0.304	0.149	0.011	0.597	0.304	574	2.04	0.042
Fri - Mon	0.062	0.147	-0.227	0.352	0.062	574	0.422	0.673
Sat - Mon	0.065	0.144	-0.218	0.348	0.065	574	0.449	0.653
Sun - Mon	0.024	0.149	-0.268	0.316	0.024	574	0.16	0.873

4178 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4179

4180 ***Supplementary Materials Table D.8.:** Results of post-hoc comparisons for
4181 Z-scored SOEP risk score for those with a Weak SOW of weekday, age, and
4182 gender.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**P**	$p_{bonferroni}$
Fri	-	Sat	-0.002	0.142	-0.017	574	0.986	1
Fri	-	Sun	0.038	0.146	0.263	574	0.792	1
Mon	-	Fri	-0.062	0.147	-0.422	574	0.673	1
Mon	-	Sat	-0.065	0.144	-0.449	574	0.653	1
Mon	-	Sun	-0.024	0.149	-0.16	574	0.873	1
Mon	-	Wed	0.173	0.152	1.14	574	0.255	1
Mon	-	Thu	-0.304	0.149	-2.04	574	0.042	0.877
Mon	-	Tue	0.002	0.15	0.015	574	0.988	1

Sat	-	Sun	0.041	0.143	0.286	574	0.775	1
Wed	-	Fri	-0.235	0.15	-1.572	574	0.117	1
Wed	-	Sat	-0.238	0.147	-1.622	574	0.105	1
Wed	-	Sun	-0.197	0.151	-1.305	574	0.192	1
Wed	-	Thu*	-0.477	0.151	-3.16	574	0.002	0.035
Thu	-	Fri	0.242	0.147	1.647	574	0.1	1
Thu	-	Sat	0.239	0.144	1.668	574	0.096	1
Thu	-	Sun	0.28	0.148	1.896	574	0.058	1
Tue	-	Fri	-0.064	0.148	-0.436	574	0.663	1
Tue	-	Sat	-0.067	0.145	-0.463	574	0.644	1
Tue	-	Sun	-0.026	0.149	-0.174	574	0.862	1
Tue	-	Wed	0.171	0.152	1.123	574	0.262	1
Tue	-	Thu	-0.306	0.149	-2.055	574	0.04	0.846

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table D.9.:** Results of generalized linear model for Z-scored DOSPERT for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**T**	**p**
(Intercept)	-0.004	0.06	-0.121	0.114	0	272	-0.059	0.953
Tue - Mon	0.164	0.216	-0.261	0.59	0.164	272	0.76	0.448
Wed - Mon	-0.048	0.212	-0.464	0.369	-0.048	272	-0.225	0.822
Thu - Mon*	-0.47	0.225	-0.912	-0.028	-0.47	272	-2.095	0.037
Fri - Mon	0.211	0.223	-0.228	0.65	0.211	272	0.947	0.344

Sat - Mon	0.019	0.23	-0.433	0.471	0.019	272	0.083	0.934
Sun - Mon	0.046	0.222	-0.391	0.482	0.046	272	0.206	0.837

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.10.:** Results of post-hoc comparisons for Z-scored DOSPERT risk score for those with a Normal/Strong SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	P	$p_{bonferroni}$
Fri	-	Sat	0.192	0.234	0.822	272	0.412	1
Fri	-	Sun	0.166	0.226	0.734	272	0.464	1
Mon	-	Fri	-0.211	0.223	-0.947	272	0.344	1
Mon	-	Sat	-0.019	0.23	-0.083	272	0.934	1
Mon	-	Sun	-0.046	0.222	-0.206	272	0.837	1
Mon	-	Wed	0.048	0.212	0.225	272	0.822	1
Mon	-	Thu	0.47	0.225	2.095	272	0.037	0.78
Mon	-	Tue	-0.164	0.216	-0.76	272	0.448	1
Sat	-	Sun	-0.026	0.232	-0.114	272	0.909	1
Wed	-	Fri	-0.259	0.216	-1.199	272	0.232	1
Wed	-	Sat	-0.067	0.223	-0.299	272	0.765	1
Wed	-	Sun	-0.093	0.215	-0.435	272	0.664	1
Wed	-	Thu	0.423	0.218	1.942	272	0.053	1
Thu	-	Fri	-0.682	0.229	-2.98	272	0.003	0.066
Thu	-	Sat	-0.489	0.235	-2.08	272	0.038	0.807
Thu	-	Sun	-0.516	0.227	-2.27	272	0.024	0.504

Tue	-	Fri	-0.047	0.22	-0.213	272	0.832	1
Tue	-	Sat	0.145	0.227	0.639	272	0.523	1
Tue	-	Sun	0.119	0.219	0.543	272	0.588	1
Tue	-	Wed	0.212	0.209	1.015	272	0.311	1
Tue	-	Thu	0.635	0.222	2.858	272	0.005	0.096

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.11.:** Results of generalized linear model for Z-scored DOSPERT risk score for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**T**	**p**
(Intercept)	0.035	0.060	-0.083	0.152	0.000	270	0.583	0.560
Age***	-0.018	0.005	-0.028	-0.007	-0.196	270	-3.362	< .001
Male – Female**	0.340	0.121	0.102	0.578	0.340	270	2.810	0.005
Tue - Mon	0.214	0.211	-0.201	0.629	0.214	270	1.016	0.311
Wed - Mon	0.025	0.206	-0.381	0.432	0.025	270	0.123	0.902
Thu - Mon	-0.386	0.219	-0.818	0.046	-0.386	270	-1.757	0.080
Fri - Mon	0.167	0.217	-0.260	0.595	0.167	270	0.771	0.441
Sat - Mon	-0.010	0.223	-0.450	0.430	-0.010	270	-0.046	0.963
Sun - Mon	0.035	0.215	-0.389	0.459	0.035	270	0.163	0.871

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.12.:** Results of post-hoc comparisons for Z-scored DOSPERT risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			Difference	SE	t	df	P	$p_{bonferroni}$
Fri	-	Sat	0.178	0.227	0.782	270	0.435	1
Fri	-	Sun	0.132	0.220	0.602	270	0.547	1
Mon	-	Fri	-0.167	0.217	-0.771	270	0.441	1
Mon	-	Sat	0.010	0.223	0.046	270	0.963	1
Mon	-	Sun	-0.035	0.215	-0.163	270	0.871	1
Mon	-	Wed	-0.025	0.207	-0.123	270	0.902	1
Mon	-	Thu	0.386	0.220	1.757	270	0.08	1
Mon	-	Tue	-0.214	0.211	-1.016	270	0.311	1
Sat	-	Sun	-0.045	0.226	-0.201	270	0.841	1
Wed	-	Fri	-0.142	0.212	-0.670	270	0.503	1
Wed	-	Sat	0.036	0.218	0.164	270	0.87	1
Wed	-	Sun	-0.010	0.210	-0.046	270	0.963	1
Wed	-	Thu	0.411	0.212	1.939	270	0.053	1
Thu	-	Fri	-0.553	0.225	-2.459	270	0.015	0.306
Thu	-	Sat	-0.375	0.231	-1.629	270	0.105	1
Thu	-	Sun	-0.421	0.222	-1.892	270	0.06	1
Tue	-	Fri	0.047	0.216	0.216	270	0.829	1
Tue	-	Sat	0.224	0.222	1.011	270	0.313	1
Tue	-	Sun	0.179	0.214	0.837	270	0.403	1
Tue	-	Wed	0.189	0.204	0.927	270	0.355	1
Tue	-	Thu	0.600	0.216	2.776	270	0.006	0.124

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table D.13.:** Results of generalized linear model for Z-scored DOSPERT for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**T**	**p**
(Intercept)	-0.003	0.041	-0.085	0.078	0	577	-0.085	0.933
Tue - Mon	-0.236	0.157	-0.545	0.073	-0.236	577	-1.501	0.134
Wed - Mon	-0.287	0.159	-0.6	0.026	-0.287	577	-1.804	0.072
Thu - Mon	0.091	0.155	-0.214	0.396	0.091	577	0.587	0.557
Fri - Mon	-0.019	0.154	-0.323	0.284	-0.019	577	-0.125	0.901
Sat - Mon	-0.092	0.151	-0.389	0.206	-0.092	577	-0.605	0.545
Sun - Mon	-0.149	0.156	-0.455	0.157	-0.149	577	-0.954	0.34

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.14.:** Results of post-hoc comparisons for Z-scored SOEP risk score for those with a Weak SOW of weekday only.

		Weekday	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	0.072	0.149	0.486	577	0.627	1
Fri	-	Sun	0.129	0.153	0.843	577	0.399	1
Mon	-	Fri	0.019	0.154	0.125	577	0.901	1
Mon	-	Sat	0.092	0.151	0.605	577	0.545	1
Mon	-	Sun	0.149	0.156	0.954	577	0.34	1
Mon	-	Wed	0.287	0.159	1.804	577	0.072	1
Mon	-	Thu	-0.091	0.155	-0.587	577	0.557	1

Mon	-	Tue	0.236	0.157	1.501	577	0.134	1
Sat	-	Sun	0.057	0.15	0.38	577	0.704	1
Wed	-	Fri	-0.268	0.157	-1.707	577	0.088	1
Wed	-	Sat	-0.196	0.154	-1.273	577	0.204	1
Wed	-	Sun	-0.139	0.158	-0.876	577	0.382	1
Wed	-	Thu	-0.379	0.158	-2.397	577	0.017	0.354
Thu	-	Fri	0.11	0.153	0.722	577	0.471	1
Thu	-	Sat	0.183	0.15	1.22	577	0.223	1
Thu	-	Sun	0.24	0.154	1.554	577	0.121	1
Tue	-	Fri	-0.217	0.155	-1.399	577	0.162	1
Tue	-	Sat	-0.144	0.152	-0.952	577	0.342	1
Tue	-	Sun	-0.087	0.156	-0.559	577	0.577	1
Tue	-	Wed	0.051	0.16	0.321	577	0.748	1
Tue	-	Thu	-0.327	0.156	-2.1	577	0.036	0.76

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.15:** Results of generalized linear model for Z-scored DOSPERT for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.110	0.043	0.026	0.194	0.000	574	2.584	0.01
Age***	-0.019	0.003	-0.025	-0.013	-0.243	574	-6.249	< .001
Male – Female***	0.548	0.086	0.380	0.717	0.548	574	6.404	< .001
Tue - Mon	-0.194	0.148	-0.484	0.097	-0.194	574	-1.310	0.191
Wed - Mon	-0.278	0.150	-0.572	0.016	-0.278	574	-1.855	0.064

Thu - Mon	0.152	0.147	-0.136	0.441	0.152	574	1.037	0.300
Fri - Mon	-0.075	0.145	-0.361	0.210	-0.075	574	-0.519	0.604
Sat - Mon	-0.093	0.142	-0.372	0.186	-0.093	574	-0.654	0.514
Sun - Mon	-0.178	0.147	-0.466	0.110	-0.178	574	-1.213	0.226

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.16.:** Results of post-hoc comparisons for Z-scored DOSPERT risk score for those with a Weak SOW of weekday, age, and gender.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	0.017	0.140	0.124	574	0.901	1
Fri	-	Sun	0.102	0.144	0.710	574	0.478	1
Mon	-	Fri	0.075	0.145	0.519	574	0.604	1
Mon	-	Sat	0.093	0.142	0.654	574	0.514	1
Mon	-	Sun	0.178	0.147	1.213	574	0.226	1
Mon	-	Wed	0.278	0.150	1.855	574	0.064	1
Mon	-	Thu	-0.152	0.147	-1.037	574	0.3	1
Mon	-	Tue	0.194	0.148	1.310	574	0.191	1
Sat	-	Sun	0.085	0.141	0.602	574	0.548	1
Wed	-	Fri	-0.202	0.148	-1.371	574	0.171	1
Wed	-	Sat	-0.185	0.145	-1.280	574	0.201	1
Wed	-	Sun	-0.100	0.149	-0.673	574	0.501	1
Wed	-	Thu	-0.430	0.149	-2.889	574	0.004	0.084
Thu	-	Fri	0.228	0.145	1.573	574	0.116	1

Thu	-	Sat	0.245	0.142	1.733	574	0.084	1
Thu	-	Sun	0.330	0.146	2.264	574	0.024	0.503
Tue	-	Fri	-0.118	0.146	-0.810	574	0.418	1
Tue	-	Sat	-0.101	0.143	-0.707	574	0.48	1
Tue	-	Sun	-0.016	0.147	-0.108	574	0.914	1
Tue	-	Wed	0.084	0.150	0.561	574	0.575	1
Tue	-	Thu	-0.346	0.147	-2.355	574	0.019	0.396

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.17:** Results of generalized linear model for Z-scored BEG for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.005	0.061	-0.124	0.115	0	268	-0.077	0.939
Tue - Mon	-0.018	0.219	-0.449	0.413	-0.018	268	-0.082	0.935
Wed - Mon	-0.035	0.216	-0.459	0.389	-0.035	268	-0.162	0.871
Thu - Mon	-0.325	0.228	-0.773	0.123	-0.325	268	-1.428	0.154
Fri - Mon	-0.189	0.229	-0.64	0.263	-0.189	268	-0.823	0.411
Sat - Mon	-0.024	0.235	-0.486	0.438	-0.024	268	-0.102	0.919
Sun - Mon	-0.245	0.225	-0.687	0.197	-0.245	268	-1.093	0.276

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.18.:** Results of post-hoc comparisons for Z-scored BEG risk score for those with a Normal/Strong SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.165	0.242	-0.681	268	0.496	1
Fri	-	Sun	0.057	0.232	0.244	268	0.807	1
Mon	-	Fri	0.189	0.229	0.823	268	0.411	1
Mon	-	Sat	0.024	0.235	0.102	268	0.919	1
Mon	-	Sun	0.245	0.225	1.093	268	0.276	1
Mon	-	Wed	0.035	0.216	0.162	268	0.871	1
Mon	-	Thu	0.325	0.228	1.428	268	0.154	1
Mon	-	Tue	0.018	0.219	0.082	268	0.935	1
Sat	-	Sun	0.221	0.237	0.933	268	0.352	1
Wed	-	Fri	0.154	0.223	0.688	268	0.492	1
Wed	-	Sat	-0.011	0.229	-0.048	268	0.961	1
Wed	-	Sun	0.21	0.218	0.963	268	0.337	1
Wed	-	Thu	0.29	0.222	1.309	268	0.192	1
Thu	-	Fri	-0.136	0.235	-0.58	268	0.562	1
Thu	-	Sat	-0.301	0.24	-1.253	268	0.211	1
Thu	-	Sun	-0.08	0.23	-0.346	268	0.73	1
Tue	-	Fri	0.171	0.227	0.753	268	0.452	1
Tue	-	Sat	0.006	0.232	0.025	268	0.98	1
Tue	-	Sun	0.227	0.222	1.024	268	0.307	1
Tue	-	Wed	0.017	0.213	0.08	268	0.936	1
Tue	-	Thu	0.307	0.225	1.364	268	0.174	1

4226 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.19:** Results of generalized linear model for Z-scored BEG for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.018	0.063	-0.105	0.142	0.000	266	0.293	0.770
Age	0.002	0.006	-0.009	0.013	0.021	266	0.341	0.734
Male - Female	0.193	0.127	-0.058	0.444	0.193	266	1.515	0.131
Tue - Mon	0.002	0.219	-0.429	0.434	0.002	266	0.011	0.991
Wed - Mon	-0.023	0.216	-0.449	0.403	-0.023	266	-0.107	0.915
Thu - Mon	-0.295	0.229	-0.745	0.155	-0.295	266	-1.289	0.198
Fri - Mon	-0.207	0.230	-0.659	0.245	-0.207	266	-0.901	0.368
Sat - Mon	-0.023	0.235	-0.485	0.439	-0.023	266	-0.098	0.922
Sun - Mon	-0.249	0.224	-0.691	0.193	-0.249	266	-1.110	0.268

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table D.20.:** Results of post-hoc comparisons for Z-scored BEG risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.184	0.242	-0.760	266	0.448	1
Fri	-	Sun	0.042	0.232	0.181	266	0.857	1
Mon	-	Fri	0.207	0.230	0.901	266	0.368	1
Mon	-	Sat	0.023	0.235	0.098	266	0.922	1
Mon	-	Sun	0.249	0.224	1.110	266	0.268	1

Mon	-	Wed	0.023	0.216	0.107	266	0.915	1
Mon	-	Thu	0.295	0.229	1.289	266	0.198	1
Mon	-	Tue	-0.002	0.219	-0.011	266	0.991	1
Sat	-	Sun	0.226	0.237	0.952	266	0.342	1
Wed	-	Fri	0.184	0.226	0.813	266	0.417	1
Wed	-	Sat	0.000	0.230	0.000	266	1	1
Wed	-	Sun	0.226	0.219	1.030	266	0.304	1
Wed	-	Thu	0.272	0.222	1.225	266	0.222	1
Thu	-	Fri	-0.088	0.239	-0.368	266	0.713	1
Thu	-	Sat	-0.272	0.242	-1.123	266	0.262	1
Thu	-	Sun	-0.046	0.232	-0.197	266	0.844	1
Tue	-	Fri	0.210	0.229	0.915	266	0.361	1
Tue	-	Sat	0.026	0.233	0.110	266	0.913	1
Tue	-	Sun	0.252	0.223	1.131	266	0.259	1
Tue	-	Wed	0.026	0.213	0.120	266	0.905	1
Tue	-	Thu	0.297	0.225	1.321	266	0.188	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.21:** Results of generalized linear model for Z-scored BEG risk score for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.003	0.042	-0.085	0.078	0	574	-0.08	0.936

Tue - Mon	-0.193	0.158	-0.504	0.117	-0.193	574	-1.225	0.221
Wed - Mon	-0.22	0.16	-0.534	0.094	-0.22	574	-1.374	0.17
Thu - Mon	-0.14	0.156	-0.447	0.167	-0.14	574	-0.897	0.37
Fri - Mon	-0.22	0.155	-0.524	0.085	-0.22	574	-1.415	0.158
Sat - Mon	0.058	0.152	-0.241	0.358	0.058	574	0.382	0.702
Sun - Mon	-0.026	0.157	-0.335	0.282	-0.026	574	-0.168	0.866

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.22.:** Results of post-hoc comparisons for Z-scored BEG risk score for those with a Weak SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.278	0.15	-1.858	574	0.064	1
Fri	-	Sun	-0.193	0.154	-1.252	574	0.211	1
Mon	-	Fri	0.22	0.155	1.415	574	0.158	1
Mon	-	Sat	-0.058	0.152	-0.382	574	0.702	1
Mon	-	Sun	0.026	0.157	0.168	574	0.866	1
Mon	-	Wed	0.22	0.16	1.374	574	0.17	1
Mon	-	Thu	0.14	0.156	0.897	574	0.37	1
Mon	-	Tue	0.193	0.158	1.225	574	0.221	1
Sat	-	Sun	0.085	0.151	0.559	574	0.576	1
Wed	-	Fri	-3.789e−4	0.157	-0.002	574	0.998	1
Wed	-	Sat	-0.278	0.155	-1.8	574	0.072	1
Wed	-	Sun	-0.194	0.159	-1.216	574	0.224	1
Wed	-	Thu	-0.08	0.158	-0.505	574	0.614	1

Thu	-	Fri	0.08	0.153	0.519	574	0.604	1
Thu	-	Sat	-0.198	0.15	-1.318	574	0.188	1
Thu	-	Sun	-0.114	0.155	-0.732	574	0.464	1
Tue	-	Fri	0.026	0.155	0.168	574	0.867	1
Tue	-	Sat	-0.252	0.152	-1.652	574	0.099	1
Tue	-	Sun	-0.167	0.157	-1.064	574	0.288	1
Tue	-	Wed	0.026	0.16	0.165	574	0.869	1
Tue	-	Thu	-0.053	0.156	-0.342	574	0.732	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.23:** Results of generalized linear model for Z-scored BEG risk score for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.053	0.045	-0.036	0.142	0.000	571	1.170	0.243
Age	0.002	0.003	-0.005	0.008	0.019	571	0.466	0.642
Male – Female**	0.269	0.091	0.090	0.447	0.268	571	2.949	0.003
Tue - Mon	-0.174	0.157	-0.483	0.135	-0.174	571	-1.104	0.270
Wed - Mon	-0.202	0.159	-0.515	0.111	-0.202	571	-1.266	0.206
Thu - Mon	-0.092	0.156	-0.399	0.215	-0.092	571	-0.588	0.557
Fri - Mon	-0.219	0.155	-0.522	0.085	-0.219	571	-1.415	0.158
Sat - Mon	0.063	0.152	-0.235	0.361	0.063	571	0.414	0.679
Sun - Mon	-0.018	0.156	-0.325	0.289	-0.018	571	-0.114	0.909

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.24.:** Results of post-hoc comparisons for Z-scored BEG risk score for those with a Weak SOW of weekday, age, and gender

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.282	0.149	-1.892	571	0.059	1
Fri	-	Sun	-0.201	0.153	-1.310	571	0.191	1
Mon	-	Fri	0.219	0.155	1.415	571	0.158	1
Mon	-	Sat	-0.063	0.152	-0.414	571	0.679	1
Mon	-	Sun	0.018	0.156	0.114	571	0.909	1
Mon	-	Wed	0.202	0.159	1.266	571	0.206	1
Mon	-	Thu	0.092	0.156	0.588	571	0.557	1
Mon	-	Tue	0.174	0.157	1.104	571	0.27	1
Sat	-	Sun	0.081	0.151	0.535	571	0.593	1
Wed	-	Fri	0.017	0.157	0.109	571	0.913	1
Wed	-	Sat	-0.265	0.154	-1.721	571	0.086	1
Wed	-	Sun	-0.184	0.158	-1.162	571	0.246	1
Wed	-	Thu	-0.110	0.158	-0.696	571	0.487	1
Thu	-	Fri	0.127	0.154	0.826	571	0.409	1
Thu	-	Sat	-0.155	0.151	-1.027	571	0.305	1
Thu	-	Sun	-0.074	0.155	-0.477	571	0.634	1
Tue	-	Fri	0.045	0.155	0.292	571	0.77	1
Tue	-	Sat	-0.236	0.152	-1.559	571	0.12	1
Tue	-	Sun	-0.156	0.156	-0.996	571	0.32	1

Tue	-	Wed	0.028	0.159	0.177	571	0.86	1
Tue	-	Thu	-0.082	0.156	-0.524	571	0.6	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.25:** Results of generalized linear model for Z-scored BART for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.005	0.06	-0.123	0.112	0	272	-0.088	0.93
Tue - Mon	0.293	0.217	-0.134	0.719	0.293	272	1.351	0.178
Wed - Mon	-0.036	0.212	-0.454	0.382	-0.036	272	-0.169	0.866
Thu - Mon	0.247	0.225	-0.196	0.69	0.247	272	1.098	0.273
Fri - Mon	-0.276	0.224	-0.717	0.164	-0.276	272	-1.236	0.217
Sat - Mon	-0.17	0.23	-0.623	0.284	-0.17	272	-0.737	0.462
Sun - Mon	-0.007	0.222	-0.444	0.43	-0.007	272	-0.032	0.974

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table D.26.:** Results of post-hoc comparisons for Z-scored BART risk score for those with a Normal/Strong SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$\mathbf{p_{bonferroni}}$
Fri	-	Sat	-0.107	0.234	-0.455	272	0.65	1
Fri	-	Sun	-0.269	0.226	-1.19	272	0.235	1

Mon	-	Fri	0.276	0.224	1.236	272	0.217	1
Mon	-	Sat	0.17	0.23	0.737	272	0.462	1
Mon	-	Sun	0.007	0.222	0.032	272	0.974	1
Mon	-	Wed	0.036	0.212	0.169	272	0.866	1
Mon	-	Thu	-0.247	0.225	-1.098	272	0.273	1
Mon	-	Tue	-0.293	0.217	-1.351	272	0.178	1
Sat	-	Sun	-0.163	0.233	-0.698	272	0.486	1
Wed	-	Fri	0.241	0.217	1.111	272	0.268	1
Wed	-	Sat	0.134	0.224	0.599	272	0.549	1
Wed	-	Sun	-0.029	0.215	-0.134	272	0.894	1
Wed	-	Thu	-0.283	0.218	-1.297	272	0.196	1
Thu	-	Fri	0.524	0.229	2.283	272	0.023	0.487
Thu	-	Sat	0.417	0.236	1.768	272	0.078	1
Thu	-	Sun	0.254	0.228	1.116	272	0.265	1
Tue	-	Fri	0.569	0.221	2.574	272	0.011	0.222
Tue	-	Sat	0.463	0.228	2.03	272	0.043	0.91
Tue	-	Sun	0.3	0.22	1.366	272	0.173	1
Tue	-	Wed	0.329	0.21	1.568	272	0.118	1
Tue	-	Thu	0.046	0.223	0.205	272	0.838	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table D.27:** Results of generalized linear model for Z-scored BART for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.017	0.061	-0.104	0.138	0.000	270	0.277	0.782
Male - Female	0.191	0.125	-0.054	0.437	0.191	270	1.536	0.126
Age	-0.002	0.005	-0.012	0.009	-0.021	270	-0.352	0.725
Tue - Mon	0.315	0.217	-0.112	0.743	0.315	270	1.453	0.147
Wed - Mon	-0.016	0.213	-0.435	0.402	-0.016	270	-0.077	0.938
Thu - Mon	0.283	0.226	-0.163	0.728	0.283	270	1.250	0.212
Fri - Mon	-0.294	0.224	-0.735	0.146	-0.294	270	-1.315	0.189
Sat - Mon	-0.177	0.230	-0.630	0.276	-0.177	270	-0.769	0.443
Sun - Mon	-0.012	0.222	-0.448	0.425	-0.012	270	-0.052	0.959

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table D.28.:** Results of post-hoc comparisons for Z-scored BART risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.117	0.234	-0.500	270	0.617	1
Fri	-	Sun	-0.283	0.226	-1.249	270	0.213	1
Mon	-	Fri	0.294	0.224	1.315	270	0.189	1
Mon	-	Sat	0.177	0.230	0.769	270	0.443	1
Mon	-	Sun	0.012	0.222	0.052	270	0.959	1
Mon	-	Wed	0.016	0.213	0.077	270	0.938	1

Mon	-	Thu	-0.283	0.226	-1.250	270	0.212	1
Mon	-	Tue	-0.315	0.217	-1.453	270	0.147	1
Sat	-	Sun	-0.166	0.233	-0.711	270	0.478	1
Wed	-	Fri	0.278	0.218	1.272	270	0.204	1
Wed	-	Sat	0.161	0.225	0.714	270	0.476	1
Wed	-	Sun	-0.005	0.216	-0.023	270	0.982	1
Wed	-	Thu	-0.299	0.219	-1.370	270	0.172	1
Thu	-	Fri	0.577	0.232	2.489	270	0.013	0.282
Thu	-	Sat	0.460	0.238	1.936	270	0.054	1
Thu	-	Sun	0.294	0.229	1.284	270	0.2	1
Tue	-	Fri	0.610	0.223	2.741	270	0.007	0.137
Tue	-	Sat	0.493	0.229	2.154	270	0.032	0.674
Tue	-	Sun	0.327	0.220	1.486	270	0.139	1
Tue	-	Wed	0.332	0.210	1.583	270	0.115	1
Tue	-	Thu	0.033	0.223	0.147	270	0.884	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.29:** Results of generalized linear model for Z-scored BART for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.001	0.042	-0.083	0.08	0	577	-0.033	0.974
Tue - Mon	0.036	0.158	-0.275	0.346	0.036	577	0.227	0.821

Wed - Mon	-0.035	0.16	-0.349	0.28	-0.035	577	-0.216	0.829
Thu - Mon	-0.049	0.156	-0.356	0.258	-0.049	577	-0.315	0.753
Fri - Mon	0.076	0.155	-0.23	0.381	0.076	577	0.487	0.627
Sat - Mon	0.053	0.152	-0.246	0.352	0.053	577	0.348	0.728
Sun - Mon	0.14	0.157	-0.168	0.448	0.14	577	0.893	0.372

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table D.30.:** Results of post-hoc comparisons for Z-scored BART risk score for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	0.023	0.15	0.152	577	0.879	1
Fri	-	Sun	-0.064	0.154	-0.416	577	0.677	1
Mon	-	Fri	-0.076	0.155	-0.487	577	0.627	1
Mon	-	Sat	-0.053	0.152	-0.348	577	0.728	1
Mon	-	Sun	-0.14	0.157	-0.893	577	0.372	1
Mon	-	Wed	0.035	0.16	0.216	577	0.829	1
Mon	-	Thu	0.049	0.156	0.315	577	0.753	1
Mon	-	Tue	-0.036	0.158	-0.227	577	0.821	1
Sat	-	Sun	-0.087	0.151	-0.576	577	0.565	1
Wed	-	Fri	-0.11	0.158	-0.698	577	0.485	1
Wed	-	Sat	-0.088	0.155	-0.566	577	0.572	1
Wed	-	Sun	-0.175	0.159	-1.096	577	0.274	1
Wed	-	Thu	0.015	0.159	0.091	577	0.927	1

Thu	-	Fri	-0.125	0.154	-0.811	577	0.418	1
Thu	-	Sat	-0.102	0.151	-0.677	577	0.498	1
Thu	-	Sun	-0.189	0.155	-1.218	577	0.224	1
Tue	-	Fri	-0.04	0.156	-0.255	577	0.799	1
Tue	-	Sat	-0.017	0.153	-0.112	577	0.911	1
Tue	-	Sun	-0.104	0.157	-0.662	577	0.508	1
Tue	-	Wed	0.071	0.161	0.439	577	0.661	1
Tue	-	Thu	0.085	0.157	0.542	577	0.588	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table D.31:** Results of generalized linear model for Z-scored BART for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.034	0.046	-0.056	0.124	0.000	574	0.747	0.455
Male - Female	0.172	0.092	-0.008	0.352	0.172	574	1.878	0.061
Age	-0.003	0.003	-0.009	0.004	-0.032	574	-0.774	0.439
Tue - Mon	0.050	0.158	-0.261	0.360	0.050	574	0.314	0.754
Wed - Mon	-0.027	0.160	-0.341	0.288	-0.027	574	-0.166	0.869
Thu - Mon	-0.026	0.157	-0.335	0.283	-0.026	574	-0.166	0.868
Fri - Mon	0.068	0.155	-0.238	0.373	0.068	574	0.436	0.663
Sat - Mon	0.055	0.152	-0.243	0.354	0.055	574	0.364	0.716
Sun - Mon	0.139	0.157	-0.169	0.447	0.139	574	0.888	0.375

[p < 0.05; ** p < 0.01, *** p < 0.001]*

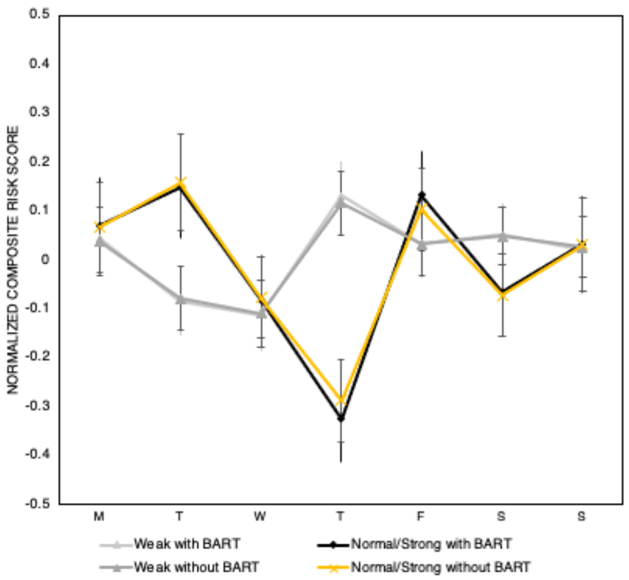
***Supplementary Materials Table D.32.:** Results of post-hoc comparisons for Z-scored BART risk score for those with a Weak SOW of weekday, age, and gender

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.013	0.150	0.084	574	0.933	1
Fri	-	Sun	-0.071	0.154	-0.463	574	0.644	1
Mon	-	Fri	-0.068	0.156	-0.436	574	0.663	1
Mon	-	Sat	-0.055	0.152	-0.364	574	0.716	1
Mon	-	Sun	-0.139	0.157	-0.888	574	0.375	1
Mon	-	Wed	0.027	0.160	0.166	574	0.869	1
Mon	-	Thu	0.026	0.157	0.166	574	0.868	1
Mon	-	Tue	-0.050	0.158	-0.314	574	0.754	1
Sat	-	Sun	-0.084	0.151	-0.555	574	0.579	1
Wed	-	Fri	-0.094	0.158	-0.597	574	0.551	1
Wed	-	Sat	-0.082	0.155	-0.529	574	0.597	1
Wed	-	Sun	-0.166	0.159	-1.041	574	0.298	1
Wed	-	Thu	-3.638e−4	0.159	-0.002	574	0.998	1
Thu	-	Fri	-0.094	0.155	-0.607	574	0.544	1
Thu	-	Sat	-0.081	0.151	-0.538	574	0.591	1
Thu	-	Sun	-0.165	0.156	-1.060	574	0.29	1
Tue	-	Fri	-0.018	0.156	-0.116	574	0.907	1
Tue	-	Sat	-0.006	0.153	-0.037	574	0.971	1
Tue	-	Sun	-0.090	0.157	-0.569	574	0.569	1

Tue	-	Wed	0.076	0.161	0.475	574	0.635	1
Tue	-	Thu	0.076	0.157	0.482	574	0.63	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Supplementary Material Figure E: Comparison of risk score calculated as in main text and calculated in the same manner but without inclusion of the BART score. Error bars represent +/- SE.



***Supplementary Table E.1:** Results of generalized linear model for composite risk score, without BART, for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval				
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**df**	**t**	**p**
(Intercept)	0.01	0.036	-0.061	0.081	266	0.28	0.779
Tue - Mon	0.078	0.13	-0.178	0.334	266	0.598	0.55
Wed - Mon	-0.152	0.127	-0.401	0.097	266	-1.201	0.231

Thu – Mon**	-0.398	0.134	-0.661	-0.135	266	-2.977	0.003
Fri - Mon	0.06	0.135	-0.205	0.325	266	0.446	0.656
Sat - Mon	-0.139	0.138	-0.411	0.132	266	-1.01	0.313
Sun - Mon	-0.039	0.132	-0.299	0.221	266	-0.296	0.767

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table E.2.:** Results of post-hoc comparisons for composite risk score, without BART, for those with a Normal/Strong SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.199	0.142	1.403	266	0.162	1
Fri	-	Sun	0.099	0.136	0.727	266	0.468	1
Mon	-	Fri	-0.06	0.135	-0.446	266	0.656	1
Mon	-	Sat	0.139	0.138	1.01	266	0.313	1
Mon	-	Sun	0.039	0.132	0.296	266	0.767	1
Mon	-	Wed	0.152	0.127	1.201	266	0.231	1
Mon	-	Thu	0.398	0.134	2.977	266	0.003	0.067
Mon	-	Tue	-0.078	0.13	-0.598	266	0.55	1
Sat	-	Sun	-0.1	0.139	-0.719	266	0.473	1
Wed	-	Fri	-0.212	0.131	-1.617	266	0.107	1
Wed	-	Sat	-0.013	0.134	-0.095	266	0.924	1
Wed	-	Sun	-0.113	0.128	-0.881	266	0.379	1
Wed	-	Thu	0.246	0.13	1.889	266	0.06	1
Thu	-	Fri*	-0.458	0.138	-3.319	266	0.001	0.022

Thu	-	Sat	-0.259	0.141	-1.833	266	0.068	1
Thu	-	Sun	-0.359	0.135	-2.653	266	0.008	0.178
Tue	-	Fri	0.018	0.135	0.132	266	0.895	1
Tue	-	Sat	0.217	0.138	1.575	266	0.116	1
Tue	-	Sun	0.117	0.132	0.887	266	0.376	1
Tue	-	Wed	0.23	0.127	1.816	266	0.07	1
Tue	-	Thu**	0.476	0.134	3.56	266	< .001	0.009

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table E.3:** Results of generalized linear model for composite risk score, without BART, for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval				
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**df**	**t**	**p**
(Intercept)	0.035	0.036	-0.036	0.106	264	0.970	0.333
Male – Female**	0.223	0.073	0.079	0.367	264	3.048	0.003
Age*	-0.008	0.003	-0.014	-0.002	264	-2.550	0.011
Tue - Mon	0.107	0.127	-0.144	0.358	264	0.837	0.403
Wed - Mon	-0.110	0.124	-0.355	0.135	264	-0.885	0.377
Thu – Mon**	-0.347	0.131	-0.606	-0.089	264	-2.645	0.009
Fri - Mon	0.020	0.132	-0.240	0.280	264	0.151	0.880
Sat - Mon	-0.153	0.135	-0.418	0.113	264	-1.133	0.258
Sun - Mon	-0.045	0.129	-0.299	0.208	264	-0.351	0.726

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table E.4:** Results of post-hoc comparisons for composite risk score, without BART, for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.173	0.139	1.242	264	0.215	1
Fri	-	Sun	0.065	0.133	0.488	264	0.626	1
Mon	-	Fri	-0.020	0.132	-0.151	264	0.88	1
Mon	-	Sat	0.153	0.135	1.133	264	0.258	1
Mon	-	Sun	0.045	0.129	0.351	264	0.726	1
Mon	-	Wed	0.110	0.124	0.885	264	0.377	1
Mon	-	Thu	0.347	0.131	2.645	264	0.009	0.182
Mon	-	Tue	-0.107	0.128	-0.837	264	0.403	1
Sat	-	Sun	-0.108	0.136	-0.789	264	0.431	1
Wed	-	Fri	-0.130	0.130	-0.999	264	0.319	1
Wed	-	Sat	0.043	0.132	0.324	264	0.746	1
Wed	-	Sun	-0.065	0.126	-0.513	264	0.608	1
Wed	-	Thu	0.238	0.127	1.864	264	0.063	1
Thu	-	Fri	-0.367	0.137	-2.681	264	0.008	0.164
Thu	-	Sat	-0.195	0.139	-1.401	264	0.162	1
Thu	-	Sun	-0.302	0.133	-2.270	264	0.024	0.504
Tue	-	Fri	0.087	0.133	0.654	264	0.514	1
Tue	-	Sat	0.259	0.135	1.920	264	0.056	1
Tue	-	Sun	0.152	0.129	1.176	264	0.241	1

Tue	-	Wed	0.217	0.124	1.749	264	0.081	1
Tue	-	Thu*	0.454	0.131	3.474	264	< .001	0.013

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table E.5:** Results of generalized linear model for composite risk score, without BART, for those with a Weak SOW of weekday only.

			95% Confidence Interval				
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**df**	**t**	**p**
(Intercept)	-6.345e−4	0.026	-0.051	0.05	574	-0.025	0.98
Tue - Mon	-0.128	0.098	-0.321	0.066	574	-1.298	0.195
Wed - Mon	-0.157	0.1	-0.353	0.039	574	-1.57	0.117
Thu - Mon	0.087	0.097	-0.104	0.278	574	0.896	0.371
Fri - Mon	-0.012	0.097	-0.202	0.178	574	-0.128	0.898
Sat - Mon	0.007	0.095	-0.179	0.194	574	0.078	0.938
Sun - Mon	-0.024	0.098	-0.216	0.169	574	-0.24	0.81

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table E.6:** Results of post-hoc comparisons for composite risk score, without BART, for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	-0.02	0.093	-0.212	574	0.832	1
Fri	-	Sun	0.011	0.096	0.116	574	0.908	1
Mon	-	Fri	0.012	0.097	0.128	574	0.898	1

Mon	-	Sat	-0.007	0.095	-0.078	574	0.938	1
Mon	-	Sun	0.024	0.098	0.24	574	0.81	1
Mon	-	Wed	0.157	0.1	1.57	574	0.117	1
Mon	-	Thu	-0.087	0.097	-0.896	574	0.371	1
Mon	-	Tue	0.128	0.098	1.298	574	0.195	1
Sat	-	Sun	0.031	0.094	0.328	574	0.743	1
Wed	-	Fri	-0.144	0.098	-1.472	574	0.142	1
Wed	-	Sat	-0.164	0.096	-1.704	574	0.089	1
Wed	-	Sun	-0.133	0.099	-1.343	574	0.18	1
Wed	-	Thu	-0.244	0.099	-2.473	574	0.014	0.287
Thu	-	Fri	0.1	0.096	1.042	574	0.298	1
Thu	-	Sat	0.08	0.094	0.851	574	0.395	1
Thu	-	Sun	0.111	0.097	1.145	574	0.253	1
Tue	-	Fri	-0.115	0.097	-1.193	574	0.233	1
Tue	-	Sat	-0.135	0.095	-1.424	574	0.155	1
Tue	-	Sun	-0.104	0.098	-1.066	574	0.287	1
Tue	-	Wed	0.029	0.1	0.289	574	0.773	1
Tue	-	Thu	-0.215	0.097	-2.21	574	0.028	0.578

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table E.7:** Results of generalized linear model for composite risk score, without BART, for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval				
Effect	Estimate	SE	Lower	Upper	df	t	p
(Intercept)	0.081	0.026	0.029	0.133	571	3.072	0.002
Male – Female***	0.395	0.053	0.291	0.500	571	7.443	< .001
Age***	-0.012	0.002	-0.015	-0.008	571	-5.999	< .001
Tue - Mon	-0.096	0.092	-0.276	0.084	571	-1.050	0.294
Wed - Mon	-0.146	0.093	-0.328	0.037	571	-1.568	0.117
Thu - Mon	0.135	0.091	-0.044	0.314	571	1.479	0.140
Fri - Mon	-0.045	0.090	-0.223	0.132	571	-0.505	0.614
Sat - Mon	0.009	0.088	-0.164	0.183	571	0.104	0.917
Sun - Mon	-0.039	0.091	-0.218	0.140	571	-0.424	0.672

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table E.8.:** Results of post-hoc comparisons for composite risk score, without BART, for those with a Weak SOW of weekday, age, and gender.

Weekday			Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.055	0.087	-0.630	571	0.529	1
Fri	-	Sun	-0.007	0.089	-0.077	571	0.939	1
Mon	-	Fri	0.045	0.090	0.505	571	0.614	1
Mon	-	Sat	-0.009	0.088	-0.104	571	0.917	1
Mon	-	Sun	0.039	0.091	0.424	571	0.672	1
Mon	-	Wed	0.146	0.093	1.568	571	0.117	1
Mon	-	Thu	-0.135	0.091	-1.479	571	0.14	1
Mon	-	Tue	0.096	0.092	1.050	571	0.294	1

Sat	-	Sun	0.048	0.088	0.545	571	0.586	1
Wed	-	Fri	-0.100	0.091	-1.097	571	0.273	1
Wed	-	Sat	-0.155	0.090	-1.728	571	0.085	1
Wed	-	Sun	-0.107	0.092	-1.159	571	0.247	1
Wed	-	Thu	-0.281	0.092	-3.045	571	0.002	0.051
Thu	-	Fri	0.180	0.090	2.013	571	0.045	0.937
Thu	-	Sat	0.126	0.088	1.431	571	0.153	1
Thu	-	Sun	0.174	0.091	1.917	571	0.056	1
Tue	-	Fri	-0.051	0.090	-0.563	571	0.574	1
Tue	-	Sat	-0.106	0.088	-1.193	571	0.233	1
Tue	-	Sun	-0.058	0.091	-0.632	571	0.528	1
Tue	-	Wed	0.049	0.093	0.532	571	0.595	1
Tue	-	Thu	-0.231	0.091	-2.543	571	0.011	0.237

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

Study 2:

Supplementary Table F: Chi-square test was used to determine any deviations in observed frequencies of males in strong [χ2(6, N = 1119) = 5.65, p = 0.46)] and weak [χ2(6, N = 114) = 6.47, p = 0.37)] groups. A t-test was used to determine whether there were significant variations in ages between the strong/normal and weak groups and was found to be significant [t(12) = 2.39, p= 0.03]. There were not significantly more males in the Normal/Strong SOW group than in the Weak SOW group [t(819.1) = -0.972, p = 0.332.

Sense of weekday	**Day of the Week**	**N**	**% Male**	**Average Age (σ_M)**
Strong, Normal	*Monday*	64	31.25	35.67 (1.43)
	Tuesday	56	33.93	31.27 (1.30)
	Wednesday	56	35.71	33.14 (1.53)
	Thursday	59	22.03	34.27 (1.72)
	Friday	50	20.00	35.64 (1.69)
	Saturday	62	32.26	32.69 (1.39)
	Sunday	54	31.48	33.15 (1.50)
Weak	*Monday*	54	27.78	31.43 (1.77)
	Tuesday	61	18.03	33.84 (1.59)
	Wednesday	64	29.69	30.34 (1.19)
	Thursday	58	24.14	32.40 (1.53)

Friday	68	27.94	32.26 (1.39)
Saturday	56	23.21	32.34 (1.55)
Sunday	67	34.33	30.39 (1.52)

***Supplementary Table G.1:** Results of generalized linear model for Z-scored composite risk score for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.025	0.027	-0.077	0.028	0	394	-0.919	0.359
Tue - Mon	0.014	0.098	-0.178	0.206	0.026	394	0.141	0.888
Wed - Mon	0.011	0.098	-0.181	0.203	0.021	394	0.117	0.907
Thu - Mon	0.092	0.096	-0.097	0.282	0.173	394	0.958	0.339
Fri - Mon	-0.056	0.101	-0.254	0.142	-0.105	394	-0.558	0.577
Sat - Mon	-0.12	0.095	-0.307	0.067	-0.225	394	-1.264	0.207
Sun - Mon	-0.083	0.099	-0.276	0.111	-0.155	394	-0.837	0.403

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.2.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Normal/Strong SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	0.064	0.101	0.631	394	0.529	1
Fri	-	Sun	0.026	0.105	0.251	394	0.802	1
Mon	-	Fri	0.056	0.101	0.558	394	0.577	1

Mon	-	Sat	0.12	0.095	1.264	394	0.207	1
Mon	-	Sun	0.083	0.099	0.837	394	0.403	1
Mon	-	Wed	-0.011	0.098	-0.117	394	0.907	1
Mon	-	Thu	-0.092	0.096	-0.958	394	0.339	1
Mon	-	Tue	-0.014	0.098	-0.141	394	0.888	1
Sat	-	Sun	-0.038	0.099	-0.379	394	0.705	1
Wed	-	Fri	0.068	0.104	0.652	394	0.515	1
Wed	-	Sat	0.132	0.098	1.338	394	0.182	1
Wed	-	Sun	0.094	0.102	0.923	394	0.357	1
Wed	-	Thu	-0.081	0.1	-0.812	394	0.418	1
Thu	-	Fri	0.148	0.103	1.447	394	0.149	1
Thu	-	Sat	0.212	0.097	2.189	394	0.029	0.613
Thu	-	Sun	0.175	0.1	1.739	394	0.083	1
Tue	-	Fri	0.07	0.104	0.674	394	0.501	1
Tue	-	Sat	0.134	0.098	1.362	394	0.174	1
Tue	-	Sun	0.096	0.102	0.946	394	0.345	1
Tue	-	Wed	0.002	0.101	0.023	394	0.982	1
Tue	-	Thu	-0.078	0.1	-0.788	394	0.431	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.3:** Results of generalized linear model for Z-scored composite risk score for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.043	0.028	-0.012	0.097	0.000	392	1.549	0.122
Age ***	-0.009	0.002	-0.013	-0.004	-0.189	392	-3.984	< .001
Male – Female ***	0.328	0.055	0.220	0.437	0.615	392	5.939	< .001
Tue - Mon	-0.034	0.092	-0.215	0.148	-0.063	392	-0.367	0.714
Wed - Mon	-0.026	0.092	-0.206	0.155	-0.048	392	-0.277	0.782
Thu - Mon	0.110	0.091	-0.068	0.289	0.206	392	1.214	0.226
Fri - Mon	-0.020	0.095	-0.206	0.167	-0.037	392	-0.206	0.837
Sat - Mon	-0.150	0.090	-0.326	0.027	-0.281	392	-1.670	0.096
Sun - Mon	-0.106	0.093	-0.288	0.077	-0.198	392	-1.136	0.257

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.4:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.130	0.096	1.359	392	0.175	1
Fri	-	Sun	0.086	0.099	0.870	392	0.385	1
Mon	-	Fri	0.020	0.095	0.206	392	0.837	1
Mon	-	Sat	0.150	0.090	1.670	392	0.096	1
Mon	-	Sun	0.106	0.093	1.136	392	0.257	1
Mon	-	Wed	0.026	0.092	0.277	392	0.782	1
Mon	-	Thu	-0.110	0.091	-1.214	392	0.226	1
Mon	-	Tue	0.034	0.092	0.367	392	0.714	1

Sat	-	Sun	-0.044	0.093	-0.474	392	0.636	1
Wed	-	Fri	-0.006	0.098	-0.061	392	0.952	1
Wed	-	Sat	0.124	0.093	1.343	392	0.18	1
Wed	-	Sun	0.080	0.096	0.836	392	0.404	1
Wed	-	Thu	-0.136	0.094	-1.444	392	0.149	1
Thu	-	Fri	0.130	0.097	1.344	392	0.18	1
Thu	-	Sat	0.260	0.091	2.841	392	0.005	0.099
Thu	-	Sun	0.216	0.095	2.278	392	0.023	0.488
Tue	-	Fri	-0.014	0.098	-0.145	392	0.884	1
Tue	-	Sat	0.116	0.093	1.252	392	0.211	1
Tue	-	Sun	0.072	0.096	0.748	392	0.455	1
Tue	-	Wed	-0.008	0.095	-0.088	392	0.93	1
Tue	-	Thu	-0.144	0.094	-1.531	392	0.126	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.5:** Results of generalized linear model for Z-scored composite risk score for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.023	0.027	-0.031	0.077	0	421	0.847	0.398
Tue - Mon	0.021	0.105	-0.186	0.228	0.037	421	0.198	0.843
Wed - Mon	0.114	0.104	-0.09	0.319	0.203	421	1.096	0.274
Thu - Mon	0.131	0.106	-0.078	0.34	0.233	421	1.231	0.219
Fri - Mon	0.018	0.103	-0.184	0.22	0.032	421	0.175	0.861

Sat - Mon	0.122	0.107	-0.089	0.333	0.217	421	1.132	0.258
Sun - Mon	0.027	0.103	-0.175	0.23	0.049	421	0.267	0.79

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.6:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.104	0.102	-1.02	421	0.308	1
Fri	-	Sun	-0.009	0.097	-0.098	421	0.922	1
Mon	-	Fri	-0.018	0.103	-0.175	421	0.861	1
Mon	-	Sat	-0.122	0.107	-1.132	421	0.258	1
Mon	-	Sun	-0.027	0.103	-0.267	421	0.79	1
Mon	-	Wed	-0.114	0.104	-1.096	421	0.274	1
Mon	-	Thu	-0.131	0.106	-1.231	421	0.219	1
Mon	-	Tue	-0.021	0.105	-0.198	421	0.843	1
Sat	-	Sun	0.094	0.102	0.924	421	0.356	1
Wed	-	Fri	0.096	0.098	0.979	421	0.328	1
Wed	-	Sat	-0.008	0.103	-0.074	421	0.941	1
Wed	-	Sun	0.087	0.098	0.88	421	0.38	1
Wed	-	Thu	-0.017	0.102	-0.167	421	0.868	1
Thu	-	Fri	0.113	0.101	1.123	421	0.262	1
Thu	-	Sat	0.009	0.106	0.089	421	0.929	1
Thu	-	Sun	0.104	0.101	1.026	421	0.306	1

Tue	-	Fri	0.003	0.099	0.029	421	0.977	1
Tue	-	Sat	-0.101	0.104	-0.967	421	0.334	1
Tue	-	Sun	-0.007	0.1	-0.066	421	0.947	1
Tue	-	Wed	-0.093	0.101	-0.925	421	0.356	1
Tue	-	Thu	-0.11	0.103	-1.067	421	0.287	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.7:** Results of generalized linear model for Z-scored composite risk score for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.092	0.030	0.034	0.151	0.000	419	3.113	0.002
Age ***	-0.008	0.002	-0.013	-0.004	-0.176	419	-3.762	< .001
Male - Female ***	0.293	0.059	0.176	0.410	0.522	419	4.936	< .001
Tue - Mon	0.070	0.101	-0.129	0.269	0.124	419	0.690	0.491
Wed - Mon	0.099	0.100	-0.097	0.296	0.177	419	0.995	0.320
Thu - Mon	0.150	0.102	-0.051	0.351	0.267	419	1.468	0.143
Fri - Mon	0.025	0.098	-0.169	0.218	0.044	419	0.250	0.803
Sat - Mon	0.143	0.103	-0.060	0.345	0.254	419	1.385	0.167
Sun - Mon	-5.191e−4	0.099	-0.195	0.194	-9.243e−4	419	-0.005	0.996

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.8.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Weak SOW of weekday, age, and gender.

DOW			Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.118	0.097	-1.212	419	0.226	1
Fri	-	Sun	0.025	0.093	0.270	419	0.788	1
Mon	-	Fri	-0.025	0.098	-0.250	419	0.803	1
Mon	-	Sat	-0.143	0.103	-1.385	419	0.167	1
Mon	-	Sun	0.001	0.099	0.005	419	0.996	1
Mon	-	Wed	-0.099	0.100	-0.995	419	0.32	1
Mon	-	Thu	-0.150	0.102	-1.468	419	0.143	1
Mon	-	Tue	-0.070	0.101	-0.690	419	0.491	1
Sat	-	Sun	0.143	0.098	1.460	419	0.145	1
Wed	-	Fri	0.075	0.094	0.794	419	0.428	1
Wed	-	Sat	-0.043	0.099	-0.439	419	0.661	1
Wed	-	Sun	0.100	0.094	1.057	419	0.291	1
Wed	-	Thu	-0.051	0.098	-0.516	419	0.606	1
Thu	-	Fri	0.125	0.097	1.298	419	0.195	1
Thu	-	Sat	0.007	0.101	0.071	419	0.943	1
Thu	-	Sun	0.150	0.097	1.549	419	0.122	1
Tue	-	Fri	0.045	0.095	0.473	419	0.636	1
Tue	-	Sat	-0.073	0.100	-0.729	419	0.466	1
Tue	-	Sun	0.070	0.096	0.730	419	0.466	1
Tue	-	Wed	-0.030	0.097	-0.304	419	0.761	1
Tue	-	Thu	-0.080	0.099	-0.808	419	0.419	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

Supplementary Table H: Individual risk measurement descriptives by weekday and Sense of Week (SOW) in Study 2.

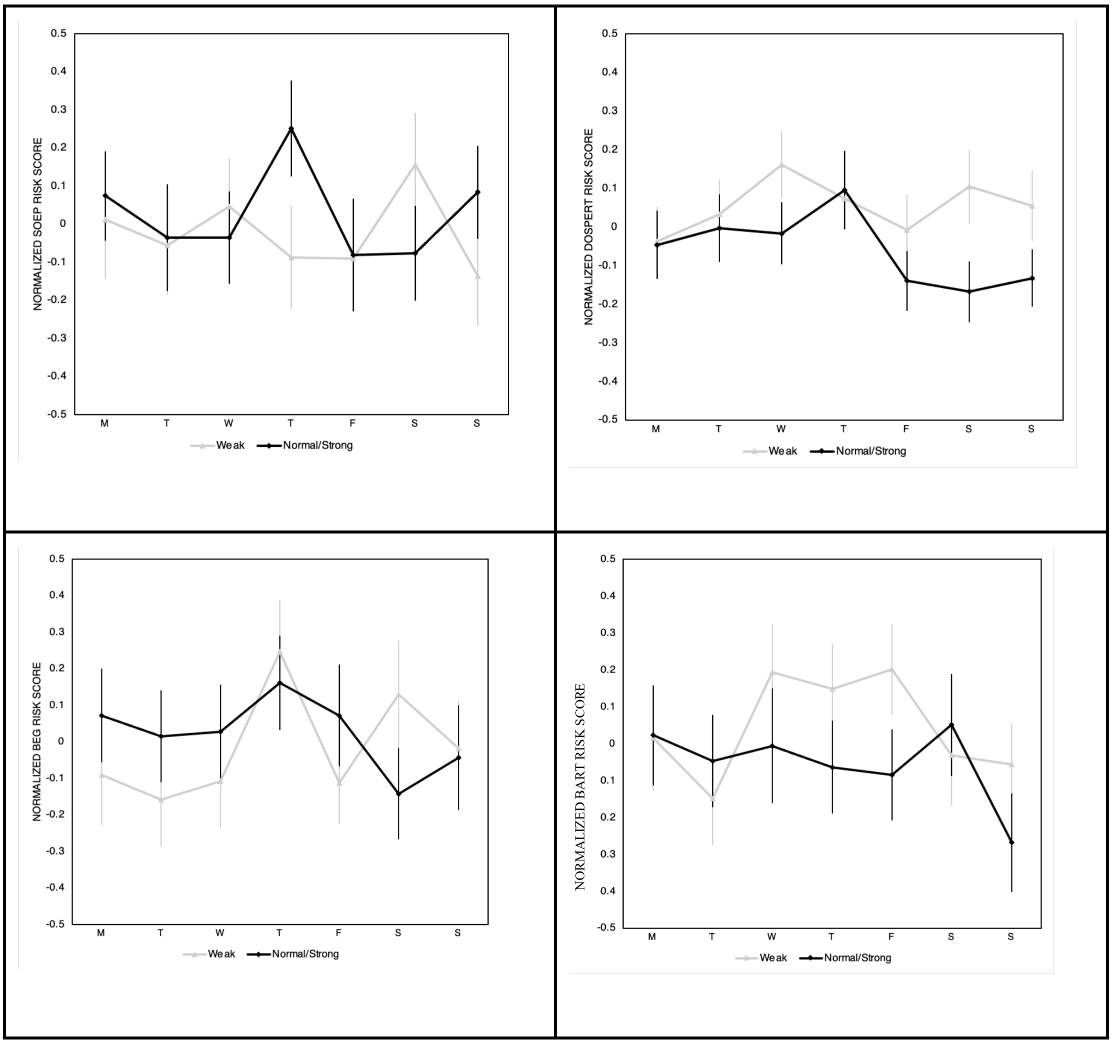
			N	Mean	σ_M
SOEP	**Strong, Normal**	*Monday*	64	0.07421	0.1177
		Tuesday	56	-0.03577	0.1402
		Wednesday	56	-0.03577	0.1211
		Thursday	59	0.2507	0.1262
		Friday	50	-0.08084	0.1477
		Saturday	62	-0.07610	0.1243
		Sunday	54	0.08371	0.1225
	Weak	*Monday*	54	0.01168	0.1519
		Tuesday	61	-0.05576	0.1271
		Wednesday	64	0.04720	0.1266
		Thursday	58	-0.08739	0.1344
		Friday	68	-0.09024	0.1266
		Saturday	56	0.1572	0.1343
		Sunday	67	-0.1364	0.1292

DOSPERT	**Strong, Normal**	*Monday*	64	-0.04650	0.08794
		Tuesday	56	-0.003154	0.08736
		Wednesday	56	-0.01669	0.08081
		Thursday	59	0.09547	0.1018
		Friday	50	-0.1398	0.07726
		Saturday	62	-0.1684	0.07874
		Sunday	54	-0.1328	0.0742
	Weak	*Monday*	54	-0.03739	0.08648
		Tuesday	61	0.03215	0.08893
		Wednesday	64	0.1611	0.0857
		Thursday	58	0.07381	0.07683
		Friday	68	-0.007734	0.08947
		Saturday	56	0.1042	0.09423
		Sunday	66	0.05519	0.08926
BEG	**Strong, Normal**	*Monday*	64	0.07248	0.1291
		Tuesday	55	0.01554	0.1258
		Wednesday	55	0.02722	0.1296

		Thursday	57	0.1612	0.1292
		Friday	48	0.07248	0.1387
		Saturday	62	-0.1425	0.1246
		Sunday	54	-0.0435	0.1435
	Weak	*Monday*	54	-0.09108	0.1348
		Tuesday	60	-0.1577	0.1272
		Wednesday	64	-0.1082	0.1257
		Thursday	58	0.2469	0.1395
		Friday	68	-0.1117	0.1115
		Saturday	56	0.1298	0.1452
		Sunday	67	-0.0174	0.1278
BART	**Strong, Normal**	*Monday*	64	0.02275	0.1352
		Tuesday	56	-0.04724	0.125
		Wednesday	56	-0.005911	0.1547
		Thursday	59	-0.06381	0.1262
		Friday	50	-0.08459	0.123
		Saturday	62	0.05096	0.1377

	Sunday	54	-0.2678	0.1336
Weak	*Monday*	54	0.01505	0.1417
	Tuesday	61	-0.1489	0.1233
	Wednesday	64	0.1929	0.1296
	Thursday	58	0.1485	0.1199
	Friday	68	0.2019	0.1221
	Saturday	56	-0.03155	0.1344
	Sunday	67	-0.05719	0.1099

Supplementary Material Figure I: The mean scores for each of the four main risk measurements across participants, separated out between a weak (rating of 1 or 2 on a scale of 1 to 5) versus normal or weak (rating of 3, 4, or 5 on the same scale) sense of the week, in Study 2, all normalized using z-scoring. A) SOEP General, B) DOSPERT General, C) BEG, D) Normalized BART scores, scored as per Lejuez et al. (2002) methodology. Error bars represent +/- SE.



***Supplementary Table G.1:** Results of generalized linear model for Z-scored SOEP for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.026	0.049	-0.07	0.121	0	394	0.53	0.597
Tue - Mon	-0.11	0.178	-0.459	0.239	-0.113	394	-0.619	0.536
Wed - Mon	-0.11	0.178	-0.459	0.239	-0.113	394	-0.619	0.536
Thu - Mon	0.176	0.175	-0.168	0.521	0.182	394	1.008	0.314
Fri - Mon	-0.155	0.183	-0.515	0.205	-0.16	394	-0.847	0.398
Sat - Mon	-0.15	0.173	-0.49	0.19	-0.155	394	-0.869	0.385

Sun - Mon	0.01	0.179	-0.343	0.362	0.01	394	0.053	0.958

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.2.:** Results of post-hoc comparisons for Z-scored SOEP for those with a Normal/Strong SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.005	0.184	-0.026	394	0.98	1
Fri	-	Sun	-0.165	0.19	-0.864	394	0.388	1
Mon	-	Fri	0.155	0.183	0.847	394	0.398	1
Mon	-	Sat	0.15	0.173	0.869	394	0.385	1
Mon	-	Sun	-0.01	0.179	-0.053	394	0.958	1
Mon	-	Wed	0.11	0.178	0.619	394	0.536	1
Mon	-	Thu	-0.176	0.175	-1.008	394	0.314	1
Mon	-	Tue	0.11	0.178	0.619	394	0.536	1
Sat	-	Sun	-0.16	0.181	-0.885	394	0.377	1
Wed	-	Fri	0.045	0.189	0.239	394	0.811	1
Wed	-	Sat	0.04	0.179	0.225	394	0.822	1
Wed	-	Sun	-0.119	0.185	-0.646	394	0.519	1
Wed	-	Thu	-0.286	0.181	-1.583	394	0.114	1
Thu	-	Fri	0.332	0.186	1.778	394	0.076	1
Thu	-	Sat	0.327	0.176	1.852	394	0.065	1
Thu	-	Sun	0.167	0.183	0.914	394	0.361	1
Tue	-	Fri	0.045	0.189	0.239	394	0.811	1

Tue	-	Sat	0.04	0.179	0.225	394	0.822	1
Tue	-	Sun	-0.119	0.185	-0.646	394	0.519	1
Tue	-	Wed	3.57E-11	0.183	1.95E-10	394	1	1
Tue	-	Thu	-0.286	0.181	-1.583	394	0.114	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.3:** Results of generalized linear model for Z-scored SOEP for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.106	0.052	0.005	0.208	0.000	392	2.063	0.04
Age ***	-0.015	0.004	-0.023	-0.007	-0.175	392	-3.580	< .001
Male - Female ***	0.394	0.103	0.191	0.598	0.407	392	3.808	< .001
Tue - Mon	-0.186	0.173	-0.525	0.154	-0.192	392	-1.076	0.283
Wed - Mon	-0.165	0.172	-0.504	0.173	-0.170	392	-0.959	0.338
Thu - Mon	0.192	0.170	-0.142	0.526	0.198	392	1.131	0.259
Fri - Mon	-0.111	0.178	-0.460	0.238	-0.115	392	-0.626	0.532
Sat - Mon	-0.198	0.168	-0.528	0.131	-0.205	392	-1.183	0.238
Sun - Mon	-0.029	0.174	-0.370	0.313	-0.030	392	-0.166	0.868

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.4:** Results of post-hoc comparisons for Z-scored SOEP for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$

Fri	-	Sat	0.087	0.179	0.487	392	0.627	1
Fri	-	Sun	-0.082	0.185	-0.445	392	0.656	1
Mon	-	Fri	0.111	0.178	0.626	392	0.532	1
Mon	-	Sat	0.198	0.168	1.183	392	0.238	1
Mon	-	Sun	0.029	0.174	0.166	392	0.868	1
Mon	-	Wed	0.165	0.172	0.959	392	0.338	1
Mon	-	Thu	-0.192	0.170	-1.131	392	0.259	1
Mon	-	Tue	0.186	0.173	1.076	392	0.283	1
Sat	-	Sun	-0.170	0.175	-0.971	392	0.332	1
Wed	-	Fri	-0.054	0.184	-0.293	392	0.769	1
Wed	-	Sat	0.033	0.173	0.193	392	0.847	1
Wed	-	Sun	-0.136	0.179	-0.761	392	0.447	1
Wed	-	Thu	-0.357	0.176	-2.032	392	0.043	0.9
Thu	-	Fri	0.303	0.181	1.679	392	0.094	1
Thu	-	Sat	0.390	0.171	2.281	392	0.023	0.485
Thu	-	Sun	0.221	0.177	1.247	392	0.213	1
Tue	-	Fri	-0.075	0.184	-0.406	392	0.685	1
Tue	-	Sat	0.013	0.173	0.073	392	0.942	1
Tue	-	Sun	-0.157	0.179	-0.876	392	0.382	1
Tue	-	Wed	-0.021	0.178	-0.117	392	0.907	1
Tue	-	Thu	-0.378	0.176	-2.147	392	0.032	0.68

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.5:** Results of generalized linear model for Z-scored SOEP for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.022	0.05	-0.12	0.076	0	421	-0.439	0.661
Tue - Mon	-0.067	0.193	-0.446	0.311	-0.066	421	-0.35	0.727
Wed - Mon	0.036	0.191	-0.339	0.41	0.035	421	0.186	0.852
Thu - Mon	-0.099	0.195	-0.482	0.284	-0.096	421	-0.508	0.612
Fri - Mon	-0.102	0.188	-0.471	0.268	-0.099	421	-0.542	0.588
Sat - Mon	0.145	0.197	-0.241	0.532	0.141	421	0.74	0.46
Sun - Mon	-0.148	0.189	-0.519	0.223	-0.144	421	-0.785	0.433

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.6:** Results of post-hoc comparisons for Z-scored SOEP for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	-0.247	0.186	-1.329	421	0.185	1
Fri	-	Sun	0.046	0.178	0.26	421	0.795	1
Mon	-	Fri	0.102	0.188	0.542	421	0.588	1
Mon	-	Sat	-0.145	0.197	-0.74	421	0.46	1
Mon	-	Sun	0.148	0.189	0.785	421	0.433	1
Mon	-	Wed	-0.036	0.191	-0.186	421	0.852	1
Mon	-	Thu	0.099	0.195	0.508	421	0.612	1
Mon	-	Tue	0.067	0.193	0.35	421	0.727	1

Sat	-	Sun	0.294	0.187	1.572	421	0.117	1	
Wed	-	Fri	0.137	0.18	0.765	421	0.445	1	
Wed	-	Sat	-0.11	0.189	-0.583	421	0.56	1	
Wed	-	Sun	0.184	0.18	1.019	421	0.309	1	
Wed	-	Thu	0.135	0.187	0.72	421	0.472	1	
Thu	-	Fri	0.003	0.184	0.015	421	0.988	1	
Thu	-	Sat	-0.245	0.193	-1.266	421	0.206	1	
Thu	-	Sun	0.049	0.185	0.265	421	0.791	1	
Tue	-	Fri	0.034	0.182	0.19	421	0.85	1	
Tue	-	Sat	-0.213	0.191	-1.115	421	0.265	1	
Tue	-	Sun	0.081	0.183	0.442	421	0.659	1	
Tue	-	Wed	-0.103	0.185	-0.558	421	0.577	1	
Tue	-	Thu	0.032	0.189	0.167	421	0.867	1	

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.7:** Results of generalized linear model for Z-scored SOEP for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.027	0.056	-0.084	0.138	0.000	419	0.478	0.633
Age*	-0.009	0.004	-0.017	-2.832e−4	-0.098	419	-2.032	0.043
Male - Female	0.207	0.113	-0.015	0.428	0.201	419	1.833	0.068
Tue - Mon	-0.026	0.192	-0.404	0.351	-0.026	419	-0.138	0.891
Wed - Mon	0.022	0.189	-0.350	0.395	0.022	419	0.117	0.907

Thu - Mon	-0.083	0.194	-0.464	0.298	-0.081	419	-0.429	0.668
Fri - Mon	-0.095	0.187	-0.462	0.272	-0.092	419	-0.509	0.611
Sat - Mon	0.163	0.196	-0.222	0.547	0.158	419	0.833	0.406
Sun - Mon	-0.171	0.188	-0.539	0.198	-0.166	419	-0.910	0.364

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table G.8.:** Results of post-hoc comparisons for Z-scored SOEP for those with a Weak SOW of weekday, age, and gender.

DOW			Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.258	0.185	-1.394	419	0.164	1
Fri	-	Sun	0.076	0.177	0.428	419	0.669	1
Mon	-	Fri	0.095	0.187	0.509	419	0.611	1
Mon	-	Sat	-0.163	0.196	-0.833	419	0.406	1
Mon	-	Sun	0.171	0.188	0.910	419	0.364	1
Mon	-	Wed	-0.022	0.189	-0.117	419	0.907	1
Mon	-	Thu	0.083	0.194	0.429	419	0.668	1
Mon	-	Tue	0.026	0.192	0.138	419	0.891	1
Sat	-	Sun	0.333	0.186	1.791	419	0.074	1
Wed	-	Fri	0.117	0.179	0.656	419	0.512	1
Wed	-	Sat	-0.141	0.188	-0.749	419	0.455	1
Wed	-	Sun	0.193	0.179	1.076	419	0.282	1
Wed	-	Thu	0.105	0.186	0.566	419	0.572	1
Thu	-	Fri	0.012	0.183	0.065	419	0.948	1

Thu	-	Sat	-0.246	0.192	-1.281	419	0.201	1
Thu	-	Sun	0.087	0.184	0.475	419	0.635	1
Tue	-	Fri	0.069	0.181	0.378	419	0.705	1
Tue	-	Sat	-0.189	0.190	-0.997	419	0.319	1
Tue	-	Sun	0.144	0.183	0.789	419	0.431	1
Tue	-	Wed	-0.049	0.184	-0.264	419	0.792	1
Tue	-	Thu	0.057	0.188	0.301	419	0.763	1

4421 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4422

4423 ***Supplementary Table G.9:** Results of generalized linear model for Z-scored
4424 DOSPERT for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.059	0.032	-0.122	0.005	0	394	-1.82	0.07
Tue - Mon	0.043	0.118	-0.189	0.276	0.067	394	0.367	0.714
Wed - Mon	0.03	0.118	-0.202	0.262	0.046	394	0.252	0.801
Thu - Mon	0.142	0.116	-0.087	0.371	0.22	394	1.219	0.224
Fri - Mon	-0.093	0.122	-0.333	0.146	-0.144	394	-0.766	0.444
Sat - Mon	-0.122	0.115	-0.348	0.104	-0.189	394	-1.06	0.29
Sun - Mon	-0.086	0.119	-0.321	0.148	-0.133	394	-0.724	0.47

4425 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4426

4427 **(Supplementary Materials Table G.10.:** Results of post-hoc comparisons for
4428 Z-scored DOSPERT for those with a Normal/Strong SOW of weekday only.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.029	0.123	0.234	394	0.815	1
Fri	-	Sun	-0.007	0.127	-0.055	394	0.956	1
Mon	-	Fri	0.093	0.122	0.766	394	0.444	1
Mon	-	Sat	0.122	0.115	1.06	394	0.29	1
Mon	-	Sun	0.086	0.119	0.724	394	0.47	1
Mon	-	Wed	-0.03	0.118	-0.252	394	0.801	1
Mon	-	Thu	-0.142	0.116	-1.219	394	0.224	1
Mon	-	Tue	-0.043	0.118	-0.367	394	0.714	1
Sat	-	Sun	-0.036	0.12	-0.297	394	0.767	1
Wed	-	Fri	0.123	0.126	0.98	394	0.328	1
Wed	-	Sat	0.152	0.119	1.275	394	0.203	1
Wed	-	Sun	0.116	0.123	0.943	394	0.346	1
Wed	-	Thu	-0.112	0.12	-0.932	394	0.352	1
Thu	-	Fri	0.235	0.124	1.896	394	0.059	1
Thu	-	Sat	0.264	0.117	2.248	394	0.025	0.527
Thu	-	Sun	0.228	0.122	1.878	394	0.061	1
Tue	-	Fri	0.137	0.126	1.088	394	0.277	1
Tue	-	Sat	0.165	0.119	1.389	394	0.166	1
Tue	-	Sun	0.13	0.123	1.053	394	0.293	1
Tue	-	Wed	0.014	0.122	0.111	394	0.912	1
Tue	-	Thu	-0.099	0.12	-0.819	394	0.413	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.11:** Results of generalized linear model for Z-scored DOSPERT for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.028	0.033	-0.037	0.094	0.000	392	0.850	0.396
Age **	-0.008	0.003	-0.013	-0.002	-0.136	392	-2.863	0.004
Male - Female ***	0.426	0.067	0.294	0.558	0.659	392	6.349	< .001
Tue - Mon	-0.002	0.112	-0.222	0.218	-0.003	392	-0.017	0.986
Wed - Mon	-0.009	0.112	-0.228	0.211	-0.013	392	-0.078	0.938
Thu - Mon	0.170	0.110	-0.046	0.387	0.264	392	1.548	0.123
Fri - Mon	-0.046	0.115	-0.272	0.181	-0.070	392	-0.395	0.693
Sat - Mon	-0.149	0.109	-0.363	0.065	-0.231	392	-1.370	0.171
Sun - Mon	-0.107	0.113	-0.328	0.115	-0.165	392	-0.946	0.345

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.12:** Results of post-hoc comparisons for Z-scored DOSPERT for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.104	0.116	0.890	392	0.374	1
Fri	-	Sun	0.061	0.120	0.510	392	0.611	1
Mon	-	Fri	0.046	0.115	0.395	392	0.693	1
Mon	-	Sat	0.149	0.109	1.370	392	0.171	1
Mon	-	Sun	0.107	0.113	0.946	392	0.345	1

Mon	-	Wed	0.009	0.112	0.078	392	0.938	1
Mon	-	Thu	-0.170	0.110	-1.548	392	0.123	1
Mon	-	Tue	0.002	0.112	0.017	392	0.986	1
Sat	-	Sun	-0.042	0.113	-0.374	392	0.708	1
Wed	-	Fri	0.037	0.119	0.310	392	0.757	1
Wed	-	Sat	0.140	0.112	1.251	392	0.212	1
Wed	-	Sun	0.098	0.116	0.844	392	0.399	1
Wed	-	Thu	-0.179	0.114	-1.571	392	0.117	1
Thu	-	Fri	0.216	0.117	1.844	392	0.066	1
Thu	-	Sat	0.320	0.111	2.878	392	0.004	0.089
Thu	-	Sun	0.277	0.115	2.412	392	0.016	0.343
Tue	-	Fri	0.044	0.119	0.365	392	0.715	1
Tue	-	Sat	0.147	0.112	1.310	392	0.191	1
Tue	-	Sun	0.105	0.116	0.901	392	0.368	1
Tue	-	Wed	0.007	0.115	0.058	392	0.953	1
Tue	-	Thu	-0.172	0.114	-1.510	392	0.132	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.13:** Results of generalized linear model for Z-scored DOSPERT for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.054	0.033	-0.011	0.12	0	420	1.637	0.102

Tue - Mon	0.07	0.128	-0.182	0.321	0.102	420	0.543	0.588
Wed - Mon	0.198	0.127	-0.051	0.448	0.29	420	1.567	0.118
Thu - Mon	0.111	0.13	-0.144	0.366	0.163	420	0.858	0.392
Fri - Mon	0.03	0.125	-0.216	0.275	0.043	420	0.237	0.813
Sat - Mon	0.142	0.131	-0.115	0.399	0.207	420	1.083	0.279
Sun - Mon	0.093	0.126	-0.155	0.34	0.135	420	0.736	0.462

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.14:** Results of post-hoc comparisons for Z-scored DOSPERT for those with a Weak SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.112	0.124	-0.905	420	0.366	1
Fri	-	Sun	-0.063	0.118	-0.531	420	0.596	1
Mon	-	Fri	-0.03	0.125	-0.237	420	0.813	1
Mon	-	Sat	-0.142	0.131	-1.083	420	0.279	1
Mon	-	Sun	-0.093	0.126	-0.736	420	0.462	1
Mon	-	Wed	-0.198	0.127	-1.567	420	0.118	1
Mon	-	Thu	-0.111	0.13	-0.858	420	0.392	1
Mon	-	Tue	-0.07	0.128	-0.543	420	0.588	1
Sat	-	Sun	0.049	0.125	0.394	420	0.694	1
Wed	-	Fri	0.169	0.119	1.414	420	0.158	1
Wed	-	Sat	0.057	0.125	0.453	420	0.651	1
Wed	-	Sun	0.106	0.12	0.88	420	0.379	1
Wed	-	Thu	0.087	0.124	0.702	420	0.483	1

Thu	-	Fri	0.082	0.123	0.665	420	0.506	1
Thu	-	Sat	-0.03	0.128	-0.237	420	0.813	1
Thu	-	Sun	0.019	0.123	0.151	420	0.88	1
Tue	-	Fri	0.04	0.121	0.33	420	0.742	1
Tue	-	Sat	-0.072	0.127	-0.568	420	0.57	1
Tue	-	Sun	-0.023	0.122	-0.189	420	0.85	1
Tue	-	Wed	-0.129	0.123	-1.051	420	0.294	1
Tue	-	Thu	-0.042	0.126	-0.331	420	0.741	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.15:** Results of generalized linear model for Z-scored DOSPERT for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.144	0.036	0.073	0.214	0.000	418	4.014	< .001
Age ***	-0.012	0.003	-0.017	-0.006	-0.201	418	-4.338	< .001
Male - Female ***	0.379	0.072	0.238	0.520	0.555	418	5.289	< .001
Tue - Mon	0.135	0.122	-0.105	0.375	0.197	418	1.104	0.270
Wed - Mon	0.179	0.120	-0.058	0.415	0.261	418	1.482	0.139
Thu - Mon	0.136	0.123	-0.106	0.379	0.200	418	1.107	0.269
Fri - Mon	0.039	0.119	-0.195	0.272	0.057	418	0.328	0.743
Sat - Mon	0.170	0.124	-0.075	0.414	0.248	418	1.365	0.173
Sun - Mon	0.052	0.120	-0.183	0.287	0.076	418	0.435	0.664

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.16.:** Results of post-hoc comparisons for Z-scored DOSPERT for those with a Weak SOW of weekday, age, and gender.

DOW		DOW	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.131	0.118	-1.112	418	0.267	1
Fri	-	Sun	-0.013	0.113	-0.116	418	0.907	1
Mon	-	Fri	-0.039	0.119	-0.327	418	0.743	1
Mon	-	Sat	-0.170	0.124	-1.365	418	0.173	1
Mon	-	Sun	-0.052	0.120	-0.435	418	0.664	1
Mon	-	Wed	-0.179	0.120	-1.482	418	0.139	1
Mon	-	Thu	-0.136	0.123	-1.107	418	0.269	1
Mon	-	Tue	-0.135	0.122	-1.104	418	0.27	1
Sat	-	Sun	0.118	0.119	0.990	418	0.323	1
Wed	-	Fri	0.140	0.114	1.229	418	0.22	1
Wed	-	Sat	0.009	0.119	0.074	418	0.941	1
Wed	-	Sun	0.127	0.114	1.106	418	0.269	1
Wed	-	Thu	0.042	0.118	0.356	418	0.722	1
Thu	-	Fri	0.098	0.117	0.837	418	0.403	1
Thu	-	Sat	-0.033	0.122	-0.272	418	0.785	1
Thu	-	Sun	0.084	0.118	0.717	418	0.474	1
Tue	-	Fri	0.096	0.115	0.833	418	0.405	1
Tue	-	Sat	-0.035	0.121	-0.288	418	0.773	1
Tue	-	Sun	0.083	0.117	0.709	418	0.478	1
Tue	-	Wed	-0.044	0.117	-0.373	418	0.71	1

Tue	-	Thu	-0.002	0.120	-0.013	418	0.99	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.17:** Results of generalized linear model for Z-scored BEG for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.023	0.05	-0.075	0.121	0	388	0.467	0.641
Tue - Mon	-0.057	0.182	-0.414	0.3	-0.058	388	-0.314	0.754
Wed - Mon	-0.045	0.182	-0.402	0.312	-0.046	388	-0.249	0.803
Thu - Mon	0.089	0.18	-0.265	0.442	0.09	388	0.493	0.622
Fri - Mon	-6.250e−11	0.189	-0.371	0.371	-6.350e−11	388	-3.315e−10	1
Sat - Mon	-0.215	0.176	-0.561	0.131	-0.218	388	-1.222	0.223
Sun - Mon	-0.116	0.182	-0.475	0.243	-0.118	388	-0.636	0.525

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.18.:** Results of post-hoc comparisons for Z-scored BEG for those with a Normal/Strong SOW of weekday only.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	0.215	0.19	1.132	388	0.258	1
Fri	-	Sun	0.116	0.196	0.592	388	0.554	1
Mon	-	Fri	6.25E-11	0.189	3.32E-10	388	1	1
Mon	-	Sat	0.215	0.176	1.222	388	0.223	1
Mon	-	Sun	0.116	0.182	0.636	388	0.525	1

Mon	-	Wed	0.045	0.182	0.249	388	0.803	1
Mon	-	Thu	-0.089	0.18	-0.493	388	0.622	1
Mon	-	Tue	0.057	0.182	0.314	388	0.754	1
Sat	-	Sun	-0.099	0.184	-0.539	388	0.591	1
Wed	-	Fri	-0.045	0.195	-0.232	388	0.817	1
Wed	-	Sat	0.17	0.183	0.928	388	0.354	1
Wed	-	Sun	0.071	0.189	0.374	388	0.709	1
Wed	-	Thu	-0.134	0.187	-0.718	388	0.473	1
Thu	-	Fri	0.089	0.193	0.459	388	0.647	1
Thu	-	Sat	0.304	0.181	1.676	388	0.095	1
Thu	-	Sun	0.205	0.188	1.092	388	0.276	1
Tue	-	Fri	-0.057	0.195	-0.292	388	0.771	1
Tue	-	Sat	0.158	0.183	0.864	388	0.388	1
Tue	-	Sun	0.059	0.189	0.312	388	0.755	1
Tue	-	Wed	-0.012	0.188	-0.062	388	0.951	1
Tue	-	Thu	-0.146	0.187	-0.78	388	0.436	1

***Supplementary Table G.19:** Results of generalized linear model for Z-scored BEG for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.038	0.055	-0.069	0.146	0.000	386	0.698	0.486
Age	0.001	0.004	-0.008	0.009	0.008	386	0.147	0.883
Male - Female	0.073	0.110	-0.142	0.289	0.075	386	0.670	0.503

Tue - Mon	-0.056	0.183	-0.416	0.303	-0.057	386	-0.309	0.758
Wed - Mon	-0.046	0.182	-0.404	0.312	-0.047	386	-0.253	0.801
Thu - Mon	0.096	0.181	-0.259	0.451	0.097	386	0.530	0.596
Fri - Mon	0.008	0.189	-0.365	0.380	0.008	386	0.040	0.968
Sat - Mon	-0.214	0.177	-0.561	0.134	-0.217	386	-1.209	0.227
Sun - Mon	-0.115	0.183	-0.475	0.246	-0.116	386	-0.625	0.532

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.20:** Results of post-hoc comparisons for Z-scored BEG for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	0.221	0.191	1.159	386	0.247	1
Fri	-	Sun	0.122	0.197	0.620	386	0.535	1
Mon	-	Fri	-0.008	0.189	-0.040	386	0.968	1
Mon	-	Sat	0.214	0.177	1.209	386	0.227	1
Mon	-	Sun	0.115	0.183	0.625	386	0.532	1
Mon	-	Wed	0.046	0.182	0.253	386	0.801	1
Mon	-	Thu	-0.096	0.181	-0.530	386	0.596	1
Mon	-	Tue	0.056	0.183	0.309	386	0.758	1
Sat	-	Sun	-0.099	0.184	-0.539	386	0.590	1
Wed	-	Fri	-0.054	0.196	-0.274	386	0.785	1
Wed	-	Sat	0.168	0.183	0.915	386	0.361	1
Wed	-	Sun	0.068	0.190	0.361	386	0.718	1

Wed	-	Thu	-0.142	0.188	-0.756	386	0.450	1
Thu	-	Fri	0.088	0.194	0.454	386	0.650	1
Thu	-	Sat	0.310	0.182	1.701	386	0.090	1
Thu	-	Sun	0.210	0.188	1.117	386	0.265	1
Tue	-	Fri	-0.064	0.197	-0.326	386	0.745	1
Tue	-	Sat	0.157	0.183	0.858	386	0.392	1
Tue	-	Sun	0.058	0.190	0.306	386	0.760	1
Tue	-	Wed	-0.010	0.189	-0.055	386	0.956	1
Tue	-	Thu	-0.152	0.188	-0.810	386	0.418	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.21:** Results of generalized linear model for Z-scored BEG for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.016	0.049	-0.112	0.081	0	420	-0.318	0.751
Tue - Mon	-0.067	0.19	-0.44	0.307	-0.066	420	-0.351	0.726
Wed - Mon	-0.017	0.187	-0.385	0.351	-0.017	420	-0.091	0.927
Thu - Mon	0.338	0.192	-0.039	0.715	0.333	420	1.764	0.078
Fri - Mon	-0.021	0.185	-0.384	0.342	-0.02	420	-0.112	0.911
Sat - Mon	0.221	0.193	-0.159	0.601	0.218	420	1.143	0.254
Sun - Mon	0.074	0.185	-0.29	0.438	0.073	420	0.398	0.691

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table G.22:** Results of post-hoc comparisons for Z-scored BEG for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.242	0.183	-1.321	420	0.187	1
Fri	-	Sun	-0.094	0.174	-0.541	420	0.589	1
Mon	-	Fri	0.021	0.185	0.112	420	0.911	1
Mon	-	Sat	-0.221	0.193	-1.143	420	0.254	1
Mon	-	Sun	-0.074	0.185	-0.398	420	0.691	1
Mon	-	Wed	0.017	0.187	0.091	420	0.927	1
Mon	-	Thu	-0.338	0.192	-1.764	420	0.078	1
Mon	-	Tue	0.067	0.19	0.351	420	0.726	1
Sat	-	Sun	0.147	0.183	0.803	420	0.423	1
Wed	-	Fri	0.004	0.176	0.02	420	0.984	1
Wed	-	Sat	-0.238	0.185	-1.284	420	0.2	1
Wed	-	Sun	-0.091	0.177	-0.513	420	0.608	1
Wed	-	Thu	-0.355	0.184	-1.933	420	0.054	1
Thu	-	Fri	0.359	0.181	1.981	420	0.048	1
Thu	-	Sat	0.117	0.19	0.617	420	0.538	1
Thu	-	Sun	0.264	0.182	1.455	420	0.147	1
Tue	-	Fri	-0.046	0.179	-0.256	420	0.798	1
Tue	-	Sat	-0.288	0.188	-1.527	420	0.127	1
Tue	-	Sun	-0.14	0.18	-0.779	420	0.436	1
Tue	-	Wed	-0.05	0.182	-0.272	420	0.786	1

Tue	-	Thu	-0.405	0.187	-2.169	420	0.031	0.644

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.23:** Results of generalized linear model for Z-scored BEG for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.020	0.056	-0.089	0.130	0.000	418	0.362	0.717
Age	0.001	0.004	-0.007	0.010	0.014	418	0.297	0.766
Male - Female	0.152	0.111	-0.067	0.372	0.150	418	1.368	0.172
Tue - Mon	-0.055	0.191	-0.430	0.319	-0.055	418	-0.291	0.771
Wed - Mon	-0.019	0.187	-0.387	0.349	-0.018	418	-0.100	0.921
Thu - Mon	0.342	0.192	-0.034	0.719	0.337	418	1.786	0.075
Fri - Mon	-0.022	0.185	-0.385	0.341	-0.022	418	-0.119	0.906
Sat - Mon	0.227	0.193	-0.153	0.607	0.223	418	1.173	0.242
Sun - Mon	0.065	0.185	-0.300	0.430	0.064	418	0.350	0.726

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.24.:** Results of post-hoc comparisons for Z-scored BEG for those with a Weak SOW of weekday, age, and gender.

DOW			**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	-0.249	0.183	-1.360	418	0.175	1
Fri	-	Sun	-0.087	0.175	-0.498	418	0.619	1
Mon	-	Fri	0.022	0.185	0.119	418	0.906	1

Mon	-	Sat	-0.227	0.193	-1.173	418	0.242	1
Mon	-	Sun	-0.065	0.186	-0.350	418	0.726	1
Mon	-	Wed	0.019	0.187	0.100	418	0.921	1
Mon	-	Thu	-0.342	0.192	-1.786	418	0.075	1
Mon	-	Tue	0.055	0.191	0.291	418	0.771	1
Sat	-	Sun	0.162	0.184	0.879	418	0.38	1
Wed	-	Fri	0.003	0.177	0.019	418	0.985	1
Wed	-	Sat	-0.245	0.186	-1.321	418	0.187	1
Wed	-	Sun	-0.084	0.177	-0.472	418	0.637	1
Wed	-	Thu	-0.361	0.184	-1.962	418	0.05	1
Thu	-	Fri	0.364	0.181	2.011	418	0.045	0.944
Thu	-	Sat	0.116	0.190	0.609	418	0.543	1
Thu	-	Sun	0.277	0.182	1.522	418	0.129	1
Tue	-	Fri	-0.033	0.180	-0.186	418	0.852	1
Tue	-	Sat	-0.282	0.189	-1.497	418	0.135	1
Tue	-	Sun	-0.120	0.182	-0.663	418	0.508	1
Tue	-	Wed	-0.037	0.183	-0.201	418	0.841	1
Tue	-	Thu	-0.398	0.187	-2.129	418	0.034	0.710

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.25:** Results of generalized linear model for Z-scored BART for those with a Normal/Strong SOW of weekday only.

95% Confidence Interval

Effect	Estimate	SE	Lower	Upper	β	df	t	p
(Intercept)	-0.057	0.051	-0.157	0.044	0	394	-1.107	0.269
Tue - Mon	-0.07	0.187	-0.437	0.297	-0.069	394	-0.375	0.708
Wed - Mon	-0.029	0.187	-0.396	0.338	-0.028	394	-0.154	0.878
Thu - Mon	-0.087	0.184	-0.448	0.275	-0.085	394	-0.47	0.638
Fri - Mon	-0.107	0.192	-0.486	0.271	-0.106	394	-0.558	0.577
Sat - Mon	0.028	0.182	-0.329	0.386	0.028	394	0.155	0.877
Sun - Mon	-0.291	0.188	-0.661	0.08	-0.286	394	-1.542	0.124

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table G.26.:** Results of post-hoc comparisons for Z-scored BART for those with a Normal/Strong SOW of weekday only.

Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	-0.136	0.194	-0.699	394	0.485	1
Fri	-	Sun	0.183	0.2	0.916	394	0.36	1
Mon	-	Fri	0.107	0.192	0.558	394	0.577	1
Mon	-	Sat	-0.028	0.182	-0.155	394	0.877	1
Mon	-	Sun	0.291	0.188	1.542	394	0.124	1
Mon	-	Wed	0.029	0.187	0.154	394	0.878	1
Mon	-	Thu	0.087	0.184	0.47	394	0.638	1
Mon	-	Tue	0.07	0.187	0.375	394	0.708	1
Sat	-	Sun	0.319	0.19	1.679	394	0.094	1
Wed	-	Fri	0.079	0.198	0.396	394	0.692	1
Wed	-	Sat	-0.057	0.188	-0.302	394	0.762	1

Wed	-	Sun	0.262	0.195	1.347	394	0.179	1
Wed	-	Thu	0.058	0.19	0.304	394	0.761	1
Thu	-	Fri	0.021	0.196	0.106	394	0.916	1
Thu	-	Sat	-0.115	0.185	-0.619	394	0.536	1
Thu	-	Sun	0.204	0.192	1.062	394	0.289	1
Tue	-	Fri	0.037	0.198	0.188	394	0.851	1
Tue	-	Sat	-0.098	0.188	-0.522	394	0.602	1
Tue	-	Sun	0.221	0.195	1.134	394	0.257	1
Tue	-	Wed	-0.041	0.193	-0.214	394	0.83	1
Tue	-	Thu	0.017	0.19	0.087	394	0.931	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.27:** Results of generalized linear model for Z-scored BART for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.098	0.056	-0.208	0.012	0.000	392	-1.758	0.08
Age	-0.001	0.004	-0.010	0.008	-0.013	392	-0.253	0.801
Male - Female	-0.204	0.112	-0.425	0.016	-0.201	392	-1.819	0.07
Tue - Mon	-0.070	0.187	-0.438	0.299	-0.068	392	-0.371	0.711
Wed - Mon	-0.022	0.187	-0.389	0.345	-0.022	392	-0.120	0.904
Thu - Mon	-0.107	0.184	-0.469	0.255	-0.105	392	-0.581	0.562
Fri - Mon	-0.130	0.193	-0.509	0.248	-0.128	392	-0.677	0.499
Sat - Mon	0.027	0.182	-0.331	0.385	0.026	392	0.148	0.883

Sun - Mon	-0.293	0.188	-0.664	0.078	-0.288	392	-1.555	0.121

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.28:** Results of post-hoc comparisons for Z-scored BART for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.157	0.194	-0.809	392	0.419	1
Fri	-	Sun	0.163	0.201	0.811	392	0.418	1
Mon	-	Fri	0.130	0.193	0.677	392	0.499	1
Mon	-	Sat	-0.027	0.182	-0.148	392	0.883	1
Mon	-	Sun	0.293	0.189	1.555	392	0.121	1
Mon	-	Wed	0.022	0.187	0.120	392	0.904	1
Mon	-	Thu	0.107	0.184	0.581	392	0.562	1
Mon	-	Tue	0.070	0.187	0.371	392	0.711	1
Sat	-	Sun	0.320	0.190	1.688	392	0.092	1
Wed	-	Fri	0.108	0.199	0.542	392	0.588	1
Wed	-	Sat	-0.049	0.188	-0.263	392	0.793	1
Wed	-	Sun	0.271	0.194	1.393	392	0.164	1
Wed	-	Thu	0.085	0.191	0.444	392	0.658	1
Thu	-	Fri	0.023	0.196	0.119	392	0.905	1
Thu	-	Sat	-0.134	0.186	-0.721	392	0.471	1
Thu	-	Sun	0.186	0.192	0.968	392	0.333	1

Tue	-	Fri	0.061	0.200	0.305	392	0.761	1
Tue	-	Sat	-0.096	0.188	-0.513	392	0.608	1
Tue	-	Sun	0.223	0.194	1.150	392	0.251	1
Tue	-	Wed	-0.047	0.193	-0.245	392	0.807	1
Tue	-	Thu	0.037	0.191	0.196	392	0.845	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table G.29:** Results of generalized linear model for Z-scored BART for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.046	0.048	-0.048	0.139	0	421	0.963	0.336
Tue - Mon	-0.164	0.183	-0.524	0.196	-0.167	421	-0.894	0.372
Wed - Mon	0.178	0.181	-0.179	0.534	0.181	421	0.981	0.327
Thu - Mon	0.133	0.186	-0.231	0.498	0.136	421	0.719	0.472
Fri - Mon	0.187	0.179	-0.165	0.538	0.19	421	1.045	0.297
Sat - Mon	-0.047	0.187	-0.414	0.321	-0.047	421	-0.249	0.803
Sun - Mon	-0.072	0.179	-0.425	0.28	-0.074	421	-0.403	0.687

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table G.30:** Results of post-hoc comparisons for Z-scored BART for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	0.233	0.177	1.318	421	0.188	1

Fri	-	Sun	0.259	0.169	1.534	421	0.126	1	
Mon	-	Fri	-0.187	0.179	-1.045	421	0.297	1	
Mon	-	Sat	0.047	0.187	0.249	421	0.803	1	
Mon	-	Sun	0.072	0.179	0.403	421	0.687	1	
Mon	-	Wed	-0.178	0.181	-0.981	421	0.327	1	
Mon	-	Thu	-0.133	0.186	-0.719	421	0.472	1	
Mon	-	Tue	0.164	0.183	0.894	421	0.372	1	
Sat	-	Sun	0.026	0.178	0.144	421	0.885	1	
Wed	-	Fri	-0.009	0.171	-0.052	421	0.958	1	
Wed	-	Sat	0.224	0.18	1.25	421	0.212	1	
Wed	-	Sun	0.25	0.171	1.458	421	0.145	1	
Wed	-	Thu	0.044	0.178	0.25	421	0.803	1	
Thu	-	Fri	-0.053	0.175	-0.304	421	0.761	1	
Thu	-	Sat	0.18	0.184	0.98	421	0.328	1	
Thu	-	Sun	0.206	0.176	1.169	421	0.243	1	
Tue	-	Fri	-0.351	0.173	-2.027	421	0.043	0.909	
Tue	-	Sat	-0.117	0.182	-0.646	421	0.519	1	
Tue	-	Sun	-0.092	0.174	-0.528	421	0.598	1	
Tue	-	Wed	-0.342	0.176	-1.947	421	0.052	1	
Tue	-	Thu	-0.297	0.18	-1.653	421	0.099	1	

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table G.31:** Results of generalized linear model for Z-scored BART for those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.072	0.054	-0.034	0.178	0.000	419	1.337	0.182
Age	-0.006	0.004	-0.014	0.002	-0.071	419	-1.455	0.147
Male - Female	0.111	0.108	-0.101	0.323	0.113	419	1.027	0.305
Tue - Mon	-0.139	0.184	-0.500	0.222	-0.141	419	-0.756	0.450
Wed - Mon	0.169	0.181	-0.187	0.525	0.172	419	0.935	0.350
Thu - Mon	0.143	0.185	-0.221	0.508	0.146	419	0.773	0.440
Fri - Mon	0.192	0.179	-0.160	0.543	0.195	419	1.073	0.284
Sat - Mon	-0.036	0.187	-0.404	0.331	-0.037	419	-0.193	0.847
Sun - Mon	-0.086	0.179	-0.438	0.267	-0.087	419	-0.477	0.633

[p < 0.05; ** p < 0.01, *** p < 0.001]*

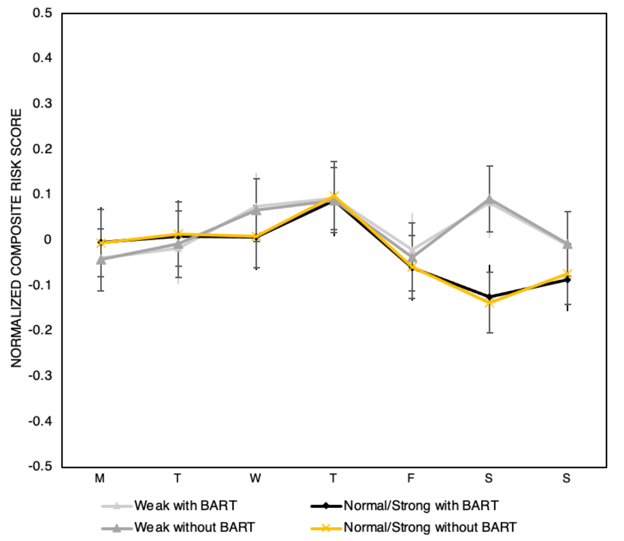
***Supplementary Materials Table G.32.:** Results of post-hoc comparisons for Z-scored BART for those with a Weak SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.228	0.177	1.288	419	0.199	1
Fri	-	Sun	0.277	0.169	1.641	419	0.102	1
Mon	-	Fri	-0.192	0.179	-1.073	419	0.284	1
Mon	-	Sat	0.036	0.187	0.193	419	0.847	1
Mon	-	Sun	0.086	0.179	0.477	419	0.633	1
Mon	-	Wed	-0.169	0.181	-0.935	419	0.350	1
Mon	-	Thu	-0.143	0.185	-0.773	419	0.440	1
Mon	-	Tue	0.139	0.184	0.756	419	0.450	1

Sat	-	Sun	0.050	0.178	0.278	419	0.781	1
Wed	-	Fri	-0.022	0.171	-0.130	419	0.896	1
Wed	-	Sat	0.205	0.180	1.144	419	0.253	1
Wed	-	Sun	0.255	0.171	1.488	419	0.137	1
Wed	-	Thu	0.026	0.178	0.147	419	0.883	1
Thu	-	Fri	-0.048	0.175	-0.276	419	0.783	1
Thu	-	Sat	0.179	0.184	0.977	419	0.329	1
Thu	-	Sun	0.229	0.176	1.299	419	0.195	1
Tue	-	Fri	-0.330	0.173	-1.908	419	0.057	1
Tue	-	Sat	-0.103	0.182	-0.566	419	0.572	1
Tue	-	Sun	-0.053	0.175	-0.305	419	0.761	1
Tue	-	Wed	-0.308	0.176	-1.748	419	0.081	1
Tue	-	Thu	-0.282	0.180	-1.568	419	0.118	1

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

Supplementary Material Figure J: Comparison of risk score calculated as in main text and calculated in the same manner but without inclusion of the BART score. Error bars represent +/- SE.



***Supplementary Table J.1:** Results of generalized linear model for Z-scored composite risk score without BART for those with a Normal/Strong SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	-0.022	0.028	-0.078	0.034	0	394	-0.783	0.434
Tue - Mon	0.02	0.104	-0.184	0.224	0.035	394	0.191	0.848
Wed - Mon	0.014	0.104	-0.19	0.219	0.025	394	0.139	0.889
Thu - Mon	0.105	0.102	-0.097	0.306	0.184	394	1.022	0.307
Fri - Mon	-0.052	0.107	-0.263	0.158	-0.092	394	-0.49	0.625
Sat - Mon	-0.131	0.101	-0.33	0.068	-0.23	394	-1.294	0.196
Sun - Mon	-0.068	0.105	-0.274	0.138	-0.119	394	-0.645	0.519

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table J.2.:** Results of post-hoc comparisons for Z-scored composite risk score without BART for those with a Normal/Strong SOW of weekday only.

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Weekday		Weekday	Difference	SE	t	df	p	$p_{bonferroni}$
Fri	-	Sat	0.078	0.108	0.727	394	0.468	1
Fri	-	Sun	0.015	0.111	0.137	394	0.891	1
Mon	-	Fri	0.052	0.107	0.49	394	0.625	1
Mon	-	Sat	0.131	0.101	1.294	394	0.196	1
Mon	-	Sun	0.068	0.105	0.645	394	0.519	1
Mon	-	Wed	-0.014	0.104	-0.139	394	0.889	1
Mon	-	Thu	-0.105	0.102	-1.022	394	0.307	1
Mon	-	Tue	-0.02	0.104	-0.191	394	0.848	1
Sat	-	Sun	-0.063	0.106	-0.598	394	0.55	1
Wed	-	Fri	0.067	0.11	0.606	394	0.545	1
Wed	-	Sat	0.145	0.105	1.389	394	0.166	1
Wed	-	Sun	0.082	0.108	0.759	394	0.448	1
Wed	-	Thu	-0.09	0.106	-0.852	394	0.395	1
Thu	-	Fri	0.157	0.109	1.441	394	0.151	1
Thu	-	Sat	0.235	0.103	2.282	394	0.023	0.483
Thu	-	Sun	0.172	0.107	1.613	394	0.108	1
Tue	-	Fri	0.072	0.11	0.655	394	0.513	1
Tue	-	Sat	0.151	0.105	1.441	394	0.151	1
Tue	-	Sun	0.087	0.108	0.809	394	0.419	1
Tue	-	Wed	0.005	0.107	0.05	394	0.96	1
Tue	-	Thu	-0.085	0.106	-0.801	394	0.423	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table J.3:** Results of generalized linear model for Z-scored composite risk score without BART for those with a Normal/Strong SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.053	0.029	-0.005	0.110	0.000	392	1.810	0.071
Age ***	-0.009	0.002	-0.014	-0.005	-0.189	392	-4.000	< .001
Male – Female ***	0.367	0.059	0.252	0.482	0.646	392	6.265	< .001
Tue - Mon	-0.031	0.098	-0.223	0.161	-0.055	392	-0.319	0.750
Wed - Mon	-0.026	0.097	-0.217	0.166	-0.045	392	-0.263	0.793
Thu - Mon	0.125	0.096	-0.063	0.314	0.221	392	1.305	0.193
Fri - Mon	-0.011	0.100	-0.209	0.186	-0.020	392	-0.114	0.909
Sat - Mon	-0.162	0.095	-0.349	0.024	-0.286	392	-1.712	0.088
Sun - Mon	-0.092	0.098	-0.285	0.101	-0.162	392	-0.938	0.349

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table J.4:** Results of post-hoc comparisons for Z-scored composite risk score without BART for those with a Normal/Strong SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	0.151	0.101	1.489	392	0.137	1.000
Fri	-	Sun	0.081	0.105	0.772	392	0.441	1.000
Mon	-	Fri	0.011	0.100	0.114	392	0.909	1.000

Mon	-	Sat	0.162	0.095	1.712	392	0.088	1.000
Mon	-	Sun	0.092	0.098	0.937	392	0.349	1.000
Mon	-	Wed	0.026	0.097	0.263	392	0.793	1.000
Mon	-	Thu	-0.125	0.096	-1.305	392	0.193	1.000
Mon	-	Tue	0.031	0.098	0.319	392	0.750	1.000
Sat	-	Sun	-0.070	0.099	-0.711	392	0.478	1.000
Wed	-	Fri	-0.014	0.104	-0.136	392	0.892	1.000
Wed	-	Sat	0.137	0.098	1.397	392	0.163	1.000
Wed	-	Sun	0.067	0.101	0.657	392	0.512	1.000
Wed	-	Thu	-0.151	0.099	-1.519	392	0.130	1.000
Thu	-	Fri	0.137	0.102	1.340	392	0.181	1.000
Thu	-	Sat	0.288	0.097	2.972	392	0.003	0.066
Thu	-	Sun	0.217	0.100	2.171	392	0.031	0.641
Tue	-	Fri	-0.020	0.104	-0.190	392	0.850	1.000
Tue	-	Sat	0.131	0.098	1.340	392	0.181	1.000
Tue	-	Sun	0.061	0.101	0.601	392	0.548	1.000
Tue	-	Wed	-0.006	0.100	-0.056	392	0.955	1.000
Tue	-	Thu	-0.157	0.100	-1.573	392	0.116	1.000

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Table J.5:** Results of generalized linear model for Z-scored composite risk score without BART for those with a Weak SOW of weekday only.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.022	0.029	-0.035	0.078	0	421	0.752	0.452
Tue - Mon	0.034	0.11	-0.182	0.251	0.058	421	0.309	0.757
Wed - Mon	0.109	0.109	-0.105	0.324	0.186	421	1.005	0.315
Thu - Mon	0.131	0.111	-0.088	0.35	0.223	421	1.174	0.241
Fri - Mon	0.006	0.107	-0.205	0.217	0.01	421	0.055	0.956
Sat - Mon	0.134	0.112	-0.087	0.355	0.227	421	1.189	0.235
Sun - Mon	0.035	0.108	-0.177	0.246	0.059	421	0.321	0.749

[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

***Supplementary Materials Table J.6:** Results of post-hoc comparisons for Z-scored composite risk score without BART for those with a Weak SOW of weekday only.

Weekday		**Weekday**	**Difference**	**SE**	**t**	**df**	**p**	$p_{bonferroni}$
Fri	-	Sat	-0.128	0.106	-1.201	421	0.231	1
Fri	-	Sun	-0.029	0.101	-0.282	421	0.778	1
Mon	-	Fri	-0.006	0.107	-0.055	421	0.956	1
Mon	-	Sat	-0.134	0.112	-1.189	421	0.235	1
Mon	-	Sun	-0.035	0.108	-0.321	421	0.749	1
Mon	-	Wed	-0.109	0.109	-1.005	421	0.315	1
Mon	-	Thu	-0.131	0.111	-1.174	421	0.241	1
Mon	-	Tue	-0.034	0.11	-0.309	421	0.757	1
Sat	-	Sun	0.099	0.107	0.928	421	0.354	1

Wed	-	Fri	0.104	0.103	1.009	421	0.314	1
Wed	-	Sat	-0.024	0.108	-0.224	421	0.823	1
Wed	-	Sun	0.075	0.103	0.727	421	0.468	1
Wed	-	Thu	-0.021	0.107	-0.2	421	0.841	1
Thu	-	Fri	0.125	0.105	1.186	421	0.236	1
Thu	-	Sat	-0.003	0.11	-0.025	421	0.98	1
Thu	-	Sun	0.096	0.106	0.911	421	0.363	1
Tue	-	Fri	0.028	0.104	0.271	421	0.787	1
Tue	-	Sat	-0.1	0.109	-0.913	421	0.362	1
Tue	-	Sun	-4.848e−4	0.104	-0.005	421	0.996	1
Tue	-	Wed	-0.075	0.105	-0.715	421	0.475	1
Tue	-	Thu	-0.097	0.108	-0.895	421	0.371	1

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Table J.7:** Results of generalized linear model for Z-scored composite risk score without BARTfor those with a Weak SOW of weekday, age, and gender.

			95% Confidence Interval					
Effect	**Estimate**	**SE**	**Lower**	**Upper**	**β**	**df**	**t**	**p**
(Intercept)	0.094	0.031	0.033	0.155	0.000	419	3.018	0.003
Age ***	-0.009	0.002	-0.013	-0.004	-0.172	419	-3.668	< .001
Male - Female ***	0.306	0.062	0.184	0.429	0.521	419	4.920	< .001
Tue - Mon	0.085	0.106	-0.124	0.293	0.144	419	0.799	0.425
Wed - Mon	0.094	0.105	-0.111	0.300	0.160	419	0.902	0.368

Thu - Mon	0.150	0.107	-0.060	0.361	0.256	419	1.405	0.161
Fri - Mon	0.013	0.103	-0.190	0.215	0.022	419	0.123	0.902
Sat - Mon	0.155	0.108	-0.057	0.368	0.265	419	1.440	0.151
Sun - Mon	0.006	0.104	-0.198	0.209	0.009	419	0.054	0.957

[p < 0.05; ** p < 0.01, *** p < 0.001]*

***Supplementary Materials Table J.8.:** Results of post-hoc comparisons for Z-scored composite risk score for those with a Weak SOW of weekday, age, and gender.

Weekday			**Difference**	**SE**	**t**	**df**	**p**	**$p_{bonferroni}$**
Fri	-	Sat	-0.143	0.102	-1.398	419	0.163	1
Fri	-	Sun	0.007	0.098	0.073	419	0.942	1
Mon	-	Fri	-0.013	0.103	-0.123	419	0.902	1
Mon	-	Sat	-0.155	0.108	-1.440	419	0.151	1
Mon	-	Sun	-0.006	0.104	-0.054	419	0.957	1
Mon	-	Wed	-0.094	0.105	-0.902	419	0.368	1
Mon	-	Thu	-0.150	0.107	-1.405	419	0.161	1
Mon	-	Tue	-0.085	0.106	-0.799	419	0.425	1
Sat	-	Sun	0.150	0.103	1.459	419	0.145	1
Wed	-	Fri	0.082	0.099	0.828	419	0.408	1
Wed	-	Sat	-0.061	0.104	-0.590	419	0.556	1
Wed	-	Sun	0.089	0.099	0.897	419	0.370	1
Wed	-	Thu	-0.056	0.103	-0.546	419	0.585	1
Thu	-	Fri	0.138	0.101	1.362	419	0.174	1

Thu	-	Sat	-0.005	0.106	-0.048	419	0.962	1
Thu	-	Sun	0.145	0.102	1.423	419	0.155	1
Tue	-	Fri	0.072	0.100	0.720	419	0.472	1
Tue	-	Sat	-0.071	0.105	-0.675	419	0.500	1
Tue	-	Sun	0.079	0.101	0.784	419	0.433	1
Tue	-	Wed	-0.010	0.102	-0.094	419	0.925	1
Tue	-	Thu	-0.066	0.104	-0.632	419	0.528	1

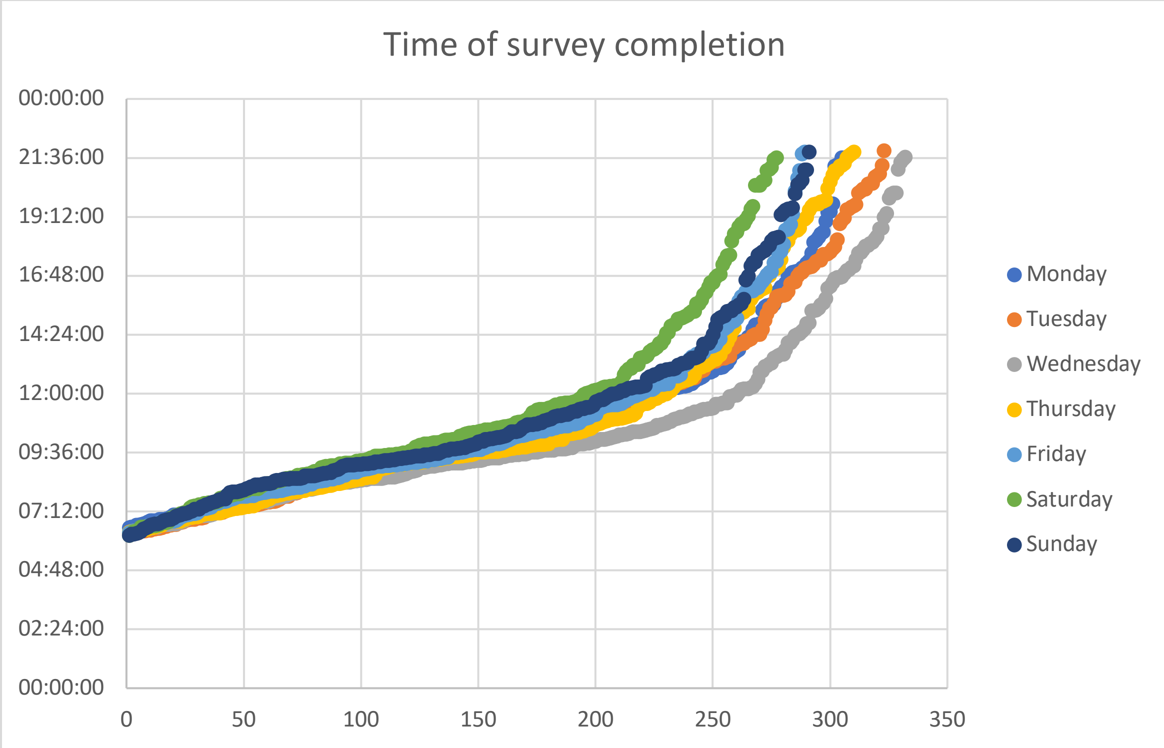
[$p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]*

Paper 3

S1. Demographic information

Day of Week	N	Number invited	Percentage of invited who completed successfully	Number failing attention checks (removed for data analyses)
Monday	313	418	74.88%	4
Tuesday	323	418	77.27%	3
Wednesday	332	417	79.62%	5
Thursday	311	418	74.40%	4
Friday	291	418	69.62%	3
Saturday	277	418	66.27%	4
Sunday	291	413	70.46%	0

To provide information on when the survey was taken over the course of the day, the course of completion over the time range of the survey being open to access (06:00 to 21:40), please see below:



To test for significance in sample sizes across days of the week, Chi square goodness of fit test was used: [$\chi^2(6, N = 2134) = 7.62$, $p = 0.27$] and revealed no significant differences.

Day of the week	Female	Male	Non-binary / third gender	Prefer not to say
Monday	198	114	1	0
Tuesday	191	129	3	0
Wednesday	188	138	5	1
Thursday	183	121	6	1
Friday	165	121	4	1
Saturday	161	115	1	0
Sunday	180	108	3	0

To test for a difference in gender proportions across days of the week, a contingency table and Chi-square test was used [$\chi^2(18, N = 2127) = 13.98$, p = 0.73)] and revealed no significant differences.

Day of week	Average Age	Age Range	Standard Error
Monday	42.74	19-71	0.7060
Tuesday	42.98	18-80	0.7776
Wednesday	41.64	19-88	0.7462
Thursday	42.57	18-86	0.7753
Friday	41.75	19-74	0.7904
Saturday	42.5	20-79	0.7825
Sunday	43.93	21-78	0.8387

To test for difference in age across days of the week, ANOVA was used [F(6, 1086) = 0.99, p = 0.34] and revealed no significant differences.

S2. Main Analyses – NHS Link Click

		95% Confidence Interval				
Predictor	**Estimate**	**Lower**	**Upper**	**SE**	**Z**	**p**
Intercept	-0.974	-1.379	-0.569	0.207	-4.711	< .001
Day of week:						
Tuesday – Monday	-0.018	-0.356	0.320	0.172	-0.102	0.919
Wednesday – Monday	0.000	-0.336	0.336	0.171	0.002	0.998

Thursday – Monday	0.043	-0.296	0.383	0.173	0.250	0.802
Friday – Monday	-0.230	-0.586	0.127	0.182	-1.262	0.207
Saturday – Monday	-0.232	-0.594	0.129	0.184	-1.260	0.208
Sunday – Monday	0.046	-0.298	0.391	0.176	0.263	0.793
Age	0.007	0.000	0.014	0.004	1.997	0.046*
Children	-0.070	-0.174	0.033	0.053	-1.329	0.184
Gender						
Male – Female	-0.234	-0.428	-0.041	0.099	-2.370	0.018*
Non-binary / third gender – Female	-0.248	-1.195	0.699	0.483	-0.514	0.607
Prefer not to say – Female	1.529	-0.883	3.940	1.230	1.243	0.214

Note. Estimates represent the log odds of "clicked = 1" vs. "clicked = 0"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S3. Main Analyses – NHS Link Time

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	26.100	5.273	15.759	36.440	4.950	< .001
Day of week:						
Tuesday – Monday	-0.383	4.419	-9.049	8.283	-0.087	0.931

Wednesday – Monday	3.349	4.394	-5.268	11.966	0.762	0.446
Thursday – Monday	0.251	4.466	-8.506	9.008	0.056	0.955
Friday – Monday	-6.064	4.541	-14.969	2.842	-1.335	0.182
Saturday – Monday	-4.965	4.605	-13.996	4.066	-1.078	0.281
Sunday – Monday	3.702	4.537	-5.197	12.600	0.816	0.415
Age	0.234	0.091	0.056	0.412	2.581	0.010*
Children	-0.133	1.307	-2.696	2.430	-0.102	0.919
Gender						
Male – Female	-2.454	2.483	-7.324	2.415	-0.988	0.323
Non-binary / third gender – Female	10.323	11.804	-12.826	33.472	0.875	0.382
Prefer not to say – Female	24.970	32.199	-38.176	88.115	0.775	0.438

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S4. Main Analyses – Sorting Quiz Score

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	8.374	0.152	8.076	8.672	55.084	< .001
Day of week:						
Tuesday – Monday	-0.141	0.127	-0.391	0.109	-1.106	0.269

Wednesday – Monday	-0.150	0.127	-0.399	0.098	-1.186	0.236
Thursday – Monday	-0.142	0.129	-0.394	0.111	-1.102	0.271
Friday – Monday	-0.039	0.131	-0.296	0.218	-0.300	0.764
Saturday – Monday	-0.050	0.133	-0.311	0.210	-0.380	0.704
Sunday – Monday	-0.093	0.131	-0.350	0.163	-0.713	0.476
Age	-0.014	0.003	-0.019	-0.008	-5.179	< .001***
Children	0.018	0.038	-0.056	0.092	0.487	0.626
Gender						
Male – Female	-0.049	0.072	-0.189	0.092	-0.680	0.497
Non-binary / third gender – Female	-0.714	0.340	-1.381	-0.046	-2.097	0.036*
Prefer not to say – Female	-0.425	0.928	-2.245	1.396	-0.457	0.647

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S5. Main Analyses – Sorting Quiz Time

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	56.398	6.629	43.398	69.398	8.508	< .001
Day of week:						
Tuesday – Monday	3.203	5.556	-7.692	14.098	0.577	0.564

Wednesday – Monday	1.439	5.524	-9.395	12.272	0.261	0.795
Thursday – Monday	-7.796	5.614	-18.806	3.213	-1.389	0.165
Friday – Monday	-3.763	5.709	-14.959	7.432	-0.659	0.510
Saturday – Monday	-2.307	5.790	-13.661	9.047	-0.398	0.690
Sunday – Monday	-5.099	5.704	-16.286	6.087	-0.894	0.371
Age	0.384	0.114	0.160	0.608	3.365	< .001***
Children	-1.836	1.643	-5.057	1.386	-1.118	0.264
Gender						
Male – Female	1.799	3.122	-4.323	7.921	0.576	0.564
Non-binary / third gender – Female	-1.849	14.840	-30.952	27.254	-0.125	0.901
Prefer not to say – Female	-20.543	40.481	-99.928	58.843	-0.508	0.612

[a] Represents reference level

4595 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

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4597 S6. Main Analyses – Knowledge Quiz Score

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	3.242	0.132	2.983	3.501	24.550	< .001
Day of week:						
Tuesday – Monday	-0.184	0.111	-0.401	0.033	-1.666	0.096

Wednesday – Monday	-0.050	0.110	-0.266	0.166	-0.457	0.648
Thursday – Monday	-0.016	0.112	-0.235	0.204	-0.141	0.888
Friday – Monday	-0.166	0.114	-0.389	0.057	-1.464	0.143
Saturday – Monday	-0.007	0.115	-0.234	0.219	-0.064	0.949
Sunday – Monday	-0.042	0.114	-0.265	0.181	-0.369	0.712
Age	-0.007	0.002	-0.011	-0.002	-3.025	0.003**
Children	-0.089	0.033	-0.153	-0.025	-2.724	0.007**
Gender						
Male – Female	-0.106	0.062	-0.228	0.016	-1.711	0.087
Non-binary / third gender – Female	0.537	0.296	-0.043	1.116	1.815	0.070
Prefer not to say – Female	0.857	0.806	-0.724	2.439	1.063	0.288

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S7. Main Analyses – Knowledge Quiz Time

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	101.912	8.009	86.206	117.618	12.725	< .001
Day of week:						
Tuesday – Monday	2.703	6.712	-10.460	15.866	0.403	0.687

Wednesday – Monday	-2.468	6.674	-15.556	10.620	-0.370	0.712
Thursday – Monday	-10.673	6.782	-23.974	2.628	-1.574	0.116
Friday – Monday	0.613	6.897	-12.913	14.139	0.089	0.929
Saturday – Monday	4.021	6.995	-9.696	17.739	0.575	0.565
Sunday – Monday	-1.517	6.892	-15.032	11.998	-0.220	0.826
Age	0.520	0.138	0.250	0.791	3.772	< .001***
Children	-2.913	1.985	-6.805	0.979	-1.468	0.142
Gender						
Male – Female	-2.844	3.772	-10.241	4.552	-0.754	0.451
Non-binary / third gender – Female	-5.950	17.929	-41.110	29.210	-0.332	0.740
Prefer not to say – Female	-22.430	48.906	-118.339	73.478	-0.459	0.647

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S8. Exploratory Analyses – Preferred One Shot

Proportions

Level	Count	Proportion
Monday	437	0.205
Tuesday	104	0.049

Wednesday	173	0.081
Thursday	67	0.031
Friday	148	0.069
Saturday	778	0.365
Sunday	427	0.200

χ^2 Goodness of Fit

χ^2	df	p
1296	6	< .001

Contingency Tables

*Note row is day of the week response was given on, column is stated preferred response

Day of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
Monday	71	16	19	10	21	108	68	313
Tuesday	54	21	23	12	26	114	71	321
Wednesday	64	19	31	10	26	117	65	332
Thursday	69	13	26	11	24	115	52	310
Friday	62	5	21	9	21	120	53	291
Saturday	73	16	23	3	16	101	45	277
Sunday	44	14	30	12	14	103	73	290
Total	437	104	173	67	148	778	427	2134

χ^2 Tests

	Value	df	p
χ^2	46.61	36	0.111
N	2134		

S9. Exploratory Analyses – Preferred Repeated

Level	Count	Proportion
Monday	1059	0.498
Tuesday	96	0.045
Wednesday	102	0.048
Thursday	43	0.020
Friday	100	0.047
Saturday	467	0.220
Sunday	260	0.122

χ^2 Goodness of Fit

χ^2	df	p
2608	6	< .001

Contingency Tables

*Note row is day of the week response was given on, column is stated preferred response

Day of week	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday	Total
Monday	166	12	13	5	12	70	33	311
Tuesday	150	24	16	6	18	65	44	323
Wednesday	154	23	12	5	20	77	40	331
Thursday	154	5	18	9	20	65	35	306
Friday	155	10	16	4	10	60	36	291
Saturday	142	9	14	5	11	61	35	277
Sunday	138	13	13	9	9	69	37	288
Total	1059	96	102	43	100	467	260	2127

χ^2 Tests

	Value	df	p
χ^2	38.51	36	0.357
N	2127		

4608

4609 **S10. Exploratory Analyses – SOEP**

Model Coefficients - SOEP G

			95% Confidence Interval			
Predictor	Estimate	SE	Lower	Upper	t	p
Intercept [a]	4.502	0.145	4.218	4.785	31.12	< .001

Day of week:						
Tuesday – Monday	0.21	0.203	-0.189	0.608	1.032	0.302
Wednesday – Monday	0.001	0.202	-0.394	0.397	0.007	0.994
Thursday – Monday	-0.277	0.205	-0.678	0.125	-1.35	0.177
Friday – Monday	0.021	0.208	-0.388	0.429	0.1	0.921
Saturday – Monday	-0.39	0.211	-0.804	0.024	-1.846	0.065
Sunday – Monday	-0.457	0.208	-0.866	-0.048	-2.193	0.028*

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	5.306	0.236	4.843	5.768	22.487	< .001
Day of week:						
Tuesday – Monday	0.190	0.198	-0.198	0.578	0.959	0.338
Wednesday – Monday	-0.085	0.197	-0.470	0.301	-0.431	0.666
Thursday – Monday	-0.319	0.200	-0.710	0.073	-1.594	0.111
Friday – Monday	-0.065	0.203	-0.463	0.333	-0.320	0.749
Saturday – Monday	-0.438	0.206	-0.842	-0.034	-2.126	0.034*

Sunday – Monday	-0.424	0.203	-0.822	-0.026	-2.089	0.037*
Age	-0.029	0.004	-0.037	-0.021	-7.024	< .001***
Children	0.135	0.058	0.021	0.250	2.317	0.021
Gender						
Male – Female	0.919	0.111	0.701	1.137	8.266	< .001***
Non-binary / third gender – Female	0.078	0.528	-0.958	1.114	0.148	0.883
Prefer not to say – Female	1.152	1.441	-1.673	3.977	0.800	0.424

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S11. Exploratory Analyses – Busyness

One-Way ANOVA (Welch's)

	F	df1	df2	p
rating	262.6	6	6647	< .001

Group Descriptives – Busyness ratings per day of the week

	day	N (# responses)	Mean Rating	SD	SE
Rating of busyness on…	Monday	2138	2.629	1.132	0.024
	Tuesday	2138	2.646	1.101	0.024
	Wednesday	2138	2.7	1.094	0.024
	Thursday	2138	2.673	1.094	0.024
	Friday	2138	2.616	1.121	0.024
	Saturday	2138	2.056	1.203	0.026
	Sunday	2138	1.642	1.194	0.026

Post Hoc Tests

Games-Howell Post-Hoc Test – rating

		Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	Mean difference	—	-0.01731	-0.07109	-0.04443	0.0131	0.5725	0.9864
	t-value	—	-0.5068	-2.088	-1.3054	0.3801	16.03	27.73
	df	—	4271	4269	4269	4274	4258	4262
	p-value	—	0.999	0.36	0.85	1	< .001 ***	< .001***
Tuesday	Mean difference		—	-0.05379	-0.02713	0.0304	0.5898	1.0037
	t-value		—	-1.602	-0.8082	0.8946	16.72	28.58
	df		—	4274	4274	4273	4241	4246
	p-value		—	0.681	0.984	0.973	< .001***	< .001***
Wednesday	Mean difference			—	0.02666	0.08419	0.6436	1.0575
	t-value			—	0.7967	2.4848	18.3	30.19
	df			—	4274	4272	4236	4242

	p-value	—	0.985	0.165	< .001***	< .001***
Thursday	Mean difference		—	0.05753	0.6169	1.0309
	t-value		—	1.6984	17.55	29.44
	df		—	4271	4236	4242
	p-value		—	0.617	< .001***	< .001***
Friday	Mean difference			—	0.5594	0.9733
	t-value			—	15.73	27.48
	df			—	4253	4257
	p-value			—	< .001	< .001***
Saturday	Mean difference				—	0.4139
	t-value				—	11.29
	df				—	4274
	p-value				—	< .001***
Sunday	Mean difference					—
	t-value					—
	df					—
	p-value					—

Note. * p < .05, ** p < .01, *** p < .001

S12. Exploratory Analyses – TIPI

TIPI – Extroversion

		95% Confidence Interval	

Predictor	Estimate	SE	Lower	Upper	t	p
Intercept [a]	3.229	0.085	3.062	3.396	37.975	< .001
Day of week:						
Tuesday – Monday	0.104	0.119	-0.13	0.337	0.869	0.385
Wednesday – Monday	0.278	0.118	0.046	0.511	2.35	0.019**
Thursday – Monday	0.179	0.12	-0.057	0.415	1.489	0.137
Friday – Monday	0.181	0.123	-0.059	0.421	1.479	0.139
Saturday – Monday	-0.034	0.124	-0.277	0.209	-0.276	0.783
Sunday – Monday	-0.018	0.122	-0.258	0.222	-0.146	0.884

[a] Represents reference level

4620 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4621

4622

Tipi – Extroversion

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	3.127	0.141	2.851	3.404	22.149	< .001
Day of week:						
Tuesday – Monday	0.124	0.118	-0.108	0.357	1.051	0.293
Wednesday – Monday	0.309	0.118	0.078	0.539	2.622	0.009

Thursday – Monday	0.197	0.12	-0.038	0.432	1.647	0.1
Friday – Monday	0.209	0.122	-0.03	0.448	1.718	0.086
Saturday – Monday	-0.021	0.123	-0.263	0.221	-0.171	0.864
Sunday – Monday	-0.008	0.122	-0.246	0.231	-0.062	0.95
Age	0.003	0.002	-0.001	0.008	1.357	0.175
Children in the home	0.114	0.035	0.046	0.183	3.269	0.001**
Gender						
Male – Female	-0.293	0.067	-0.423	-0.162	-4.402	< .001***
Non-binary / third gender – Female	-0.784	0.316	-1.404	-0.164	-2.482	0.013*
Prefer not to say – Female	-1.108	0.862	-2.798	0.583	-1.285	0.199

[a] Represents reference level

4623 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4624

TIPI – Openness to Experience

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	4.617	0.067	4.485	4.748	68.881	< .001
Day of week:						
Tuesday – Monday	0.069	0.094	-0.115	0.254	0.735	0.462
Wednesday – Monday	0.115	0.093	-0.069	0.298	1.225	0.221

Thursday – Monday	-0.036	0.095	-0.222	0.15	-0.382	0.703
Friday – Monday	0.073	0.097	-0.116	0.263	0.756	0.45
Saturday – Monday	-0.073	0.098	-0.265	0.119	-0.747	0.455
Sunday – Monday	-0.094	0.097	-0.284	0.095	-0.976	0.329

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI – Openness to Experience

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	4.891	0.112	4.671	5.111	43.629	< .001
Day of week:						
Tuesday – Monday	0.063	0.094	-0.121	0.247	0.668	0.504
Wednesday – Monday	0.097	0.093	-0.086	0.28	1.037	0.3
Thursday – Monday	-0.049	0.095	-0.235	0.137	-0.514	0.607
Friday – Monday	0.057	0.097	-0.133	0.246	0.588	0.556
Saturday – Monday	-0.081	0.098	-0.274	0.111	-0.831	0.406
Sunday – Monday	-0.096	0.096	-0.285	0.094	-0.991	0.322
Age	-0.006	0.002	-0.01	-0.002	-3.052	0.002**
Children in the home	-0.038	0.028	-0.093	0.016	-1.37	0.171

Gender						
Male – Female	0.004	0.053	-0.1	0.108	0.075	0.94
Non-binary / third gender – Female	0.527	0.251	0.035	1.019	2.099	0.036*
Prefer not to say – Female	0.84	0.684	-0.502	2.182	1.227	0.22

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI – Conscientiousness

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	5.16	0.071	5.02	5.299	72.606	< .001
Day of week:						
Tuesday – Monday	0.02	0.1	-0.176	0.215	0.199	0.842
Wednesday – Monday	0.059	0.099	-0.136	0.253	0.592	0.554
Thursday – Monday	0.004	0.101	-0.193	0.202	0.042	0.966
Friday – Monday	-0.033	0.103	-0.235	0.168	-0.326	0.744
Saturday – Monday	0.005	0.104	-0.199	0.208	0.044	0.965
Sunday – Monday	0.02	0.102	-0.181	0.221	0.191	0.849

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI – Conscientiousness

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	4.394	0.117	4.164	4.624	37.449	< .001
Day of week:						
Tuesday – Monday	0.015	0.098	-0.178	0.208	0.15	0.881
Wednesday – Monday	0.074	0.098	-0.117	0.266	0.761	0.447
Thursday – Monday	0.007	0.099	-0.188	0.202	0.068	0.946
Friday – Monday	-0.02	0.101	-0.218	0.179	-0.194	0.846
Saturday – Monday	-0.002	0.102	-0.203	0.199	-0.017	0.986
Sunday – Monday	0.002	0.101	-0.196	0.2	0.017	0.987
Age	0.016	0.002	0.012	0.02	8.12	< .001***
Children in the home	0.044	0.029	-0.013	0.101	1.504	0.133
Gender						
Male – Female	0.109	0.055	1.54E-04	0.217	1.964	0.05
Non-binary / third gender – Female	-0.211	0.263	-0.726	0.304	-0.804	0.422
Prefer not to say – Female	-0.759	0.716	-2.164	0.645	-1.06	0.289

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI -- Agreeableness

Predictor	Estimate	SE	95% Confidence Interval Lower	Upper	t	p
Intercept [a]	5.153	0.068	5.021	5.286	76.157	< .001
Day of week:						
Tuesday – Monday	0.044	0.095	-0.143	0.23	0.461	0.645
Wednesday – Monday	0.051	0.094	-0.133	0.236	0.546	0.585
Thursday – Monday	-0.062	0.096	-0.25	0.126	-0.644	0.52
Friday – Monday	0.029	0.097	-0.162	0.22	0.295	0.768
Saturday – Monday	-0.067	0.099	-0.26	0.127	-0.676	0.499
Sunday – Monday	0.017	0.097	-0.174	0.208	0.172	0.864

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI -- Agreeableness

Predictor	Estimate	SE	95% Confidence Interval Lower	Upper	t	p
Intercept [a]	4.665	0.111	4.446	4.883	41.87	< .001
Day of week:						
Tuesday – Monday	0.05	0.093	-0.134	0.233	0.53	0.596
Wednesday – Monday	0.079	0.093	-0.103	0.261	0.856	0.392
Thursday – Monday	-0.055	0.094	-0.24	0.13	-0.587	0.557

Friday – Monday	0.055	0.096	-0.133	0.243	0.571	0.568
Saturday – Monday	-0.053	0.097	-0.244	0.138	-0.543	0.587
Sunday – Monday	8.78E-04	0.096	-0.187	0.189	0.009	0.993
Age	0.014	0.002	0.01	0.017	7.077	< .001***
Children in the home	0.037	0.028	-0.017	0.091	1.348	0.178
Gender						
Male – Female	-0.3	0.052	-0.403	-0.197	-5.724	< .001***
Non-binary / third gender – Female	-0.132	0.249	-0.621	0.357	-0.53	0.596
Prefer not to say – Female	-0.42	0.68	-1.754	0.913	-0.618	0.537

[a] Represents reference level

4634 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4635

TIPI – Emotional Stability

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	4.354	0.087	4.183	4.525	49.931	< .001
Day of week:						
Tuesday – Monday	0.069	0.122	-0.171	0.308	0.564	0.573
Wednesday – Monday	0.145	0.121	-0.093	0.383	1.193	0.233
Thursday – Monday	-0.016	0.123	-0.258	0.226	-0.13	0.896

Friday – Monday	-0.028	0.126	-0.274	0.218	-0.222	0.825
Saturday – Monday	0.116	0.127	-0.134	0.365	0.908	0.364
Sunday – Monday	0.079	0.125	-0.167	0.325	0.632	0.527

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

TIPI – Emotional Stability

			95% Confidence Interval			
Predictor	**Estimate**	**SE**	**Lower**	**Upper**	**t**	**p**
Intercept [a]	2.967	0.139	2.693	3.24	21.273	< .001
Day of week:						
Tuesday – Monday	0.052	0.117	-0.177	0.282	0.447	0.655
Wednesday – Monday	0.142	0.116	-0.086	0.37	1.218	0.223
Thursday – Monday	-0.033	0.118	-0.265	0.199	-0.281	0.779
Friday – Monday	-0.035	0.12	-0.271	0.201	-0.289	0.773
Saturday – Monday	0.1	0.122	-0.139	0.339	0.82	0.412
Sunday – Monday	0.056	0.12	-0.179	0.292	0.469	0.639
Age	0.025	0.002	0.02	0.03	10.385	< .001***
Children in the home	0.168	0.035	0.1	0.235	4.851	< .001***
Gender						
Male – Female	0.601	0.066	0.472	0.73	9.143	< .001***

Non-binary / third gender – Female	-0.172	0.312	-0.784	0.44	-0.55	0.582
Prefer not to say – Female	0.043	0.851	-1.626	1.712	0.051	0.96

[a] Represents reference level

[p < 0.05; ** p < 0.01, *** p < 0.001]*

S13. Exploratory Analyses – Stone Affect

Stone Enjoyment

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-0.045	0.113	-0.396	0.692
Day of week:				
Tuesday – Monday	0.25	0.159	1.57	0.116
Wednesday – Monday	0.262	0.158	1.661	0.097
Thursday – Monday	0.161	0.16	1.004	0.316
Friday – Monday	0.259	0.163	1.583	0.113
Saturday – Monday	0.417	0.167	2.505	0.012*
Sunday – Monday	0.413	0.164	2.514	0.012*

Note. Estimates represent the log odds of "Enjoyment = Yes" vs. "Enjoyment = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone Enjoyment

Predictor	Estimate	SE	Z	p
Intercept	-0.366	0.191	-1.911	0.056
Day of week:				
Tuesday – Monday	0.264	0.16	1.648	0.099
Wednesday – Monday	0.289	0.159	1.809	0.07
Thursday – Monday	0.163	0.162	1.008	0.313
Friday – Monday	0.282	0.165	1.71	0.087
Saturday – Monday	0.432	0.168	2.568	0.01*
Sunday – Monday	0.413	0.166	2.492	0.013*
Age	0.008	0.003	2.552	0.011*
Gender				
Male – Female	-0.317	0.09	-3.514	< .001***
Non-binary / third gender – Female	-0.089	0.426	-0.209	0.834
Prefer not to say – Female	-1.035	1.23	-0.841	0.4
Children in the home	0.133	0.048	2.761	0.006**

Note. Estimates represent the log odds of "Enjoyment = Yes" vs. "Enjoyment = No"

4642 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4643

Stone – Happy

Predictor	Estimate	SE	Z	p
Intercept	0.462	0.116	3.978	< .001
Day of week:				

Tuesday – Monday	0.131	0.164	0.797	0.425
Wednesday – Monday	0.187	0.164	1.139	0.255
Thursday – Monday	0.025	0.165	0.152	0.879
Friday – Monday	0.185	0.169	1.094	0.274
Saturday – Monday	0.237	0.172	1.373	0.17
Sunday – Monday	0.374	0.173	2.169	0.03*

Note. Estimates represent the log odds of "Happy = Yes" vs. "Happy = No"

4644 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4645

Stone Happy

Predictor	Estimate	SE	Z	p
Intercept	0.24	0.197	1.216	0.224
Day of week:				
Tuesday – Monday	0.146	0.166	0.883	0.377
Wednesday – Monday	0.21	0.165	1.27	0.204
Thursday – Monday	0.027	0.166	0.164	0.869
Friday – Monday	0.205	0.171	1.197	0.231
Saturday – Monday	0.248	0.174	1.426	0.154
Sunday – Monday	0.381	0.174	2.194	0.028
Age	0.005	0.003	1.46	0.144
Gender				
Male – Female	-0.258	0.094	-2.752	0.006**

Non-binary / third gender – Female	-0.502	0.426	-1.177	0.239
Prefer not to say – Female	-1.473	1.233	-1.195	0.232
Children in the home	0.193	0.052	3.704	< .001***

Note. Estimates represent the log odds of “Happy = Yes" vs. "Happy = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone – Worry

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-0.323	0.115	-2.818	0.005
Day of week:				
Tuesday – Monday	0.093	0.16	0.581	0.561
Wednesday – Monday	0.093	0.159	0.586	0.558
Thursday – Monday	0.123	0.162	0.762	0.446
Friday – Monday	0.137	0.164	0.835	0.404
Saturday – Monday	-0.124	0.168	-0.739	0.46
Sunday – Monday	-0.146	0.166	-0.875	0.381

Note. Estimates represent the log odds of "Worry = Yes" vs. "Worry = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone – Worry

Predictor	**Estimate**	**SE**	**Z**	**p**

Intercept	0.347	0.193	1.793	0.073
Day of week:				
Tuesday – Monday	0.106	0.162	0.657	0.511
Wednesday – Monday	0.092	0.161	0.574	0.566
Thursday – Monday	0.126	0.163	0.773	0.439
Friday – Monday	0.138	0.166	0.832	0.406
Saturday – Monday	-0.12	0.17	-0.705	0.481
Sunday – Monday	-0.134	0.168	-0.801	0.423
Age	-0.012	0.003	-3.698	< .001
Gender				
Male – Female	-0.362	0.092	-3.951	< .001***
Non-binary / third gender – Female	-0.471	0.436	-1.081	0.28
Prefer not to say – Female	13.589	308.356	0.044	0.965
Children in the home	-0.008	0.048	-0.158	0.875

Note. Estimates represent the log odds of "Worry = Yes" vs. “Worry = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone -- Sad

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-0.987	0.127	-7.764	< .001
Day of week:				
Tuesday – Monday	-0.175	0.182	-0.959	0.337

Wednesday – Monday	-0.276	0.184	-1.502	0.133
Thursday – Monday	-0.268	0.186	-1.438	0.15
Friday – Monday	-0.259	0.19	-1.368	0.171
Saturday – Monday	-0.06	0.187	-0.319	0.75
Sunday – Monday	-0.492	0.197	-2.497	0.013*

Note. Estimates represent the log odds of "Sad = Yes" vs. "Sad = No"

4652 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4653

Stone -- Sad

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-0.942	0.22	-4.28	< .001
Day of week:				
Tuesday – Monday	-0.186	0.183	-1.016	0.31
Wednesday – Monday	-0.279	0.184	-1.516	0.129
Thursday – Monday	-0.273	0.187	-1.457	0.145
Friday – Monday	-0.262	0.19	-1.377	0.169
Saturday – Monday	-0.075	0.188	-0.399	0.69
Sunday – Monday	-0.509	0.198	-2.577	0.01*
Age	0.002	0.004	0.394	0.693
Gender				
Male – Female	-0.107	0.107	-1.003	0.316
Non-binary / third gender – Female	0.351	0.463	0.758	0.448

Prefer not to say – Female	0.575	1.23	0.468	0.64
Children in the home	-0.116	0.059	-1.97	0.049*

Note. Estimates represent the log odds of "Sad = Yes" vs. "Sad = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone -- Stress

Predictor	Estimate	SE	Z	p
Intercept	-0.251	0.114	-2.199	0.028
Day of week:				
Tuesday – Monday	-0.005	0.16	-0.03	0.976
Wednesday – Monday	0.099	0.159	0.625	0.532
Thursday – Monday	0.063	0.161	0.394	0.694
Friday – Monday	0.037	0.164	0.223	0.823
Saturday – Monday	-0.243	0.168	-1.444	0.149
Sunday – Monday	-0.412	0.168	-2.449	0.014*

Note. Estimates represent the log odds of "Stress = Yes" vs. "Stress = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone -- Stress

Predictor	Estimate	SE	Z	p
Intercept	0.663	0.195	3.404	< .001

Day of week:				
Tuesday – Monday	0.004	0.162	0.022	0.982
Wednesday – Monday	0.082	0.161	0.51	0.61
Thursday – Monday	0.056	0.163	0.341	0.733
Friday – Monday	0.02	0.166	0.12	0.905
Saturday – Monday	-0.248	0.171	-1.454	0.146
Sunday – Monday	-0.401	0.17	-2.358	0.018*
Age	-0.02	0.003	-5.865	< .001***
Gender				
Male – Female	-0.238	0.092	-2.585	0.01*
Non-binary / third gender – Female	-0.108	0.428	-0.253	0.8
Prefer not to say – Female	0.704	1.23	0.573	0.567
Children in the home	0.051	0.048	1.071	0.284

Note. Estimates represent the log odds of "Stress = Yes" vs. "Stress = No"

4658 *[* p < 0.05; ** p < 0.01, *** p < 0.001]*

4659

Stone -- Anger

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-2.138	0.184	-11.618	< .001
Day of week:				
Tuesday – Monday	-0.141	0.266	-0.529	0.597
Wednesday – Monday	-0.032	0.258	-0.126	0.9

Thursday – Monday	0.007	0.26	0.028	0.978
Friday – Monday	-0.102	0.271	-0.375	0.707
Saturday – Monday	-0.415	0.296	-1.401	0.161
Sunday – Monday	-0.365	0.288	-1.268	0.205

Note. Estimates represent the log odds of "Anger = Yes" vs. "Anger = No"

[p < 0.05; ** p < 0.01, *** p < 0.001]*

Stone -- Anger

Predictor	**Estimate**	**SE**	**Z**	**p**
Intercept	-1.617	0.32	-5.058	< .001
Day of week:				
Tuesday – Monday	-0.133	0.266	-0.498	0.618
Wednesday – Monday	-0.038	0.259	-0.148	0.883
Thursday – Monday	0.005	0.261	0.02	0.984
Friday – Monday	-0.106	0.272	-0.391	0.696
Saturday – Monday	-0.458	0.301	-1.519	0.129
Sunday – Monday	-0.352	0.289	-1.217	0.224
Age	-0.012	0.006	-2.109	0.035*
Gender				
Male – Female	-0.153	0.156	-0.976	0.329
Non-binary / third gender – Female	-0.265	0.752	-0.352	0.725
Prefer not to say – Female	-12.512	509.46	-0.025	0.98

Children in the home	0.086	0.076	1.139	0.255

Note. Estimates represent the log odds of "Anger = Yes" vs. "Anger = No"

[* $p < 0.05$; ** $p < 0.01$, *** $p < 0.001$]

Paper 4

SUPPLEMENTARY MATERIALS

S1. Demographic information

Day of Week	**N**
Monday	313
Tuesday	323
Wednesday	332
Thursday	311
Friday	291
Saturday	277
Sunday	291

To test for significance in sample sizes across days of the week, Chi square goodness of fit test was used: [$\chi^2(6, N = 2134) = 7.62, p = 0.27$] and revealed no significant differences.

Day of the week	**Female**	**Male**	**Non-binary / third gender**	**Prefer not to say**
Monday	198	114	1	0
Tuesday	191	129	3	0
Wednesday	188	138	5	1
Thursday	183	121	6	1
Friday	165	121	4	1

Saturday	161	115	1	0
Sunday	180	108	3	0

To test for a difference in gender proportions across days of the week, a contingency table and Chi-square test was used [$\chi^2(18, N = 2127) = 13.98$, p = 0.73)] and revealed no significant differences.

Day of week	**Average Age**	**Age Range**	**Standard Error**
Monday	42.74	19-71	0.7060
Tuesday	42.98	18-80	0.7776
Wednesday	41.64	19-88	0.7462
Thursday	42.57	18-86	0.7753
Friday	41.75	19-74	0.7904
Saturday	42.5	20-79	0.7825
Sunday	43.93	21-78	0.8387

To test for difference in age across days of the week, ANOVA was used [$F(6, 1086) = 0.99$, $p = 0.34$] and revealed no significant differences.

S2: Post-hoc comparisons of all categories of heuristic (EVmax, mini-max) and category of decision (affect-rich, affect-poor) groups.

Post Hoc Comparisons - Heuristic ✻ Category of Decision

Comparison

Heuristic	Category of Decision		Heuristic	Category of Decision	Mean Difference	SE	df	t	p_{tukey}
MiniMax	Affect-poor	-	MiniMax	Affect-rich	-0.0655	0.0077	1832.0000	-8.4897	< .001
		-	EV	Affect-poor	-0.3451	0.0071	1832.0000	-48.6374	< .001
		-	EV	Affect-rich	-0.1528	0.0076	1832.0000	-20.2078	< .001
	Affect-rich	-	EV	Affect-poor	-0.2796	0.0067	1832.0000	-41.6561	< .001
		-	EV	Affect-rich	-0.0873	0.0070	1832.0000	-12.3961	< .001
EV	Affect-poor	-	EV	Affect-rich	0.1923	0.0054	1832.0000	35.6926	< .001

S3: Correlation matrix between the composite affect score and percentage of preference reversals between affect-rich and affect-poor decisions as well as the proportion of decisions made using mini-max or EVmax in affect-rich or affect-poor choices. Note: NA denotes "affect-poor" and A denotes "affect-rich."

Correlation Matrix

		Preference Reversals	Composite_Affect		Weekend	NA_%EVMax	NA_%MinMax	A_%EVMax	A_%MinMax
Preference Reversals	Pearson's r	—							
	p-value	—							
Composite_Affect	Pearson's r	0.021	—			0.020	-0.043	-0.029	-0.000
	p-value	0.332	—			0.389	0.068	0.205	0.991
Weekend	Pearson's r	0.013	0.068	**	—	0.030	0.009	-0.004	0.017

	p-value	0.540	0.002	—	0.186	0.692	0.875	0.438
NA_%EVMax	Pearson's r	-0.170 ***	0.020		—			
	p-value	< .001	0.389		—			
NA_%MinMax	Pearson's r	-0.048 *	-0.043		0.050 *	—		
	p-value	0.040	0.068		0.034	—		
A_%EVMax	Pearson's r	-0.631 ***	-0.029		0.098 ***	-0.027	—	
	p-value	< .001	0.205		< .001	0.239	—	
A_%MinMax	Pearson's r	0.158 ***	-0.000		-0.047 *	0.149 ***	-0.014	—
	p-value	< .001	0.991		0.040	< .001	0.531	—

Note. * p < .05, ** p < .01, *** p < .001