Integrating Psychology and Neuroscience Approaches to Optimize Physical Activity Behavior Change

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor of
Philosophy in the Department of
Psychology and Neuroscience in the Graduate School
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ABSTRACT

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Abstract

Physical activity has many benefits including promoting healthy aging, reducing risk of chronic disease, and supporting general well-being. Despite this, many adults do not get significant amounts of daily physical activity. The effects of interventions promoting physical activity are highly variable and typically modest. Even when behavioral interventions are effective, the understanding of how and why they work is lacking. Understanding the determinants of physical activity behavior change, along with identifying evidence-based behavior change techniques that target these determinants, is critical for developing effective interventions.

In this dissertation, across two studies, I examine the role of neural and behavioral determinants of physical activity behavior change. Chapter 1 provides a review of the two prominent theoretical approaches to physical activity behavior change, social cognitive theory and dual-process theory, and highlights how neuroimaging techniques can be utilized to help inform gaps in both theoretical and applied knowledge of physical activity.

Chapter 2 (Study 1) evaluates if there are brain regions correlated with physical activity behavior change. In the study, participants wore a pedometer for a week before and after an fMRI session where they read and heard statements about walking. Behavioral analysis demonstrated that participants walked significantly more following exposure to the walking-related messages. Whole-brain analysis examined regions positively associated with walking behavior change and produced two significant clusters in the frontal pole region and the precuneus/posterior cingulate gyrus region. The

frontopolar cortex is implicated in pre-commitment, a self-control strategy where people anticipate self-control failures and prospectively restrict their access to tempting alternatives. The precuneus/posterior cingulate cortex region has been found to play a role in self-relevant processing. Both self-control and self-relevant processing are believed to be important for behavior change.

Chapter 3 (Study 2) focuses on neural and self-report responses to different types of health messages and their ability to predict physical activity behavior change. In the study, participants completed an fMRI task where they read positively or negatively framed walking-related messages with either social or non-social based content and rated how personally motivating they were as well as other self-reported ratings. Neural activity in regions involved in positive valuation and self-referential processing were measured to evaluate whether sensitivity in these regions to individual messages could predict the effectiveness of those messages when delivered in an intervention weeks or months later. For the next 80 days, participants completed a SMS-based mHealth intervention where they received one of the same walking-related messages from the scanner task daily. We assessed physical activity using a wearable fitness tracker throughout the 80 days and a baseline period. Individual participant ratings on how relevant the message would be to others predicted the effectiveness of the messages. People were more physically active on days when they received messages that were rated as more relevant to others. Brain activation in the regions of interest selected were not associated with message effectiveness during the intervention.

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1. Introduction

Regular physical activity has shown to decrease risk of many chronic health conditions, including cardiovascular disease, type 2 diabetes, and cancer (Rhodes, Janssen, Bredin, Warburton, & Bauman, 2017; Warburton, Nicol, & Bredin, 2006). Beyond reducing risk for adverse health conditions, being physically active has shown to contribute to mental and cognitive health as well, improving mood, reducing symptoms of anxiety and depression, and buffering against age-related cognitive decline (Penedo & Dahn, 2005). Despite these benefits, more than 25% of the global adult population does not get enough physical activity (World Health Organization, 2022). It is estimated that up to 5 million deaths per year could be prevented if the global population were more active (Ding et al., 2016). Given this information, understanding how to effectively promote physical activity behavior is an urgent public health priority.

The effects of interventions promoting physical activity are highly variable and typically modest (Foster, Hillsdon, Thorogood, Kaur, & Wedatilake, 2005), and when behavioral interventions are effective, the understanding of how and why they work is lacking (Michie, Abraham, Whittington, McAteer, & Gupta, 2009). Understanding the determinates of physical activity behavior change, along with identifying evidence-based behavior change techniques that target these determinates, is critical for developing effective interventions, but first, there must be sound theoretical understanding of physical activity behavior (Glanz & Bishop, 2010; Michie & Abraham, 2004; Presseau et al., 2021).

Effective theories would give us a greater understanding of physical activity and its variation between individuals, while also identifying targets for interventions aimed at changing physical activity behavior (Michie, Johnston, Francis, Hardeman, & Eccles, 2008). There are multiple pathways through which theory can achieve this. First, by identifying theoretical constructs to target, theory provides a means for selecting component intervention techniques (Michie et al., 2008) and for refining or tailoring intervention techniques (Noar, Benac, & Harris, 2007). Second, collecting empirical data within a theoretical framework facilitates the accumulation of evidence of effectiveness across different contexts, populations, and behaviors (Michie et al., 2005). Third, as well as using theory to inform intervention development, theory-based interventions can aid understanding of why interventions are effective or ineffective, thus facilitating an understanding of mechanisms of change and providing a basis for refining and developing better theory (Michie & Abraham, 2004).

While the use of theory has multiple potential benefits and is viewed as 'good practice' by researchers in the field, evidence suggesting a relationship between theory use and increased intervention effectiveness is mixed for both health behavior change interventions, in general (Dalgetty, Miller, & Dombrowski, 2019; Greaves et al., 2011), and physical activity interventions (Prestwich et al., 2014). Some reviews have found that interventions utilizing theory-based behavior change techniques generate larger effects (Michie et al., 2009; Samdal, Eide, Barth, Williams, & Meland, 2017), while others have found that overall effects on physical activity behavior did not significantly differ between theory-based and no-stated-theory interventions (Conn, Hafdahl, & Mehr, 2011;

McEwan et al., 2019; Prestwich et al., 2014; Rhodes, Janssen, Bredin, Warburton, & Bauman, 2017).

The inconclusive evidence for a relationship between theory use and intervention effectiveness does not necessarily mean that theory is not important for intervention design. Poor reporting of theory usage, using multiple theoretical constructs, and unclear operationalization of constructs make finding connections between theory and effectiveness difficult (Rothman, 2004). For example, even when an intervention does not state using a specific theory, the behavior change techniques utilized can often be mapped to a theory construct retrospectively (McEwan et al., 2019). Another limitation in understanding theory use in interventions is that most physical activity interventions lack a theoretical basis (Dombrowski, Sniehotta, Avenell, & Coyne, 2007; Noar & Zimmerman, 2005), which can stem from the multitude of theoretical frameworks and lack of understanding regarding what works and for whom.

In the following sections, I will review two predominant theoretical approaches in physical activity research: the social cognitive approach and the dual-process approach. By discussing the literature regarding each approach's key constructs, their relationships with physical activity behavior, and how they have been utilized to encourage physical activity, I will outline the contributions each framework has made to our theoretical understanding of physical activity behavior and our knowledge regarding effective interventions. While there are multitudes of models from various fields of study that examine behavior at varying levels, they are beyond the scope of this paper (for an excellent review, see King, Stokols, Talen, Brassington, & Killingsworth, 2002). Instead, this paper focuses on health psychology models under the two frameworks that examine physical activity behavior at the level of the individual.

1.2 Social Cognitive Approach

The social cognitive framework followed from a transition in psychology from behaviorism to cognitive paradigms involving social learning and cognitive processes underlying behavior (Conner & Norman, 2007). The approach was quickly applied to health behaviors and has continued to be the dominant approach in health psychology for understanding, predicting, and intervening upon physical activity behavior (Conner & Norman, 2007; Rebar & Rhodes, 2020). Social cognitive models emphasize the rationality of human decision making and thus behavior is the result of a deliberate, but subjective, weighing of costs and benefits associated with likely outcomes and acting on the choice with the highest expected utility (Maddux, 1993; Maddux, Norton, & Stoltenberg, 1986). In terms of physical activity behavior, from a social cognitive perspective, an individual will intend to and subsequently be physically active if they believe that physical activity is important and that they are truly capable of performing physical activity. Thus, intervention upon physical activity requires a rational and value-based approach, appealing to an individual's values and beliefs and/or using techniques to increase perceptions of capability.

There are many theoretical models developed to explain health behavior under the social cognitive umbrella, the most common being the health belief model (HBM; Janz & Becker, 1984; Rosenstock, 1974), protection motivation theory (PMT; Rogers, 1975), social cognitive theory (SCT; Bandura, 1998), and the theory of planned behavior (TPB;

Ajzen, 1991; Ajzen & Fishbein, 1977). With SCT and TPB being the most studied theories in physical activity behavior change research (Buchan, Ollis, Thomas, & Baker, 2012), they will be used as exemplars for social cognitive models.

Despite the variety of models, the majority involve variables relating to beliefs about one's ability to carry out the specific behavior and attitudes towards the expected outcomes of changing behavior, that ultimately form the decision to act or not (Maddux et al., 1986). The considerable overlap in constructs has led authors to posit that they are more alike than different, with their largest differences being the labels given to the constructs (Gourlan et al., 2016; Rhodes et al., 2017; Sheeran, Klein, & Rothman, 2017). For example, TPB and SCT both include a variable related to people's appraisals of their ability to perform a behavior. In TPB this is referred to as perceived behavioral control (Ajzen, 1991), while in SCT the construct is known as perceived self-efficacy (Bandura, 1989; Trafimow, Sheeran, Conner, & Finlay, 2002). Regardless of terminology, each of the variables is an example of reflective, flexible, goal-driven processes. It is important to note that some models under this framework also include a socio-structural variable that represents social norms or environmental factors. While they have shown to have effects on health behavior (e.g., McLeroy, Bibeau, Steckler, & Glanz, 1988), this paper will focus on the cognitive features of these models. Throughout this paper, the terms used to refer to the three common variables of social cognitive models are self-efficacy, outcome expectancy, and intention.

1.2.1 Key Theoretical Constructs

Self-efficacy refers to an individual's belief in their ability to successfully execute necessary courses of action to perform a goal behavior despite obstacles (Bandura, 1986, 1998, 2004). Self-efficacy perceptions are thought to be strengthened or reduced by several sources, including past experiences, verbal persuasion, mental imagery, and perceptions of one's emotional state (Bandura, 1998; Jackson, Smith, & Conner, 2003). It is hypothesized to affect physical activity behavior directly and indirectly through outcome expectancies and intention (Bandura, 1998, 2004). Most social cognitive models of health behavior also focus on the perceived consequences of performing a behavior, or outcome expectancies. Outcome expectancies encompass a person's belief that a given behavior will or will not lead to a specific outcome, as well as beliefs about the consequences that will occur without deciding to enact the behavior (Bandura, 1977; Williams et al., 2005). Finally, according to the social cognitive perspective, self-efficacy beliefs and outcome expectancies produce intention, or motivation to enact a certain behavior, the most proximate determinant of behavior (see Figure 1).

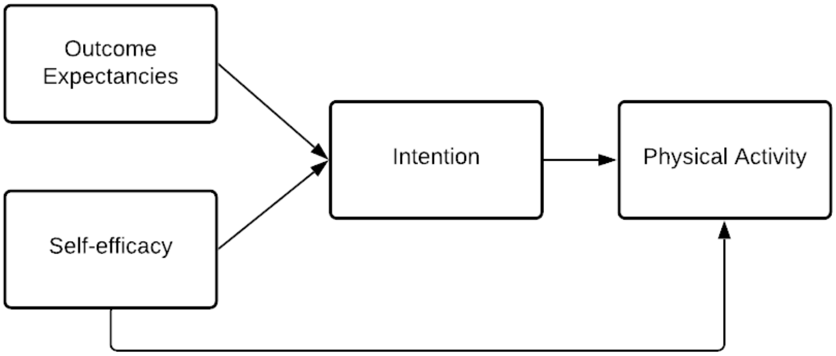

Figure 1: General Schematic of Social Cognitive Theories of Physical Activity

Many studies have examined the efficacy and predictive capabilities of the social cognitive framework as a whole and the core constructs individually (Conner & Norman, 2007; Maddux, 1993; Young, Plotnikoff, Collins, Callister, & Morgan, 2014). Social cognitive theories, in general, have consistently shown to be useful for explaining physical activity behavior (McEachan, Conner, Taylor, & Lawton, 2011; Young et al., 2014), with meta-analytic studies examining the explanatory power of social cognitive models finding that they accounted for around 30% of the variance in both adult (Young et al., 2014) and adolescent populations (Plotnikoff, Costigan, Karunamuni, & Lubans, 2013). However, no single model has consistently shown to be better than others (McEwan et al., 2019; Plotnikoff et al., 2013; Prestwich et al., 2014) which could be due, in part, to the considerable amount of conceptual overlap between the theories (Gourlan et al., 2016; Rhodes, 2017; Sheeran et al., 2017).

Outcome expectancies. From a social cognitive perspective, outcome expectancies are generally defined as an expectation that an outcome will follow a given behavior

(Williams et al., 2005). Outcome expectancies are hypothesized to indirectly affect subsequent behavior through intention or directly (Bandura, 1984, 1986, 1998, 2004). However, evidence regarding the utility of outcome expectancies for predicting physical activity behavior is mixed (Phipps, Hannan, Rhodes, & Hamilton, 2021; Plotnikoff et al., 2013; Williams, Anderson, & Winett, 2005).

Self-efficacy. In contrast to outcome expectancies, self-efficacy has consistently shown to be a reliable determinant of physical activity behavior across multiple domains (for a review see Mcauley & Blissmer, 2000). Belief in personal capabilities has shown to predict physical activity behavior across various groups of individuals including different ages (e.g., Ayotte, Margrett, & Hicks-Patrick, 2010; Craggs, Corder, van Sluijs, & Griffin, 2011) and socioeconomically and racially diverse groups (e.g, Anderson, Wojcik, Winett, & Williams, 2006). While some authors have criticized the validity of the construct because of the way it is typically operationalized and measured (Cahill, Gallo, Lisman, & Weinstein, 2006; Williams, 2010; Williams & Rhodes, 2016), it has been the most studied construct and is the target of many behavior change interventions (for reviews, see Bandura, 1984; Hyde, Hankins, Deale, & Marteau, 2008).

1.2.2 Intervention applications

Interventions employing social cognitive models have shown to be effective for increasing physical activity, however meta-analytic work indicates these interventions yield a small effect size (Rhodes et al., 2017). In line with the basic premise of social cognitive models, interventions in their most basic form focus on the reflective determinants of behavior and assume that intervening on a person's conscious cognitions (e.g., risk perception, health benefits, etc.) will increase physical activity by increasing intention. However, providing information alone has not shown to have consistent or long-lasting effects on physical activity behavior (e.g., French, Cameron, Benton, Deaton, & Harvie, 2017; Marcus, Owen, Forsyth, Cavill, & Fridinger, 1998). More involved interventions attempt to promote physical activity by teaching various skills to increase an individuals' self-efficacy beliefs considering their relationship with physical activity (Michie et al., 2009). Meta-analytic studies of intervention effects on self-efficacy have found a small, yet significant, relationship between interventions and changes in self-efficacy in a range of populations (e.g., Ashford, Edmunds, & French, 2010; French, Olander, Chisholm, & Mc Sharry, 2014; Olander et al., 2013). While no self-efficacy behavior change technique has consistently shown to be effective for all populations (Tang, Smith, Mc Sharry, Hann, & French, 2019), evidence suggests that interventions incorporating 'demonstration of the behavior', 'graded tasks', 'behavior practice/rehearsal', and 'feedback' may be more effective (Howlett, Trivedi, Troop, & Chater, 2019; O'Brien et al., 2015; Samdal et al., 2017). While it is encouraging that some behavior change techniques show promise, the inconsistency across different studies highlights the need for a more precise understanding of how to enact behavior change, especially regarding what works and for whom, or boundary conditions.

Intention-behavior gap. Social cognitive models have consistently shown to be effective in increasing the most central construct, intention (Hagger, Chatzisarantis, & Biddle, 2002). However, the effect of intention strength on subsequent behavior change is less clear-cut (Hagger et al., 2002; Webb & Sheeran, 2006). In correlational analyses, the relationship between intention and behavior, in general, is consistent and of medium to large magnitude (Armitage & Conner, 2000; Hagger et al., 2002; McEachan et al., 2011; Sheeran, 2002), and this effect is also seen in studies of intention and physical activity (Hagger et al., 2002). From correlational analyses it is tempting to suggest that intention is a reliable determinant of physical activity, but correlational studies preclude causal inferences which are necessary to examine if intention is a key determinant of physical activity – a central argument to SCTs (Bauman, Sallis, Dzewaltowski, & Owen, 2002; Weinstein & Rothman, 2005). To clarify the intention behavior relationship, Webb and Sheeran (2006) conducted a meta-analysis of experimental tests of intention and behavior across a variety of behavioral outcomes and found that even large changes in intention (d = .66) result in only small changes in behavior (d = .36). For physical activity behavior specifically, the experimental evidence for changing behavior through intention is even less convincing, with medium to large changes in intention leading to near trivial effects on behavior (Rhodes & Dickau, 2012). Other work has also found disappointing rates of people actualizing their intention to increase physical activity (Rhodes & de Bruijn, 2013; Rhodes, Plotnikoff, & Courneya, 2008). In all, the discrepancy between intentions and subsequent physical activity behavior represents a key limitation of social cognitive models.

A growing body of research has attempted to find explanations for the ‘intention-behavior’ gap. For example, a review examining intention-behavior discordance in physical activity behavior, found that the most consistent moderator was intention stability (Rhodes & Bruijn, 2013; Sniehotta, Scholz, & Schwarzer, 2005), suggesting that the discrepancy between intention and behavior is likely due to wavering motivational strength between initial intention and later opportunities to be physically active (Rhodes & Yao, 2015; Sniehotta et al., 2005). This phenomenon could also be conceptualized as self-control, or choosing to act accordingly with overarching goals despite goal-incongruent alternatives (Duckworth, 2011). Indeed, evidence has found that higher levels of trait self-control were associated with a stronger intention-behavior relationship in physical activity (de Ridder, Lensvelt-Mulders, Finkenauer, Stok, & Baumeister, 2012; Pfeffer & Strobach, 2020), suggesting that individuals with higher trait self-control exhibit higher intention-behavior concordance. Despite self-control presenting a potential boundary condition of social cognitive models' effectiveness, the construct has not been integrated into the framework, presenting an area for future research.

1.2.3 Social Cognitive Approach Summary

Overall, social cognitive models represent the earliest attempts of organizing knowledge about physical activity behavior into parsimonious conceptual models that include testable hypotheses, giving direction to subsequent studies, and forming the basis of contemporary models (Rebar & Rhodes, 2020). In terms of behavior change techniques, studies utilizing the social cognitive framework have identified multiple intervention components useful for behavior change such as providing feedback and demonstrating how to engage in physical activity (Howlett et al., 2019). Despite the contributions of the framework, the amount of variability in behavior not explained by intention and the magnitude of the intention-behavior gap call into question the main assumption of the expectancy-value, or reasoned action approach, characteristic of social cognitive models: the rationality of human decision-making (Armitage & Conner, 2000; Conner & Norman, 2007). This combined with the large portion of physical activity behavior not accounted for in interventions makes it plausible to suggests that the social cognitive approach is not comprehensive and warrants the need for conceptual refinement or amendment.

1.3 Dual-Process Approach

A large body of research suggests that individual's decisions and behaviors are often at odds with what is expected and are easily influenced by factors outside of their immediate awareness (Bargh & Ferguson, 2000; Heatherton & Wagner, 2011; Sherman, Gawronski, & Trope, 2014; Strack & Deutsch, 2004; Wood & Neal, 2007). This, combined with evidence that intentions do not automatically lead to intended behavior (Rhodes & de Bruijn, 2013; Sheeran & Webb, 2016), has led some researchers to suggest that there has been an overemphasis on the reflective, deliberative, rule-based processes involved in behavior and to consider a paradigm shift that also considers automatic, associative, impulsive influences (Aarts, 2007; Hofmann, Friese, & Wiers, 2008; Lowe & Norman, 2013; Marteau, Hollands, & Fletcher, 2012; Sheeran, Gollwitzer, & Bargh, 2013). To answer this call, contemporary models of physical activity have recently adopted a dual-process perspective (Gawronski & Bodenhausen, 2006; Strack & Deutsch, 2004) that suggests that physical activity behavior is the result of two qualitatively distinct types of mental processes, distinguished by the levels of automaticity or reflectiveness of actions (Brand & Ekkekakis, 2018; Chaiken & Trope, 1999; Conroy & Berry, 2017; Hofmann, Schmeichel, & Baddeley, 2012).

1.3.1 Key theoretical constructs

While there are differences in specific terminology and assumptions between dual-process models, the existence of two distinct, yet interacting, cognitive processes are central to the framework. Implicit or non-conscious processes ("type 1") represent well learned, fast, and automatic influences on action, while reflective or conscious processes ("type 2") are thought to be reflective or deliberative and represent rational, flexible decision-making influences (Chaiken & Trope, 1999; Evans, 2008; Evans & Stanovich, 2013; Pfeffer & Strobach, 2020) akin to the key constructs in social cognitive theories (i.e., intention, self-efficacy, outcome expectancies). Both implicit and reflective processes play a role in behavior, but a common assumption of these theories is that type 1 and type 2 processes "will not always converge and, in some cases, may be discordant" (Conroy & Berry, 2017, p. 231) resulting in a self-control conflict.

Implicit attitudes. Automatic processes encapsulate the spontaneously activated evaluations, motivational tendencies, and cognitions that are elicited by a stimulus (Aarts, Verplanken, & Van Knippenberg, 1998; Chen & Bargh, 1999; Conroy & Berry, 2017; Rebar et al., 2016). Of the automatic processes, implicit attitudes have been the most widely studied in terms of physical activity behavior (Rebar et al., 2016; Rhodes, Fiala, & Conner, 2009). From a dual-process perspective, implicit attitudes, the automatic affective valuations that arise when a concept is activated in one's mind, form the basis of other automatic behaviors such as attentional biases and behavioral impulses and are a product of repeated positive or negative experiences with a stimulus (Brand & Ekkekakis, 2018; Conroy & Berry, 2017; Greenwald & Banaji, 1995). A significant body of literature recognizes that implicit attitudes are positively related to physical activity behavior (Calitri, Lowe, Eves, & Bennett, 2009; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Rebar, Ram, & Conroy, 2015) and that they are able to predict physical activity behavior beyond that of self-reported reflective variables seen in social cognitive models (e.g. intention, outcome expectancies; Chevance, Bernard, Chamberland, & Rebar, 2019; Chevance, Héraud, Guerrieri, Rebar, & Boiché, 2017; Conroy et al., 2010; Rebar et al., 2016). Together this evidence suggests that implicit attitudes likely have a role in physical activity behavior. However, how implicit attitudes produce effects, or their mechanisms of action, is less understood.

Attentional bias and implicit motivation. Two automatic processes through which implicit attitudes might affect physical activity behavior are attentional biases and implicit motivation (Sheeran et al., 2013). Attentional bias, defined as a person's automatic tendency to selectively attend to certain types of stimuli while overlooking, ignoring, or disregarding others, is thought to occur towards stimuli most relevant to the participant, signaling a strongly accessible and positive implicit attitude (Berry, 2006; Calitri et al., 2009). In the same vein, implicit motivation, or the automatic behavioral urge to move towards (approach) or away (avoid) from a stimulus, is thought to be a function of implicit attitudes, with stronger, more positive implicit attitudes towards physical activity stimuli prompting stronger approach tendencies (Cheval et al., 2018; Rebar et al., 2016). Both attentional biases (Berry, 2006; Calitri et al., 2009) and approach/avoid tendencies (Cheval, Sarrazin, Isoard-Gautheur, Radel, & Friese, 2015, 2016; Cheval, Sarrazin, & Pelletier, 2014) have shown to positively correlate with physical activity and each process has shown to explain unique variance in physical activity behavior (Conroy et al., 2010; Hannan et al., 2019). While evidence suggests that attentional biases and approach/avoid tendencies are related to physical activity, the idea that positive implicit attitudes result in more positive cognitive and motivational tendencies is unclear. For example, Oliver and Kemps (2018) found that participants, in general, had positive implicit attitudes towards incidental physical activity, but an avoidance away from physical activity cues, and no attentional bias towards them, suggesting that implicit attitudes may act independently from attentional biases and approach/avoid tendencies. This finding is incongruent with previously shown positive correlations between implicit attitudes and physical activity (Calitri et al., 2009; Conroy et al., 2010). Despite the inconsistencies, the above evidence demonstrates that implicit motivation and attentional biases may play a role in physical activity behavior.

Reflective-implicit relationship. While the previous evidence examined how automatic processes relate to each other, other studies have examined how automatic and reflective processes interact. Three potential pathways through which automatic processes may affect behavior have been proposed (Perugini, 2005; Rebar et al., 2016): a direct effect, an indirect effect via reflective processes, and an interdependent effect with reflective processes (Figure 2). However, regarding physical activity, direct effects and interdependent effects have been the most widely investigated (Rebar et al., 2016).

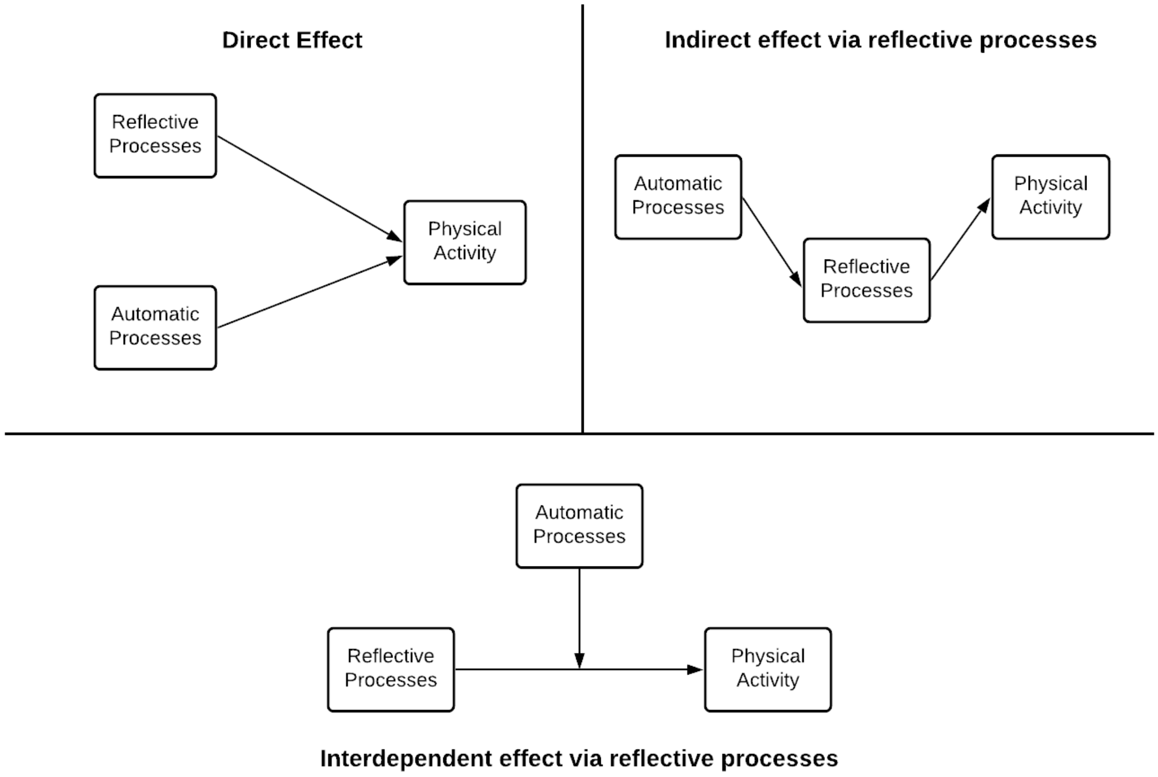

Figure 2: Possible Models of Automatic Processes Effects on Physical Activity (adapted from Rebar et al., 2016)

One way that automatic processes could affect physical activity behavior is directly and independently from reflective processes, each having separate additive effects (Orbell & Verplanken, 2010; Wilson, Lindsey, & Schooler, 2000). For example, Conroy et al., (2010) found that implicit attitudes positively predicted physical activity after controlling for reflective predictors variables (i.e., self-efficacy, outcome expectancies, and intention). Other studies have also found an independent, additive effect of automatic processes (implicit attitudes: Hyde, Doerksen, Ribeiro, & Conroy, 2010; habit: Rebar et al., 2016; Gardner et al., 2011).

Automatic processes could also affect physical activity behavior indirectly via reflective processes, mediating the relationship (Dimmock & Banting, 2009; Wood & Neal, 2007). For example, automatic processes could enhance intentions to be physically activity, thereby increasing physical activity. Evidence has found that automatic processes interact with reflective variables. For example, implicit attitudes were found to predict intention, which in turn predicted behavior (Muschalik, Elfeddali, Candel, & de Vries, 2018). Similarly, Brand and Schweizer (2015) found that automatic evaluations of physical activity predicted situated decisions, which predicted physical activity. Important to note, however, neither study tested mediation.

Finally, automatic processes might affect physical activity behavior interdependently via reflective processes, serving as a moderating variable (Rhodes & de Bruijn, 2013; Strack & Deutsch, 2004). For example, Muschalik et al., (2018) examined the relationship between automatic and reflective processes in a longitudinal study and found evidence for a moderating effect of automatic processes on the relationship between reflective processes and physical activity. More specifically, using hierarchical multiple regression, the results revealed that baseline positive implicit attitudes moderated the relationship between baseline self-efficacy and physical activity at 3 months follow-up. In contrast to Cheval et al., (2014) and Conroy et al., (2010), this study did not find evidence for a direct effect.

The research on automatic and reflective correlates of physical activity is vast and quickly growing, unfortunately, most dual-process studies have utilized automatic processes as add-on variables to physical activity theories based on conscious introspection (Rebar et al., 2016). In the future, testing variables in terms of comprehensive models could help clarify the mixed evidence reviewed above.

1.3.2 Intervention applications

Interventions directly targeting implicit processes aim to either reshape the automatic associations that automatically arise from stimuli (e.g., evaluative conditioning; Levey and Martin, 1975) or alter how people respond to stimuli (e.g., approach/avoidance training; Chen and Bargh, 1999), each with variable success. For example, some studies have found that using evaluative conditioning as an intervention tool is a successful way to shape automatic associations towards physical activity and the behavior itself (Antoniewicz & Brand, 2016; Cheval, Sarrazin, Pelletier, & Friese, 2016). However, physical activity was measured as the level of effort expended on an exercise task immediately after the training, and taken together with studies not showing an effect (Chevance, Berry, Boiché, & Heraud, 2019) or only a short term effect (Qiu & Zhang, 2020), the efficacy of evaluative conditioning as an intervention approach is inconclusive. Similarly, approach/avoidance training has also demonstrated mixed results (Cheval, Sarrazin, Pelletier, et al., 2016; Hannan, Moffitt, Neumann, & Kemps, 2019; Preis, Zellerhoff, & Brockmeyer, 2020).

One behavior change technique that has shown to be effective for increasing physical activity is setting implementation intentions (e.g., Bélanger-Gravel, Godin, & Amireault, 2013; Ziegelmann, Luszczynska, Lippke, & Schwarzer, 2007). Implementation intentions are if-then plans that support the goal-congruent behavior by specifying when, where, and how a behavior should be carried out (the action plan) and by associating situational cues (the “if”) with the appropriate behavioral response (the “then”) (Gollwitzer, 1993, 1999; Gollwitzer & Sheeran, 2006) and are thought to work by forming a strong association between the cue and behavioral response, which gives the cue the ability to automatically (i.e. without the need for conscious effort) elicit the goal-congruent behavior (Gollwitzer & Sheeran, 2006). In a meta-analysis of the effect of implementation intentions of physical activity behavior, Bélanger-Gravel et al., (2013) found that implementation intentions had a small-to-medium effect size on physical activity at the time of intervention. Importantly, despite the small-to-medium effect size, implementation intention interventions were not only effective at post-intervention, but also after no-contact follow-up periods. These findings, along with that of implicit training interventions, are important as they suggest that targeting behavior solely through implicit processes may not be an effective approach. Instead, in line with the premise of dual-process models, targeting behavior through both reflective and automatic processes may be advantageous for promoting physical activity behavior.

While incorporating automatic processes has resulted in better explanatory models and increased our understanding of physical activity behavior, the methods used in health psychology research present major limitations affecting conceptual clarity and the underlying mechanisms (Zenko & Ekkekakis, 2019). A few of the outstanding criticisms of response latency measures of implicit processes include low reliability, low intercorrelations with each other, and high susceptibility to outside variables (for reviews, see: Hahn & Gawronski, 2018; Znanewitz, Braun, Hensel, Altobelli, & Hattke, 2018). In the realm of physical activity, research on response latency measures of automatic processes is widely heterogeneous in both measurement and procedures, which bars any worthwhile conclusions about effect sizes in meta-analytic studies (Chevance et al., 2017, 2019; Rebar et al., 2016).

Amongst these weaknesses, another potentially more striking criticism lies in the nature of the paradigms themselves: using observed behavior to infer internal mental processes. For example, if a participant chooses to enroll in an exercise class, then that is attributed to successful self-control, but if they do not enroll then their behavior is attributed to failed self-control/giving into impulsive behavior (Divine, Berry, Rodgers, & Hall, 2020). This circular logic bars the models from falsification given that if there are only two outcomes, then only two processes can be inferred (Kriegeskorte, Simmons, Bellgowan, & Baker, 2009). These methodological and theoretical weaknesses in combination with the lack of specific mechanisms used to explain how self-control conflict is resolved between the two processes present key limitations to dual-process models in physical activity behavior.

1.3.3 Dual-process approach summary

In conclusion, dual-process approaches challenged the traditional perspective of physical activity by its conceptualization of self-control being the product of competition between two distinct processes, one fast and automatic, the other effortful and reflective. Although the utility of implicit training interventions hasn't shown promise in terms of physical activity, behavior change techniques targeting both regulatory processes, like implementation intentions, might be worthwhile additions to interventions. In sum, the dual-process perspective has certainly made important contributions to our understanding of physical activity behavior. However, the lack of clarity regarding how self-control conflict is mediated and the heavy reliance on observed response latency measures to infer internal states represent critical weaknesses of the perspective.

Social cognitive models illuminated a major gap in the understanding of physical activity behavior: why don't people follow through with their intentions to be physically active? In other words, what contributes to individuals' lack of self-control? Dual-process models addressed this question suggesting that self-control isn't solely the result of deliberately weighing costs and benefits and acting in accordance with the most objectively valued outcome, instead, self-control is likely the result of an antagonistic relationship between reflective and implicit processes. However, how these two processes interact and resolve self-control conflicts are not clear in dual-process models of physical activity. Although these theoretical contributions are invaluable, two outstanding questions remain: what are the mechanisms underlying the processes involved in successful self-control and how can we effectively intervene upon them to increase physical activity? I propose that approaching these two questions from a health neuroscience perspective will not only contribute to our theoretical understanding of physical activity, but also help identify behavior change techniques and clarify their mechanisms of action.

1.4 Health Neuroscience Approach

Health neuroscience is an emerging field that combines theories and techniques from health and cognitive psychology, cognitive and affective neuroscience, public health, behavioral medicine, and epidemiology to understand how the brain affects and is affected by health (Inagaki, 2020; Stillman & Erickson, 2018). Health neuroscience incorporates an emphasis on understanding mechanistic mediators, finding intervention targets, and elucidating determinants of health behavior. This perspective is positioned to be valuable for understanding health behaviors and decisions, including physical activity, by using neuroimaging techniques like functional magnetic resonance imaging (fMRI). By using neural indicators of behavior and internal mental states, we can better understand the questions left unanswered by previous approaches (Morris, Öhman, & Dolan, 1998).

Most health behavior change research utilizes self-report to measure hypothesized determinants of behavior. Although self-report measures are simple and economical to administer, they are not always accurate methods to access information about higher-order, unconscious processes. Individuals may be unaware of the process occurring and unaware of the stimulus that triggered a response (Webb & Sheeran, 2006). Moreover, introspection can change how we think or feel and can ultimately affect our preferences and decisions (Wilson & Schooler, 1991). Taken together, it is not surprising that people are not very accurate when predicting their future behavior or identifying their mental states through reflection (Nisbett & Wilson, 1977). Neuroimaging methods, like fMRI, are particularly advantageous for measuring cognitive processes that may be inaccessible to individuals and have shown to capture elements of behavior change beyond self-report alone across a variety of behaviors (Berns & Moore, 2012; Falk, Berkman, Mann, & Harrison, 2010; Falk, Berkman, Whalen, & Lieberman, 2011; Knutson, Rick, Wimmer, Prelec, & Loewenstein, 2007; Tusche, Bode, & Haynes, 2010). When used in tandem with other measures like self-report, neuroimaging has the potential to further enhance our theoretical understanding of physical activity behavior, particularly regarding how people choose to engage or not to engage in physical activity and how can this process be modulated to increase the behavior.

Choosing to exercise involves selecting to engage in a behavior that is consistent with an overarching goal when it conflicts with goal-inconsistent alternatives, or self-control (Duckworth, 2011). A growing body of research has begun to examine the neural mechanisms of self-control in terms of health behavior. One area receiving a majority of research attention is healthy eating (e.g., Hare, Camerer, & Rangel, 2009; Hare, Malmaud, & Rangel, 2011; Jasinska et al., 2012; Wagner, Boswell, Kelley, & Heatherton, 2012), although a few studies have examined physical activity behavior (Buckley, Cohen, Kramer, McAuley, & Mullen, 2014; Falk et al., 2015). In the next section, I will discuss two neural frameworks of self-control in the realm of healthy eating. However, these perspectives have been studied across a variety of self-control decisions including temporal (e.g., McClure, 2004) and pro-social choices (e.g., Strombach et al., 2015), suggesting that the findings may be applicable to other realms involving short term choices that vary in multiple attributes.

1.4.1 Neural evidence for value-based and dual-processes models

Neuroimaging research has consistently implicated three brain regions implicated in self-control (Figure 3): dorsolateral prefrontal cortex (dlPFC), ventral striatum (VS), and ventromedial prefrontal cortex (vmPFC). The dlPFC is thought to be implicated in cognitive control (Miller & Cohen, 2001) such as modulation of reward signals (Hare et al., 2009) and flexible behavior control (Braver, Paxton, Locke, & Barch, 2009). Regions in the mesolimbic dopamine system, including VS, are thought to be key regions for reward processing (McClure, Ericson, Laibson, Loewenstein, & Cohen, 2007), and regions in vmPFC are posited to play a role in value computation (Bartra, McGuire, & Kable, 2013; Clithero & Rangel, 2014). How these regions are thought to work together form two different frameworks of self-control: value-based models and dual-process models.

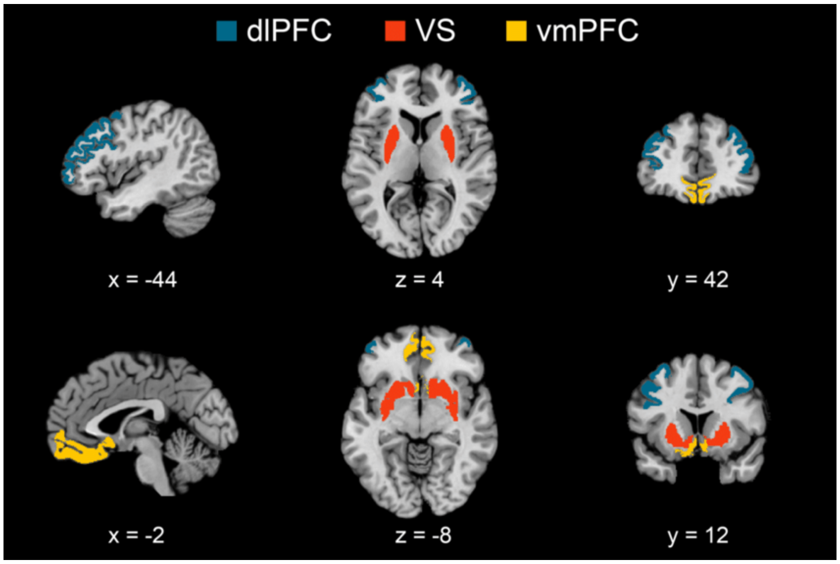

Figure 3: Brain Regions Implicated in Self-Control
This figure shows dlPFC, VS, and vmPFC ROIs in volumetric space. Adapted from (Cosme et al., 2020).

In value-based choice models of self-control, akin to social cognitive/expectancy-value models, self-control is the product of evidence accumulation and valuation. More specifically, decisions are made by dynamically integrating information into a value signal that measures the relative value for each option (Berkman, Hutcherson, Livingston, Kahn, & Inzlicht, 2017). Evidence for each option is accumulated over time until one choice reaches a threshold for enactment, thus determining self-control outcomes (Tusche & Hutcherson, 2018). Neural models from this perspective hypothesize that inputs from dlPFC and VS independently encode the subjective value of different choice attributes which are ultimately integrated in vmPFC (Berkman et al., 2017).

According to dual-process models, self-control is thought to be a balance between 'hot' affective states and 'cold' cognitive states (Figner et al., 2010). According to these models, areas including ventral striatum, vmPFC, and orbitofrontal cortex are thought to represent reward areas, favoring immediate hedonic rewards (McClure, 2004; McClure, Ericson, Laibson, Loewenstein, & Cohen, 2007), while control areas like the dlPFC regulate this bottom-up activity in reward areas (Figner et al., 2010). More specifically, self-control outcomes are the product of which system demonstrates the most activity, with greater activity in control areas relative to reward areas predicting better self-control (Heatherton & Wagner, 2011; Lopez et al., 2017).

Neurobiological research on self-control has found that self-controlled choices corresponded with more activity in the dlPFC and less activity in areas associated with reward like the vmPFC (McClure et al., 2004, 2007), supporting the idea of a dual-process model of self-control. However, further research has found that value signals in the vmPFC correlate with choice regardless of whether the choice is for the hedonic, immediate choice or the goal-congruent choice (Hare et al., 2011; Levy & Glimcher, 2011; Plassmann, O'Doherty, & Rangel, 2010). Moreover, while vmPFC is thought to only represent automatic reward responses in dual-process models, evidence has found it can instead reflect the values of both controlled and impulsive choices (e.g., Hare et al., 2011; Tom, Fox, Trepel, & Poldrack, 2007). Taken together, these two findings seem to suggest a value integration process rather than an antagonistic, push-pull relationship.

Several neuroimaging studies have found that activity in the dlPFC correlates with self-control choices, with increased activity predicting better self-control outcomes. For example, successful dieters showed greater dlPFC activation in response to healthy food choices compared to unhealthy options (Hare et al., 2009), and this effect has also been seen when individuals choose self-control relevant choices in other realms including social decision making (Strombach et al., 2015) and intertemporal choice (McClure, 2004). Further, guiding attention to the health attributes of the healthy option or purposefully focusing on decreasing craving has shown to increase dlPFC activity and improve self-control relevant choice (Hare et al., 2011; Kober et al., 2010). In the same vein, electrical disruption of the dlPFC decreases self-control relevant choices and increases impatient choices (Figner et al., 2010; Ruff, Ugazio, & Fehr, 2013). Taken together, this evidence suggests that the role of dlPFC may be to bias choices in favor of self-control relevant choices, potentially even more so when that option conflicts with an individual's automatic preferences.

However, several studies have found results at odds with the idea that dlPFC works to promote self-control relevant options. For example, directing attention towards health features resulted in *increased* self-control choices, but *decreased* activity in the dlPFC (Hutcherson & Tusche, 2020). Also, researchers often fail to find increased dlPFC activity when individuals choose long-term benefits over short-term rewards (Magen, Kim, Dweck, Gross, & McClure, 2014; Tusche, Böckler, Kanske, Trautwein, & Singer, 2016). In sum, these findings are incongruent with the view that this region consistently promotes goal-congruent choices over hedonic, immediate rewards.

What are possible reasons for the discrepancy? One possible factor is that neural models of self-control are almost always tested in isolation. While notably few studies have examined the models together, potentially because traditional univariate analyses are not particularly fit for model comparison, a small body of research has approached this question using novel modeling processes (Cosme, Zeithamova, Stice, & Berkman, 2020; Hutcherson & Tusche, 2020). For example, Cosme et al., (2020) directly compared value-based choice and dual-process models of self-control using a trial-by-trial modeling approach, giving them the ability to relate neural activity to self-control relevant decisions and obtain model fit indices. Their results found that vmPFC improved model fit and that dlPFC and VS were both positively related to vmPFC activation, supporting the hypotheses of value-based choice models. In addition, with the value-based choice model being the best fitting model, these results suggest that self-control choices are less likely to be the result of competition between dlPFC and VS, and are more likely the result of vmPFC activation driven by inputs from dlPFC and VS. Similarly, Hutcherson et al., (2020), using an attribute-based neural drift-diffusion model, found that dlPFC response during self-control relevant choices may depend more on value-based evidence accumulation, rather than inhibition of hedonic, automatic urges. In sum, this evidence not only suggests that value-based choice approaches might better explain self-control decisions but also highlight the utility of neuroimaging data for refining our theoretical understanding of self-control decisions.

1.4.2 Intervention applications

By better understanding the neurobiological mechanisms underlying self-control, neuroscience approaches can also help inform the development of intervention targets and their corresponding behavior change techniques. As vmPFC has shown to track with self-control relevant choices at the time of choice, activity in this area has also shown to predict the eventual degree of health behavior change over time, such as sunscreen usage (Falk et al., 2010), smoking (Falk et al., 2011), and physical activity (Falk et al., 2015). Further, a meta-analysis using the Neurosynth database found that vmPFC was one of the most consistent areas of overlap in studies on identity ('self' and 'self-referential' terms in the database) and subjective value and reward ('value' in the database) (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011). Taken together, these finding suggest that interventions aiming to promote self-control behaviors might want to amplify the subjective value or identity relevant attributes of a behavior.

A growing body of research has begun to examine this possibility, first by examining how activity within these regions can be modulated and how it affects valuation and self-relevance. For example, having participants deliberately engage in cognitive-regulation strategies where they were asked to up-regulate their appraisals of persuasive messages about binge drinking increased perceived self-relevance of the messages, and this effect was mediated by modulation of vmPFC activity (Doré et al., 2019). Relatedly, Hare et al., (2011) found that exogenous cues to direct attention to health attributes of healthy foods influenced vmPFC activity during choice and increased self-controlled choices. These results suggest that merely increasing the salience of certain attributes can alter activity in regions associated with value and self-relevance and affect subsequent behavior.

Researchers have also begun to examine the neural effects underlying established behavior change techniques to better understand mechanisms of action. For example, self-affirmation, a psychological technique wherein an individual reflects on their core values (for a review, see Sherman & Cohen, 2006), has shown to be effective in augmenting intervention effects in multiple domains (Sweeney & Moyer, 2015), including physical activity (Cooke, Trebaczyk, Harris, & Wright, 2014). Successful self-affirmation is hypothesized to affect health behavior by increasing receptivity to potentially threatening health messages. To better understand how self-affirmation affects behavior, Falk et al., (2015) investigated the neural mechanisms underlying self-affirmation effects during exposure to health messages and subsequent physical activity behavior. Compared to unaffirmed participants, participants who completed a self-affirmation exercise demonstrated greater activity in vmPFC during message exposure, which was further associated with increased objectively measured physical activity behavior. This evidence is congruent with models of self-affirmation suggesting that the exercise might positively affect receptibility of health messages (Sherman & Cohen, 2006), but also extends it by demonstrating that self-affirmation may increase receptibility by allowing people to see potentially threatening information as more self-relevant or more valuable to oneself. These results also speak to potential mechanisms explaining prior findings that demonstrate relationships between neural activity in vmPFC and health behavior change, suggesting that up-regulating activity within vmPFC is an effective pathway to behavior change.

1.5 Brain-as-predictor Approach

In the previous sections, I have discussed how health neuroscience techniques have helped refine our theoretical understanding of self-control behaviors and how these findings can be utilized to inform behavior change techniques by elucidating their mechanisms of action. Thus far, studies have utilized a technique from cognitive neuroscience, brain mapping, where psychological processes are manipulated and the subsequent neural activity is observed as the dependent measure (e.g., Cabeza & Nyberg, 2000; Lieberman, 2010). While the brain mapping approach is undoubtedly useful, health neuroscience has leveraged the technique to develop a novel and exciting approach to understanding brain and behavior: the brain-as-predictor approach (Berkman & Falk, 2013). In contrast to brain mapping, the brain-as-predictor approach utilizes neural measures as independent variables in models that predict longitudinal outcomes as dependent variables (Figure 4). In this framework, the brain is viewed as an additional window into the black box of psychological processes complementing other measures, like self-report, to advance theory and application.

The brain-as-predictor approach has been applied to improve the design of health interventions and elucidate the neural foundations of their effectiveness. For example, evidence suggests that mass media campaigns can be effective for facilitating smoking cessation (Durkin, Brennan, & Wakefield, 2012), but the underlying mechanisms for their success were unclear. By utilizing data from fMRI, self-report surveys, and biological measures of smoking, Falk and colleagues (2011) were able to link neural responses during health message exposure in the lab to smoking behavior in the real world. More specifically, greater vmPFC activity while viewing antitobacco ads predicted successful quitting (greater decreases in expired CO) one month following scanning. Similarly, Chua et al., (2011) examined the neural mechanisms underlying tailored health messages, another behavior change technique that has been effective for smoking cessation, and found that activity in self-related processing regions predicted real-life smoking cessation at 4 months following the intervention. These studies highlight the potential of brain-as-predictor approaches to link multiple levels of analysis and examine outcomes beyond observed behavior.

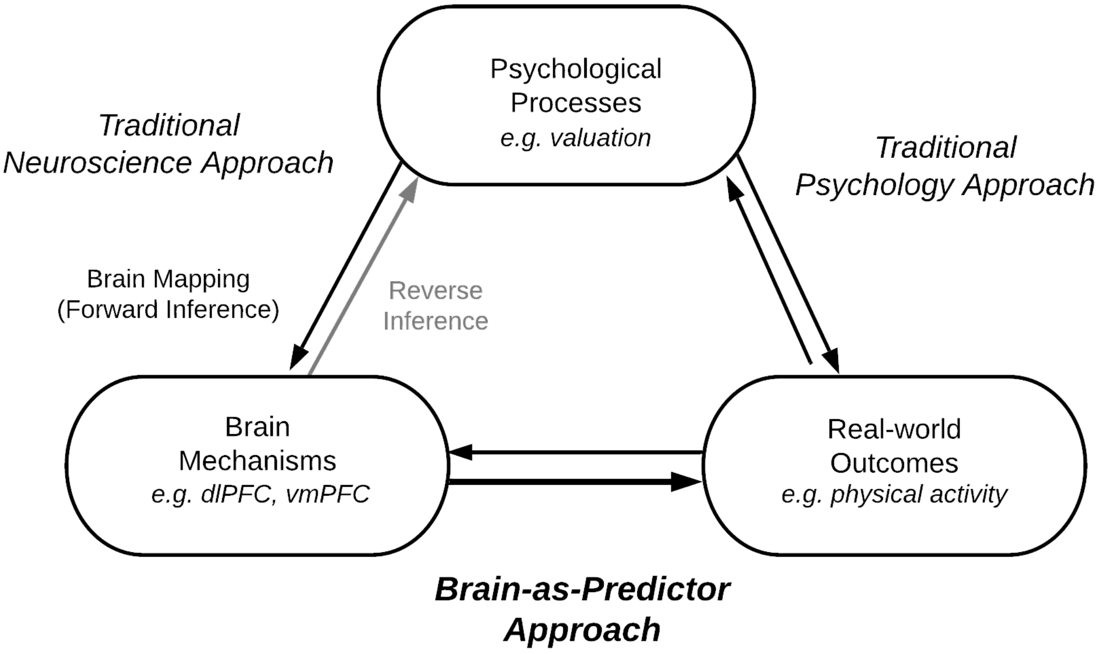

Figure 4: Brain-As-Predictor Approach
Traditional psychology approach concerns the relationship between psychological processes and real-world outcomes. A traditional neuroscience approach uses neuroimaging to map the relationship between psychological processes and brain mechanisms. The brain-as-predictor approach combines the traditional approaches by using brain mechanisms that have been implicated in specific psychological processes to predict real-world outcomes. The bidirectional arrows depict that each construct likely affects the others. Arrows in this figure indicate conceptual relationships rather than causality. Adapted from (Berkman & Falk, 2013).

The evidence discussed above certainly highlights the utility of neuroimaging for the prospective prediction of outcomes. This tool could predict whether people will change their behavior and would undoubtedly be transformative for public health and disease prevention. However, neuroimaging is costly and requires extensive expertise, making it infeasible to use on an individual basis. Considering this, researchers have begun to examine the possibility of translating associations from in-lab samples to predict population-wide outcomes. For example, Berns and Moore (2012) found that reward-related neural activity in a group of adolescents while listening to various songs was able to predict the cultural popularity of the songs measured as total sales for three years following the scan. Similarly, neural evidence has shown to predict out of sample behavior in other realms including economic decisions (e.g., Levy, Lazzaro, Rutledge, & Glimcher, 2011; Tusche et al., 2010) and clinical outcomes (e.g., Costafreda, Khanna, Mourao-Miranda, & Fu, 2009; Paulus, Tapert, & Schuckit, 2005), demonstrating that small groups of individuals can efficiently predict population-level behavior.

Further, researchers have utilized the brain-as-predictor approach to inform public health campaigns. Falk and colleagues (2012) examined neural activity from a group of smokers while viewing three different television ads promoting the National Cancer Institute's telephone hotline to help smokers quit. The results demonstrated that activity in vmPFC during ad viewing predicted population-level success, measured by comparing hotline call volume in the month before and after the launch of each campaign. Moreover, self-reported judgments of advertisement effectiveness or self-relevance did not predict call volume suggesting that neuroimaging data was able to capture information not accessible from traditional self-report approaches characteristic of traditional focus groups used to inform health campaigns.

This novel "neural focus group" approach to intervention design undoubtedly demonstrates the utility of a health neuroscience perspective to understand and encourage positive health behaviors. However, it also demonstrates the ability to bridge theoretical research and implementation research. Partnerships between researchers and interventionists would not only lead to more theory-driven interventions, but also provide an arena for theory testing and revision, thus simultaneously improving both.

1.6 Conclusion

In this review, I've discussed two predominant theoretical frameworks in physical activity research: the social cognitive approach and the dual-process approach. By reviewing the literature regarding each framework's key constructs, their relationships with physical activity behavior, and how they have been utilized to encourage physical activity, I've outlined the contributions each framework has made to our understanding of physical activity behavior and what questions remained. From a health neuroscience perspective, I discussed how neuroimaging techniques can be utilized to help inform gaps in both theoretical and applied knowledge of physical activity. Finally, by reviewing studies utilizing a brain-as-predictor approach, I demonstrated how health neuroscience ultimately broadens our ability to test theory and facilitates the translation of laboratory results.

2. Functional Neural Correlates of Physical Activity Behavior Change

2.1 Introduction

Regular physical activity has shown to decrease risk of many chronic health conditions, including cardiovascular disease, type 2 diabetes, and cancer (Rhodes, Janssen, Bredin, Warburton, & Bauman, 2017; Warburton, Nicol, & Bredin, 2006). Beyond reducing risk for adverse health conditions, being physically active has shown to contribute to mental and cognitive health as well, improving mood, reducing symptoms of anxiety and depression, and buffering against age-related cognitive decline (Penedo & Dahn, 2005). Despite these benefits, more than 25% of the global adult population does not get enough physical activity (World Health Organization, 2022). The effects of interventions promoting physical activity are highly variable and typically modest (Foster, Hillsdon, Thorogood, Kaur, & Wedatilake, 2005), and when behavioral interventions are effective, the understanding of how and why they work is lacking (Michie, Abraham, Whittington, McAteer, & Gupta, 2009). To develop effective interventions, there must be understanding of the determinates of physical activity behavior change, along with identification of evidence-based behavior change techniques that target these determinates. In other words, what are the mechanisms underlying the processes involved in successful behavior change and how can we effectively intervene upon them to increase physical activity?

One approach to elucidating mechanisms underlying behavior change is through a health neuroscience perspective, which focuses on understanding on how the brain affects and is affected by physical health (Erickson, Creswell, Verstynen, & Glanaros., 2014).

Recent studies in this area have applied a new neuroimaging methodology, a ‘brain-as-predictor’ approach (Berkman & Falk, 2013) and have found that measures of brain structure and function can predict long-term health and clinical outcomes like smoking cessation (Falk, Berkman, Whalen, & Lieberman, 2011), relapse in illicit drug users (Kosten et al., 2006), and therapy responsiveness in depressed patients (Costafreda, Khanna, Mourao-Miranda, & Fu, 2009). These findings suggest that the knowledge of central neural characteristics underlying certain health behaviors, along with knowledge of individual differences in said characteristics could be utilized to identify individuals most likely to respond to a standard intervention versus those who may need an alternative approach.

Recent research has begun to examine whether features of the brain might be predictive of physical activity behavior change. For example, studies in older adults, found that greater volume in several regions including prefrontal, temporal, and parietal regions predicted greater exercise adherence above and beyond traditional physical or psychological variables (Best, Chiu, Hall, & Liu-Ambrose, 2017; Grujal, McAuley, Oberlin, Kramer, & Erickson, 2018). Functional MRI studies have found that areas involved in self-referential processing and positive valuation may be key regions for health behavior change (Chua et al., 2009). Activity in vmPFC, a region involved in positive valuation, is implicated in behavior change in response to health messages across a variety of behaviors including physical activity (Falk et al., 2015; Kang et al., 2018).

Before utilizing neuroimaging to design intervention components, it first needs to be established if there are brain regions that are correlated with behavior change. The purpose of this study, therefore, was to investigate baseline differences in neural responses to health messages about walking and subsequent changes in physical activity. We predicted that, in general, people would walk more following the health message intervention. We also predicted that individuals with greater activity in regions associated with self-processing (mPFC and PCC/precuneus) and positive valuation (VS and vmPFC) during health message exposure would show greater increases in walking.

2.2 Methods

2.2.1 Participants

Two separate samples of participants were recruited (Sample 1: N=33, ages 65-85, M = 73.3 years, SD = 6.20 years, 23 female; Sample 2: N=37 ages = 22-80 years, M=47.5 years, SD=23.6 years, 18 female; see Table 1 for study characteristics). Participants were recruited from the San Francisco Bay area through flyers posted in the community, advertisements on Craigslist, and from a name bank in the Life-Span Development Laboratory which includes people who have indicated that they are interested in participating in research. Participants were pre-screened by a phone interview to determine eligibility. The structured phone interview included questions concerning potential participants' safety and history of physical and mental disorders (e.g., stroke, neurological damage, heart failure). Additionally, all participants were screened for cognitive ability using the telephone version of the Mini-Mental State Examination (Newkirk, et al., 2004). Only those who scored at least 23 out of a possible 26 were recruited to participate.

Participants were informed that the study was about physical activity, emotion, and attention. They were enrolled in the study for two weeks and completed three study sessions, one at the beginning (intake), one in the middle (MRI), and one at the end (exit).

Table 1: Study Characteristics

Variable	Sample 1	Sample 2	Total
N	33	37	70
Sex	10 M, 23 F	19 M, 18 F	29 M, 41 F
Age	73.3±6.2	47.5±23.6	59.6 ±21.9
Mean steps pre-scanner	5641.01 ± 3529.2	7545.5 ± 3128.6	6647.7 ± 3435.1
Mean steps post-scanner	6223.04 ± 4025.04	8370.3 ± 3366.3	7358 ± 3819.8

2.2.2 Walking

Walking was measured using Yamax Digi-walker SW200 pedometers. Participants were given the pedometers at intake and steps were measured for 1 week prior and 1 week following the MRI session (Figure 5a). Participants recorded the number of steps from the pedometer on a paper log sheet each day. The Yamax Digi-walker SW200 was chosen because it has shown to be consistent and accurate in research settings (Crouter, Schneider, Karabulut, & Bassett, 2003; Schneider, Crouter, & Bassett, 2004) and is also an economical option. Although Dijkstra and colleagues (2008) concluded that accelerometers are better tools for determining the number of footfalls in older adults because they more accurately detect the number of steps taken by adults with shuffling gaits, the Yamax pedometers are known for being among the most accurate with regards to correctly counting the number of steps taken in a variety of conditions, including speed and surface (Bassett, et al., 1996).

2.2.3 MRI Session

One week after the intake session, participants returned to the laboratory. In this session, participants underwent a functional MRI. While in the scanner, participants read (to themselves) and heard statements about walking (Figure 5b). Participants read positively-framed (e.g., “People who do walk regularly have lower rates of diseases like diabetes”), negatively-framed (e.g., “People who don’t walk regularly have higher rates of diseases like diabetes.”), and/or neutral statements about walking (e.g., “When people walk, their head stays level while their eyes look around.”). The walking-related statements were presented on a computer screen. Participants simultaneously listened to an audio recording of each statement that started 3 seconds after each statement appeared on the screen. When participants finished reading each statement they pressed a button on an MRI-compatible button box. Each statement remained on the screen for a fixed period of 16 seconds; the audio recording was only played once. Between statements, participants viewed a fixation for variable amounts of time (ranging between 6 and 16 seconds). Positively-framed and negatively-framed statements were content-matched; participants were presented either with the positive or negative version of any given statement. Neutral statements were matched on word count. Statements were presented in randomized order.

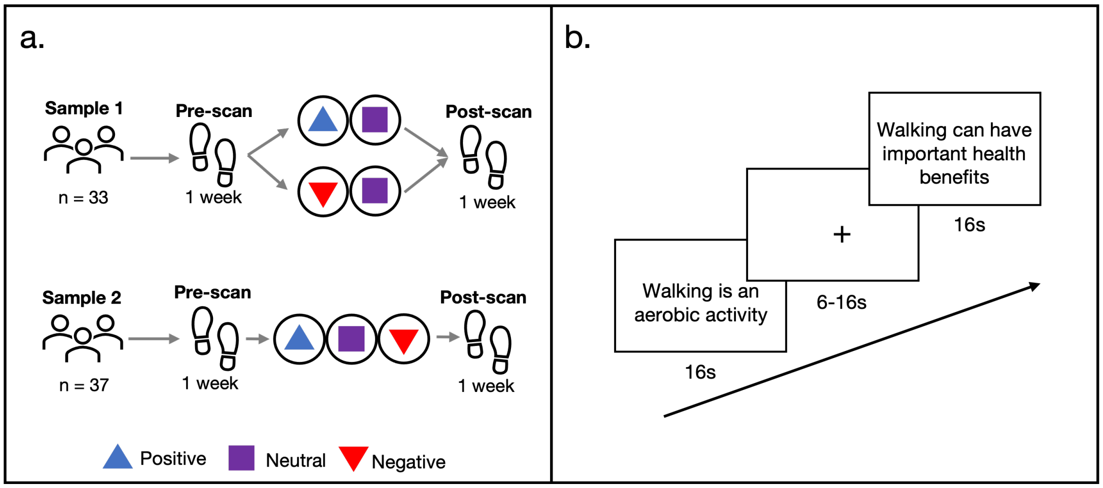

Figure 5: Study Design

2.2.4 Neuroimaging Data Acquisition and Processing

Neuroimaging data were acquired with a 3.0-T General Electric MRI scanner model 750, using a Nova Medical 32-channel head coil. Thirty-six 3.3 mm thick slices were acquired in oblique orientation lined up with the anterior and posterior commissure to the top of the scull. Functional scans of the whole brain were collected at a repetition time of 2 s with an EPI pulse sequence (TE = 30 ms, flip angle = 77°). High-resolution structural scans were acquired with a T1-weighted fast spoiled gradient-recalled-echo (FSPGR) sequence (TR = 2 s, TE = 3.3 ms, flip angle = 15°).

Data preprocessing was performed using fMRIPrep v1.1.4, a Nipype v.1.12 based tool. Each T1-weighted (T1w) volume was corrected for non-uniformity using N4BiasFieldCorrection (v2.2.0) and skull-stripped using antsBrainExtraction.sh (v2.2.0), using OASIS template. Spatial normalization to the ICBM 152 Nonlinear Asymmetrical template version 2009c was performed through a nonlinear transformation implemented in ANTs v2.1.0, using the skull-stripped T1w volume. Brain tissues segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the skull-stripped T1w using FAST v.5.0.9.

Functional data was slice time corrected using 3dTshift from AFNI and motion corrected using MCFLIRT v5.0.9. A deformation field to correct for susceptibility distortion was estimated based on fMRIPrep's "fieldmap-less" approach by co-registering the functional image to the same participant's T1w image with its intensity inverted and constrained with an average fieldmap template, implemented with antsRegistration v2.2.0. This was followed by co-registration to the corresponding T1w volume using boundary-based registration with 9 degrees of freedom in FreeSurfer v6.0.0. Motion correction, T1w transformation and MNI template warp were applied in a single interpolation step using antsApplyTransformations configured with Lanczos interpolation to minimize the smoothing effects of other kernels. Frame-wise displacement was calculated for each functional run using Nipype.

Voxelwise nuisance signal removal was performed using publicly available scripts (https://github.com/arielletambini/denoiser) to clean the data. The data was denoised for 10 fMRIPrep-derived confounds: CSF, white matter, standardized DVARS, framewise displacement over 0.5 mm, and six motion parameters. Both functional and structural image registration was verified by visual inspection of quality assessment reports generated by the fMRIPrep software used in preprocessing.

FSL FEAT was run for each participant with fixed effects across runs. Functional data were high-pass filtered at a cutoff of 100 seconds, spatially smoothed with a 5mm full-width-half-maximum (FWHM) Gaussian kernel, and grand-mean intensity normalized. FSL FILM pre-whitening was conducted for autocorrelation correction. The task was modeled for participants at the single subject level, comparing activity while reading and listening to messages about walking to activity at rest.

2.2.5 Statistical Analysis

Because the focus of the study was on health messages in general, rather than message content, the two samples were collapsed into one for statistical analysis. Pre-scan and post-scan walking behavior represents the average daily steps recorded in the week before or after the scanner session. Behavior change was calculated as percent change in average daily steps. Behavioral analysis was conducted using JASP (v0.14.1).

For regions significantly associated with changes in average daily steps, a whole-brain analysis of the fMRI data was conducted. Whole-brain fMRI analyses were carried out in FSL FEAT with mixed effects using FLAME 1. Statistical maps were thresholded using a cluster-forming threshold with a height of $Z>2.3$, and a cluster-corrected significance of $p<0.05$. Analyses were run to examine: (1) the mean effect of walking-related message exposure across all participants and (2) the correlation between neural activity during walking-related message exposure and percent change in average daily steps.

2.3 Results

2.3.1 Behavioral data

Across both samples, participants walked more in the post-scan that the pre-scan week [$M_{prescan} = 6647.7$, $M_{postscan} = 7358$, $M_{increase} = 710.3$, $t_{(69)}= -3.61$, $p = <.001$].

Average percent change in weekly steps before and after the scanner task was 13.9% (SD = 33.6%). There was no significant difference in average percent step change between the two samples [$M_{sample1}$ = 13.2%, $M_{sample2}$= 14.5%, $t_{(68)}$=-0.16, p=0.87]. Change in average daily steps was negatively, but not significantly correlated with age (p = 0.31) and there was no significant effect of sex (p = 0.42).

2.3.2 Whole-brain analysis

Whole-brain analysis examining mean activity during walking-related health message exposure produced two significant clusters (Table 2). The first cluster involving left and right lateral occipital cortex and precuneus, with peak coordinates lying in left cerebral white matter and the second cluster involving left paracingulate gyrus and right frontal pole, with peak coordinates in the left anterior cingulate cortex.

A second analysis examining regions positively associated with step change also produced two significant clusters (Table 3), a frontal pole cluster and precuneus/posterior cingulate gyrus cluster.

Table 2: Mean Activity During Message Exposure

Region	Hemisphere	Voxels	Peak Z	MNI Coordinates		
				X	Y	Z
Cerebral White Matter	L	29211	8.73	-34.5	-58.5	3.5
Lateral Occipital	L		8.54	-14.5	-84.5	35.5
Lateral Occipital	R		8.36	-24.5	-64.5	19.5
Precuneus	R		8.22	23.5	-60.5	19.5

Cerebral White Matter	L		8.06	-34.5	-42.5	-4.5
Anterior Cingulate Cortex	L	12034	7.74	-0.5	41.4	5.5
Cerebral White Matter	R		7.26	-14.5	55.5	-0.5
Paracingulate Gyrus	L		7.06	-8.5	43.5	-0.5
Frontal Pole	R		6.99	11.5	59.5	-0.5
Anterior Cingulate Cortex	L		6.91	-10.5	47.5	3.5
Frontal Pole	R		6.91	-0.5	55.5	-0.5

Note. Significant clusters at a z-statistic threshold of 2.3, cluster corrected at $p < 0.05$. Peak-Z refers to the peak z-statistic. MNI Coordinates (X,Y,Z) given for peak voxels within clusters.

Table 3: Positive Correlation with Step Change

Region	Hemisphere	Voxels	Peak Z	MNI Coordinates		
				X	Y	Z
Frontal Pole	R	1283	4.41	15.5	59.5	15.5
Frontal Pole	L		4.07	-16.5	61.5	13.5
Frontal Pole	L		3.93	-12.5	69.5	13.5
Frontal Pole	R		3.92	27.5	67.5	11.5
Frontal Pole	L		3.72	-12.5	63.5	21.5
Frontal Pole	R		3.68	3.5	69.5	21.5
Precuneus	R	642	3.53	7.5	-64.5	23.5
Cerebral White Matter	R		3.49	19.5	-44.5	35.5
Posterior Cingulate Gyrus	R		3.02	3.5	-36.5	37.5
Posterior Cingulate Gyrus	R		3.02	1.5	-48.5	27.5
Precuneus	R		2.96	7.5	-58.5	31.5
Posterior Cingulate Gyrus	R		2.95	3.5	-48.5	17.5

Note. Significant clusters at a z-statistic threshold of 2.3, cluster corrected at $p < 0.05$. Peak-Z refers to the peak z-statistic. MNI Coordinates (X,Y,Z) given for peak voxels within clusters.

2.4 Discussion

This paper revealed that brain activation in the posterior cingulate cortex (PCC)/precuneus and lateral and medial frontal cortex in response to health messages about walking was associated with greater increases in average daily steps. Also, as hypothesized, participants walked more after the in-scanner message task.

Consistent with previous research (Berns and Moore, 2012), we found that message-related activation in the PCC and precuneus was associated with behavior change. The PCC/precuneus region has been associated with self-referential processing (Chua et al., 2011; Northoff et al., 2006). Also called ‘self-related’ or ‘self-relevant’ processing, it concerns stimuli that are strongly experienced as relating to one’s own self. The extent to which people view messages as self-relevant is thought to play a role in attitude and behavior change (Chua et al., 2009). Our finding is consistent with theoretical models emphasizing the role of self-relevance in persuasion and provides further support for this hypothesis in the context of health messages and walking behavior.

The frontopolar cortex is broadly implicated in cognitive control, motivation, and goal directed behavior (Koechlin, Ody, & Kouneiher, 2003). Our study found activity in two subclusters, a medial cluster and a lateral cluster, associated with increased average daily steps. Previous work has found FPC to play a role in pre-commitment, a self-control strategy where people anticipate self-control failures and prospectively restrict their access to tempting alternatives (Ariely and Wertenbroch, 2002). It is possible that FPC activation is due to participants pre-committing to increasing their walking behavior.

In contrast to a number of previous studies examining neural mechanisms of health behavior change (e.g. Falk et al., 2011; Kang et al., 2018), this study did not find activation in vmPFC and VS. These regions are implicated in positive valuation, which is thought to be an important component in message receptivity and subsequent health behavior change (Vezich, Katzman, Ames, Falk, & Lieberman, 2016). One possible explanation for this difference could be the health behaviors examined. For example, the mechanisms involved in changing smoking and eating behavior, which involve regulation of craving, could be different than mechanisms involved in increasing physical activity behavior. It is also worthwhile to note that previous studies (Falk et al., 2015; Kang et al., 2018) have also applied a self-affirmation task, which has shown to increase VS activity (Cascio et al., 2016). No additional interventions, like a self-affirmation exercise, were used in the present study.

The findings of this study should be interpreted in light of the limitations of the current design. One limitation is the relatively short physical activity measurement period. Future studies may want to extend the number of weeks participants record their daily steps. Regarding step measurement, another limitation of the current design is reliance on pedometers and manual reporting. Future studies could consider using newer fitness tracking wearables and utilizing software that automatically retrieves step count data from participant devices.

In the present study, participants were exposed to walking-related messages while in the scanner. Future work might consider extending the messaging component by sending walking-related messages via SMS daily for multiple weeks following the scanner session with days without messages interspersed randomly throughout the intervention. This design would allow two important questions to be examined: 1) do participants walk more on days when they receive walking-related messages? and 2). does the effect of receiving messages on walking persist over time?

The present study aimed to examine baseline differences in neural responses to health messages about walking and subsequent changes in physical activity. We predicted that, in general, people would walk more following the health message intervention. We also predicted that individuals with greater activity in regions associated with self-processing (mPFC and PCC) and positive valuation (VS and vmPFC) during health message exposure would show greater increases in walking. Overall, we found that, as hypothesized, participants walked more after the in-scanner message task. Further, brain activation in the posterior cingulate cortex (PCC)/precuneus and lateral and medial prefrontal cortex in response to health messages about walking was associated with greater increases in average daily steps. Taken together, these findings suggest that brain regions implicated in self-referential processing and pre-commitment are correlated with changes in walking behavior. These findings have important implications for increasing physical activity.

3. Self-report and Neural Predictors of Message Effectiveness

3.1 Introduction

The benefits of physical activity, along with the health risks of sedentary behavior have been well established. Despite this, a considerable portion of the global adult population does not get enough physical activity (Hallal et al., 2012). Interventions promoting physical activity are highly variable and typically modest (Foster, Hillsdon, Thorogood, Kaur, & Wedatilake, 2005), and when behavioral interventions are effective, the understanding of why they work is poorly understood (Michie, Abraham, Whittington, McAteer, & Gupta, 2009).

Mobile health (mHealth) interventions have promising applications as tools to motivate physical activity. mHealth interventions provide opportunities to customize messaging and integrate knowledge concerning the various ways different individuals respond to health messaging. These intervention techniques range from SMS messaging to wearable health technology. Previous research has demonstrated that mHealth activity tracking is a successful strategy to increase physical activity for adults (Poirier et al., 2016). mHealth interventions are not only cost-effective, but also an intervention that can be easily disseminated, allowing a large segment of the population access to tools to monitor their physical activity (King et al., 2016).

Persuasive messages, like those used in health media campaigns and mHealth interventions, can motivate behavior change and prevent disease (Wakefield, Loken, & Hornik 2010). However, individuals are not uniformly responsive to health-promoting information. Instead, there are substantial differences in how people process and respond to persuasive messaging (Orbell and Kyriakaki, 2008).

Regarding message content, a considerable amount of research has examined the effects of message framing. Gain or positively framed messages that emphasize the benefits of changing behavior, have shown to be more effective in promoting physical activity behavior change compared to loss or negatively frame messages, or messages emphasizing the negative consequences of not changing behavior (Latimer, Brawley & Bassett, 2010; Notthoff & Carstensen, 2014). Similarly, messages highlighting the social aspect of adopting a certain behavior by focusing on social comparisons, norms, and support have shown to be beneficial, especially amongst older adults (King et al., 2016; Pandey et al., 2021). A health neuroscience perspective can give a better understanding of how health messages can motivate physical activity behavior change.

The health neuroscience perspective has utilized the brain in better understanding health outcomes, including physical activity, in three distinct approaches: *as an outcome, a mediator, and a predictor.* Each giving unique information on the relationship between the brain and behavior. For example, studies taking the most widely studied approach, the brain as an outcome, have demonstrated that physical activity increases structural and functional connectivity and might offer protective effects against cognitive decline (Erickson et al., 2011; Sofi et al., 2011). In comparison, the brain as a mediator of cognitive outcomes is less studied, but preliminary studies have examined the relationship between changes in the brain and physical activity related cognitions and suggests that physical activity effects on gray and white matter volume might be mediating the effect of physical activity on cognition (Erickson, Leckie, & Weinstein, 2014; Gons et al., 2013). Of particular concern for this paper is the brain as predictor approach, where structural and functional brain characteristics are used to predict physical activity behavior and other relevant physical activity outcomes (Berkman & Falk, 2013). From this perspective, the brain is utilized as an additional measure in tandem with other measures, like self-report and behavioral measures, which together have the potential to enhance our theoretical understanding of physical activity and help us better optimize interventions that target physical activity behavior change.

A growing body of neuroimaging research has provided insight into how messages are processed and how they relate to health behavior change. Increases in activity in key default mode regions including medial prefrontal cortex (mPFC), precuneus, anterior cingulate cortex (ACC), and posterior cingulate cortex (PCC) during health message exposure have been linked to increases in subjective valuation in response to health promoting stimuli and greater message induced reductions in smoking (Chua et al., 2011; Falk et al., 2011; Riddle et al., 2016), decreases in sedentary behavior (Falk et al., 2015, Kang et al., 2018), and increased sunscreen usage (Falk et al., 2010; Vezich et al., 2017). A previous study we conducted demonstrated that activity in the frontopolar cortex, a region implicated in precommitment (Wang et al., 2021) and motivation (Soutschek et al., 2018), may also be related to message-related physical activity behavior change (Chapter 2).

Persuasive messaging and mHealth interventions can be useful tools for increasing physical activity (Poirier et al., 2016; Wakefield et al., 2010), but they are not always uniformly effective (Orbell et al., 2008). Neuroimaging evidence has provided some insight into how messages are processed in the brain and how brain responses relate to health behavior change (Jovanova et al., 2021), however more information is still needed regarding how persuasion unfolds in the brain, how these processes translate into differences in real life behavior change, and how we can leverage these findings to build better interventions. More specifically, can we use hidden signals in the brain to predict the outcome of health messages on physical activity?

The present study consisted of self-reported ratings of walking-related messages, brain activity measured while viewing messages, an 80-day SMS mHealth intervention, and physical activity tracking using a wearable fitness tracker. In this study, we evaluated how different types of health messages motivate people across adulthood to be physically active. More specifically, we hypothesized that positively and socially framed walking messages would be more effective at increasing total daily steps than negatively and non-socially framed messages. In addition, we were interested in if we could evaluate how particular messages would work for certain people based off their self-report ratings of the messages alone and in conjunction with neural activity while viewing the messages. Drawing from previous research, we predicted that self-relevance would be a significant predictor of message effectiveness along with neural activity in regions associated with positive valuation and self-referential processing. Understanding the behavioral and neural predictors of the effectiveness of health-related messaging and behavior change could help optimize digital health interventions for physical activity, tailoring interventions to the individual level.

3.2 Methods

The study consisted of three in-person visits spread across 101 days of participation. The initial visit included a consent session, questionnaires including an fMRI screening questionnaire, and neuropsychological assessments. Participants were also given a wearable activity tracker to use for the duration of the study. Following the first visit, participants' baseline physical activity levels were collected over a 14-day period. The second visit consisted of motor assessments, physical health measurements, and a functional magnetic resonance imaging (fMRI) session. During the fMRI session, structural brain images and functional brain activity were collected as participants read statements about walking and rated how motivating each message was. After the scanning session, participants' physical activity levels were tracked in response to messages delivered to them via text message for 80 days. In the third visit, specific cognitive and motor assessments were repeated, the activity tracking devices were returned, and participants were debriefed.

3.2.1 Motivational Health Messages

Before the study began, over 300 motivational messages were created by lab personnel. Messages were then surveyed through Qualtrics participants. All messages were framed socially or non-socially and either had a positive or negative valence. Social messages highlighted how physical activity or inactivity may affect one's social relationships with friends and family and conveyed social incentives, whereas nonsocial messages centered on the impact of activity on aspects of one's life that did not involve relationships with others. Positive messages drew attention to the benefits of exercise, whereas negative messages emphasized the risks of sustained low levels of activity. In this way, messages were divided into four subcategories: positive social, negative social, positive non-social, and negative non-social. The top 20 statements for each category with the highest rating and least variance were selected for the study.

3.2.2 Recruitment and Screening

Adults between ages 20 to 80 were recruited through the Interdisciplinary Behavioral Research Center (IBRC), Craigslist, DukeList, and advertising across Durham (N=22, ages 29-76, M = 52.05, SD = 15.98, 15 female). Participants were compensated $20 per hour for 6-8 hours of in-person sessions in addition to $100 for wearing the activity tracking device.

Participants were screened for age, health, and physical activity over the phone. Participants with a history of substance abuse, psychostimulant usage, alcoholism (drinking more than five standard drinks a week), and tobacco or nicotine users were excluded from the study. Any medications that were prescribed were also noted. Participants were also excluded if they had a history of major psychiatric illness, neurological issues, or any additional significant medical condition(s) that would impair physical activity. Participants that had major surgeries or conditions that would interfere with MRIs were also excluded. Pregnant or lactating women or those who did not have normal or corrected-to-normal vision were also excluded from the study.

Eligible participants were required to lead sedentary lifestyles. Initially, this meant that participants partook in moderate-intensity physical activity for less than 45 minutes daily or 180 minutes weekly, or that they engaged in vigorous-intensity aerobic activity for less than 90 minutes weekly. Under this criterion, participants that exceeded a threshold of 180 minutes of moderate to intense physical activity were excluded. However, this requirement was later omitted to allow participants of varying activity levels. A smartphone that was compatible with the Fitbit app was required. All answers were recorded in REDCap, a browser-based application that manages online surveys and databases.

3.2.3 Consent and Questionnaires

If participants were deemed eligible, they were sent an electronic consent form and a series of 23 questionnaires. Participants were asked to read the expectations for the study and sign the electronic consent form before attending their first session. Participants were also offered an alternative option to sign the consent form in-person during their first visit, where lab personnel read the document for consent. Questionnaires were administered through REDCap surveys, either at home prior to the first visit or in-person during the first visit. These questionnaires surveyed participants about their demographic information, health and medical history, physical activity, as well as their values, beliefs, and attitudes.

Of the questionnaires, the Beck Depression Index-Short Form (BDI-SF; Beck & Steer, & Brown, 1987) was particularly important in screening participants. Participants who scored between 10-16 were deemed mildly depressed, between 17-29 were deemed moderately depressed, and between 30-63 were deemed severely depressed. These three groups were considered ineligible to continue the study and were redirected to appropriate psychological resources. Participants who scored less than 9 were deemed to have minimal symptoms of depression and were able to participate. Over the course of our study, exclusionary criteria were relaxed to allow individuals who were screened as mildly depressed to enroll in the study. There were considerable participants deemed mildly depressed, though not clinically depressed, and not diagnosed with depression, who otherwise would be excluded from the study. Since these participants could potentially benefit from the intervention, they were subsequently deemed eligible and enrolled in the study.

3.2.4 Intake Session

The first study visit consisted of a consent session, questionnaires, neuropsychological assessments, signing a Magnetic Resonance Imaging (MRI) safety form and personal health inventory form, and wearable activity tracker setup and training. Consent forms and questionnaires were verified by lab personnel before the start of the visit. If they were not completed upon arrival, these forms were completed at the start of the session.

Neuropsychological Assessments. The Montreal Cognitive Assessment (MOCA) and the National Institute of Health Toolbox Cognition Battery (NIH-CB) for adults with the addition of the Auditory Verbal Learning Test (Rey) 8+ were used to assess the cognitive abilities of participants. The MOCA is a brief 30-question assessment used to detect mild cognitive impairments by testing seven subdomains of cognition: attention and concentration, short-term and working memory, language, visuospatial skills, and executive function (Nasreddine et al., 2005). Participants that scored below 26 were excluded from further participation. The NIH-CB is a series of seven computer-based instruments assessing six cognitive subdomains: attention and executive function, episodic memory, working memory, language, executive function, and processing speed (Heaton et al., 2014). The Rey was added to measure learning and memory (Schmidt, 1996).

3.2.5 Wearable Activity Tracker Set-up

Participants were each set up with a wrist worn wearable activity tracker (Fitbit model Charge 3) to collect baseline activity levels. The activity trackers gathered data on participants' daily step count, distance, hours asleep, energy expenditure in calories, heart rate, and intensity of activity. Lab personnel asked participants for their smartphones to install the Fitbit app. When neuropsychological assessments were completed, participants were briefed on how to sync, charge, and engage with the Fitbit app. Participants were then instructed that they would wear the Fitbit at all times, except while charging the device, for the duration of the study. Additionally, participants were asked for their average wake-up time and were sent short daily surveys to their mobile phones within four hours of their wake-up time asking about their affect and self-efficacy (inclination to exercise) that day. Participants were told to expect 14 days of these surveys, to maintain their normal physical activity, and not to manipulate any of the Fitbit settings. Following this 14-day period, participants returned for their MRI session.

3.2.6 MRI Session

The second study session consisted of an MRI scan, computer based-effort task, a motor assessment, a post-scan survey, and a detailed account of the following days of the study. Before the scan, participants reviewed their MRI safety forms and were briefed on MRI safety guidelines and what to expect inside the scanner. Participant height, body weight, body mass index (BMI), body fat, muscle weight, bone mass, basal metabolic rate (BMR), body water, and visceral fat level (VF) were later calculated and recorded. Additionally, participants completed a modified version of the Effort Expenditure for Rewards Task (“EEfRT”) (Treadway et al., 2009). This 15-minute task asked participants to make monetary choices based on the effort they’re willing to exert, where effort is expressed in the form of pinky presses. Finally, participants were informed of the directions for the task inside the scanner.

The MRI scan lasted for one hour and included both structural and functional scans. The structural scan consisted of T1-weighted whole-brain anatomical scans. In between two structural scans, functional scans were performed while participants completed a message rating task. The message rating task was a 40-minute activity showing participants 80 messages and asking them to rate each message on how personally motivating they found the statement to be on a 10-point Likert scale (1 represents not very motivating and 10 represents very motivating). Participants indicated their rating by using a control pad on their dominant hand to move the cursor to the left or right. The tasks in the functional scan consisted of two sets of 40 messages with a brief break between the sets. During the task, participants were presented with each message for 8 seconds.

The National Institute of Health Toolbox Motor Measures were administered following the MRI scan, including the 4 Meter Walk Gait Speed Test Age 7+, 2-Minute

Walk Endurance Test Age 3+, Grip Strength Test Age 3+, and Standing Balance Test Age 7+. These measures collectively assessed locomotion, endurance, strength, and balance (Reuben et al., 2013). Participants then completed a post-MRI scan survey where they revisited each of the 80 statements and were asked five additional questions about them. On a 7-point Likert scale (1 being not at all and 7 being very), participants were asked, "How personally relevant is this message for you", "How motivating do you think this message is for others", and "How relevant is this message for others?". They were subsequently asked to determine "How does this message make you feel about engaging in physical activity?" and "How does this message make you feel?". Both questions were answered by responding with either "positive" or "negative."

3.2.7 Message Delivery and Activity Tracking

For the remaining duration of the study, participants engaged in 87 days of motivational health messaging. For the first 7 days, participants received the same daily surveys asking about their affect and ability to exercise that day. Next, participants received 80 motivational health messages that were previously seen in the scanner in addition to the daily surveys. Messages were randomized from the four different categories (positive social, negative social, positive non-social, and negative non-social) and one was delivered daily through the TextMagic website within four hours of their reported wakeup time. All messages were randomly assigned to each participant.

All activity tracking data were tracked through Fitabase, an online database that monitored the battery levels, wearable device syncs, and sleep, heart rate, and step data in real time. Any participant with low battery levels and/or incomplete syncs was sent a reminder to do so. All reported issues with Fitbit malfunction or an inability to receive texts were recorded under REDCap by lab personnel.

3.2.8 Final Session

The third and final study visit consisted of cognitive and motor assessments, surveys, and a debriefing. In addition, participants were asked the following open-ended questions about any barriers they faced throughout the duration of the study: “Were there any barriers that made it difficult for you to be physically active over the course of your participation?”, “Was there anything that you believe would help you exercise?”, and “What are the reasons you chose to exercise?” If participants were unable to answer these questions, they were then prompted with pre-existing examples of barriers to physical activity to stimulate ideas. Upon completion, participants were debriefed on the study, and feedback was collected and recorded under REDCap. Personal health inventory forms were submitted when all aspects of the study were completed. Participants were then compensated for their time spent in the visits and surveys completed.

3.2.9 Neuroimaging Data Acquisition and Preprocessing

Brain images were collected using a 3 T GE (model) scanner with a 48 channel head coil. We acquired high resolution anatomical scans using T1-weighted imaging (repetition time = 2.223 seconds, echo time = 3.2 milliseconds, acquisitions = 272, flip angle = 8 degrees, slice thickness = 1mm). We acquired functional images using a T2 weighted multiband scan with 63 2 mm slices (repetition time = 2 secons, echo time = 30 milliseconds, flip angle = 77 degrees).

Data preprocessing was performed using fMRIPrep v1.1.4 , a Nipype v.1.12 based tool. Each T1-weighted (T1w) volume was corrected for non-uniformity using N4BiasFieldCorrection (v2.2.0) and skull-stripped using antsBrainExtraction.sh (v2.2.0), using OASIS template. Spatial normalization to the ICBM 152 Nonlinear Asymmetrical template version 2009c was performed through a nonlinear transformation implemented in ANTs v2.1.0, using the skull-stripped T1w volume. Brain tissues segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the skull-stripped T1w using FAST v.5.0.9.

Functional data was slice time corrected using 3dTshift from AFNI and motion corrected using MCFLIRT v5.0.9. A deformation field to correct for susceptibility distortion was estimated based on fMRIPrep's "fieldmap-less" approach by co-registering the functional image to the same participant's T1w image with its intensity inverted and constrained with an average fieldmap template, implemented with antsRegistration v2.2.0. This was followed by co-registration to the corresponding T1w volume using boundary-based registration with 9 degrees of freedom in FreeSurfer v6.0.0. Motion correction, T1w transformation and MNI template warp were applied in a single interpolation step using antsApplyTransformations configured with Lanczos interpolation to minimize the smoothing effects of other kernels. Frame-wise displacement was calculated for each functional run using Nipype.

Voxelwise nuisance signal removal was performed using publicly available scripts (https://github.com/arielletambini/denoiser) to clean the data. The data was denoised for 10 fMRIPrep-derived confounds: CSF, white matter, standardized DVARS, framewise displacement over 0.5 mm, and six motion parameters. Both functional and structural image registration was verified by visual inspection of quality assessment reports generated by the fMRIPrep software used in preprocessing.

At the subject level, we did a trial level model where each individual message was modeled as a regressor, such that for each of the 80 messages there was a unique beta coefficient representing activation associated with that message across the brain. From these whole brain maps, data was extracted from a priori anatomical and functional regions of interest. The anatomical ROIs were ventromedial prefrontal cortex (vmPFC), ventral striatum (VS), and posterior cingulate cortex (PCC) and were taken from predefined maps from the Harvard Oxford Atlas. For the functional ROIs, masks were extracted from Neurosynth (Yarkoni, Poldrack, Nichols, Van Essen, & Wager, 2011) to identify networks of regions associated with mentalizing and value. For both anatomical and functional ROIs, we averaged all voxels within each mask and used these values in the analyses.

3.3 Results

Welch's T-tests were used to determine effects for message valence and message social content on total daily steps. There was no significant difference between positive messages (*M* = 9937.68, *SD* = 4700.08) and negative messages (*M* = 10009.94, *SD* = 4868.61) on total daily steps, *t*(1751.2) = 0.32, *p* = 0.75. There was also not a significant difference between social (*M* = 9977.19, *SD* = 4653.19) or non-social (*M* = 9970.56, *SD* = 4913.56) messages on total daily steps, *t*(1748.5) = -0.02, *p* = 0.98.

Two multiple linear regression models were used to predict daily steps across participants with both self-reported message ratings and functional brain activity in response to each message. The first model included overall message motivation ratings collected in the scanner and self-reported message ratings collected after the fMRI (feeling in general, motivating to others, relevant to others, and relevant to self) as predictors for daily steps. The second model included the predictors from Model 1 in conjunction with functional brain activity (VS, vmPFC, PCC, regions involved in mentalizing, and regions involved in valuation).

First, stepwise regression evaluated whether self-report message ratings from the beginning of the study predicted daily steps throughout the intervention (Table 4, Model 1). Overall, Model 1 predicted 2% of the variance in daily steps, F(6, 2550) = 7.4, p = <.001. $R^2 = 0.02$. After robust clustering of standard errors, none of the predictors were significant. Next, stepwise regression evaluated whether self-reported message ratings combined with functional brain activity predicted greater variance in daily steps than Model 1(Table 4, Model 2). Overall, Model 2 predicted 4% variance, F(11, 1701) = 5.77, p = <.001. $R^2 = 0.04$. In Model 2, how motivating the message would be to others was a significant predictor, b = -662.46, CI = [-1261.55, -63.37]. This suggests that messages that were rated as more motivating to others by the participants were more likely to lead to fewer daily steps. How relevant to others the messages were rated was also a significant predictor of total daily steps, b = 908.81, CI = [49.05, 1768.58], t = 2.07, p = 0.04. This finding demonstrates that messages rated as more relevant to others led to an increase in daily steps.

In exploratory analyses, multiple linear regression models were used to predict moderately active minutes and lightly active minutes using the same predictors as the models above. First, stepwise regression analysis examined whether self-report message ratings predicted moderately active minutes (Table 5, Model 3). In the model, none of the predictors were significant. A second linear regression analysis was run using self-report ratings in conjunction with functional brain activity to predict moderately active minutes (Table 5, Model 4). In this model, how relevant to others the messages were rated was the only significant predictor, b = 5.23, CI = [-0.02, 10.47], t = 1.95, p = 0.05. For lightly active minutes, in the self-report only model (Table 6, Model 5), how positive or negative the message made the participants feel in general was a significant predictor, b = -20.29, CI = [-40.26, -0.32], t = -1.99, p = 0.05. When adding in neural predictors (Table 6, Model 6), the only significant predictor of lightly active minutes was the 'Relevant to Others' rating, b = 16.21, CI = [5.58, 26.83], t = 2.99, p = 0.003.

Table 4: Regression results for Model 1 and Model 2 Using Total Daily Steps as the Criterion

Model 1				**Model 2**			
Predictor	**Estimate**	**95% CI**		**Predictor**	**Estimate**	**95% CI**	
		LL	***UL***			***LL***	***UL***
Intercept	8280.37***	6236.58	10324.17	*Intercept*	8772***	6394.97	11148.44
Motivation	-30.14	-207.19	146.92	*Motivation*	18.09	-222.36	259.54
Feel PA	477.70	-1119.59	2074.99	*Feel PA*	442.81	-1410.88	2296.49
Feel General	-156.13	-1335.44	1023.17	*Feel General*	69.29	-1260.32	1398.9
Motivating to Others	-106.21	-897.1	684.68	*Motivating to Others*	-662.46*	-1261.55	-63.37
Self Relevance	-271.27	-663.51	120.96	*Self Relevance*	-202.36	-627.07	222.35
Relevant to Others	633.97	-193.42	1461.36	*Relevant to Others*	908.81*	49.05	1768.58

vmPFC	-0.36	-38.71	37.98
VS	-10.56	-54.1	32.98
Mentalizing	-85.79	-245.03	73.44
Value	4.06	-129.4	137.53
PCC	122.24	-13.36	257.85

*Note. Feel PA is participant's rating of how the message makes them feel towards physical activity. * indicates $p < 0.05$, ** indicates $p < 0.01$, *** indicates $p < 0.001$*

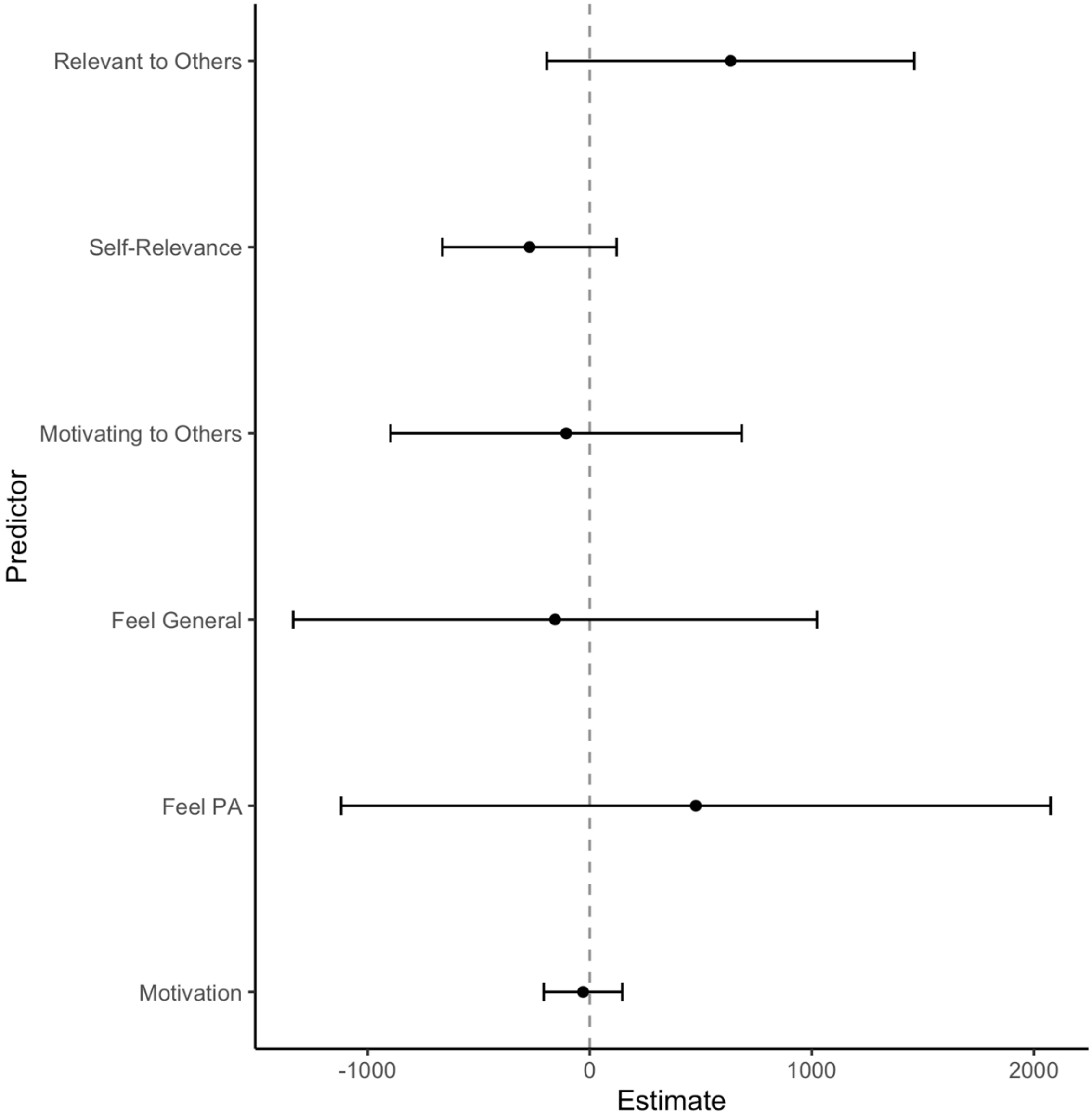

Figure 6: Self-report Predictors of Total Daily Steps (Model 1)

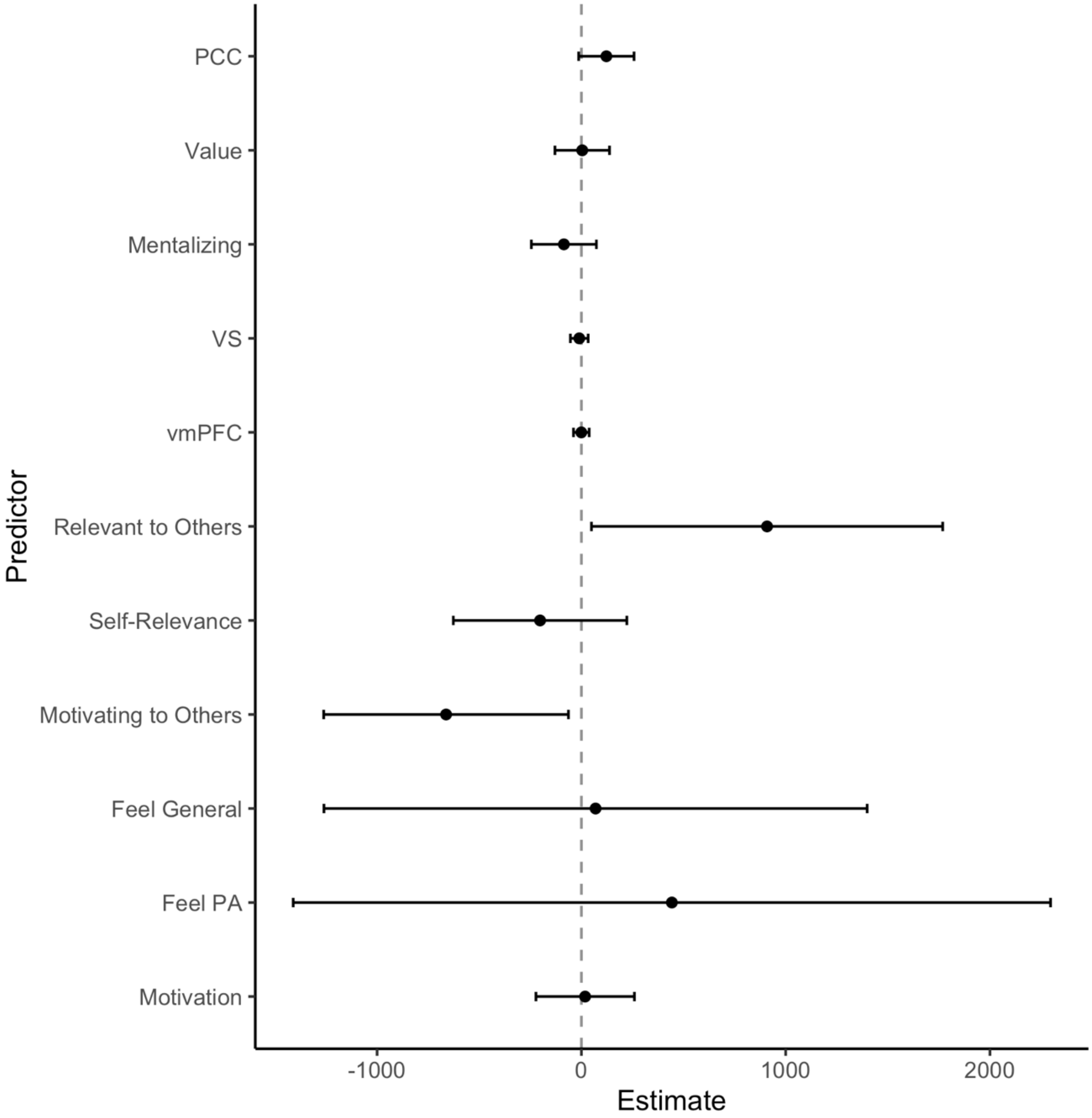

Figure 7: Self-report and Neural Predictors of Total Daily Steps (Model 2)

Table 5: Regression Results for Model 3 and Model 4 using Moderately Active Minutes as the Criterion

Model 3				**Model 4**			
Predictor	**Estimate**	**95% CI**		**Predictor**	**Estimate**	**95% CI**	
		LL	***UL***			***LL***	***UL***
Intercept	18.34*	4.30	32.39	*Intercept*	12.01	-3.63	27.67
Motivation	0.06	-1.56	1.67	*Motivation*	0.85	-1.22	2.91
Feel PA	5.24	-6.70	17.18	*Feel PA*	3.04	-10.69	16.77
Feel General	0.25	-7.34	7.83	*Feel General*	1.90	-5.72	9.51
Motivating to Others	-0.38	-4.11	3.35	*Motivating to Others*	-3.73	-8.31	0.86
Self Relevance	-1.60	-3.68	0.49	*Self Relevance*	-1.58	-4.02	0.86
Relevant to Others	1.62	-2.24	5.48	*Relevant to Others*	5.23*	-0.02	10.47
				vmPFC	-0.06	-0.33	0.21
				VS	-0.05	-0.33	0.23
				Mentalizing	-0.65	-1.84	0.54
				Value	-0.01	-0.83	0.81
				PCC	0.58	-0.20	1.36

*Note. Feel PA is participant's rating of how the message makes them feel towards physical activity. * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001*

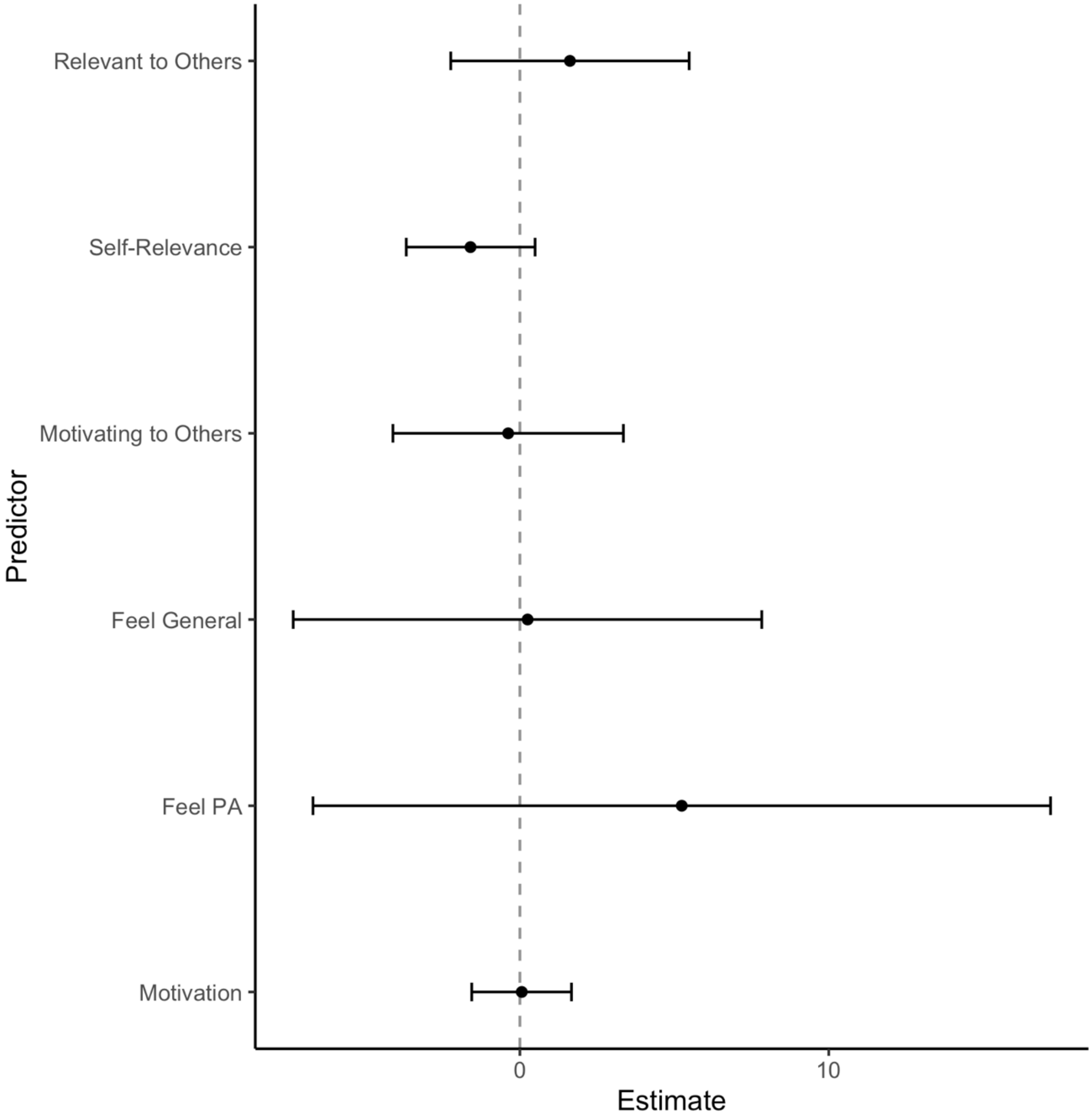

Figure 8: Self-report Predictors of Moderately Active Minutes (Model 3)

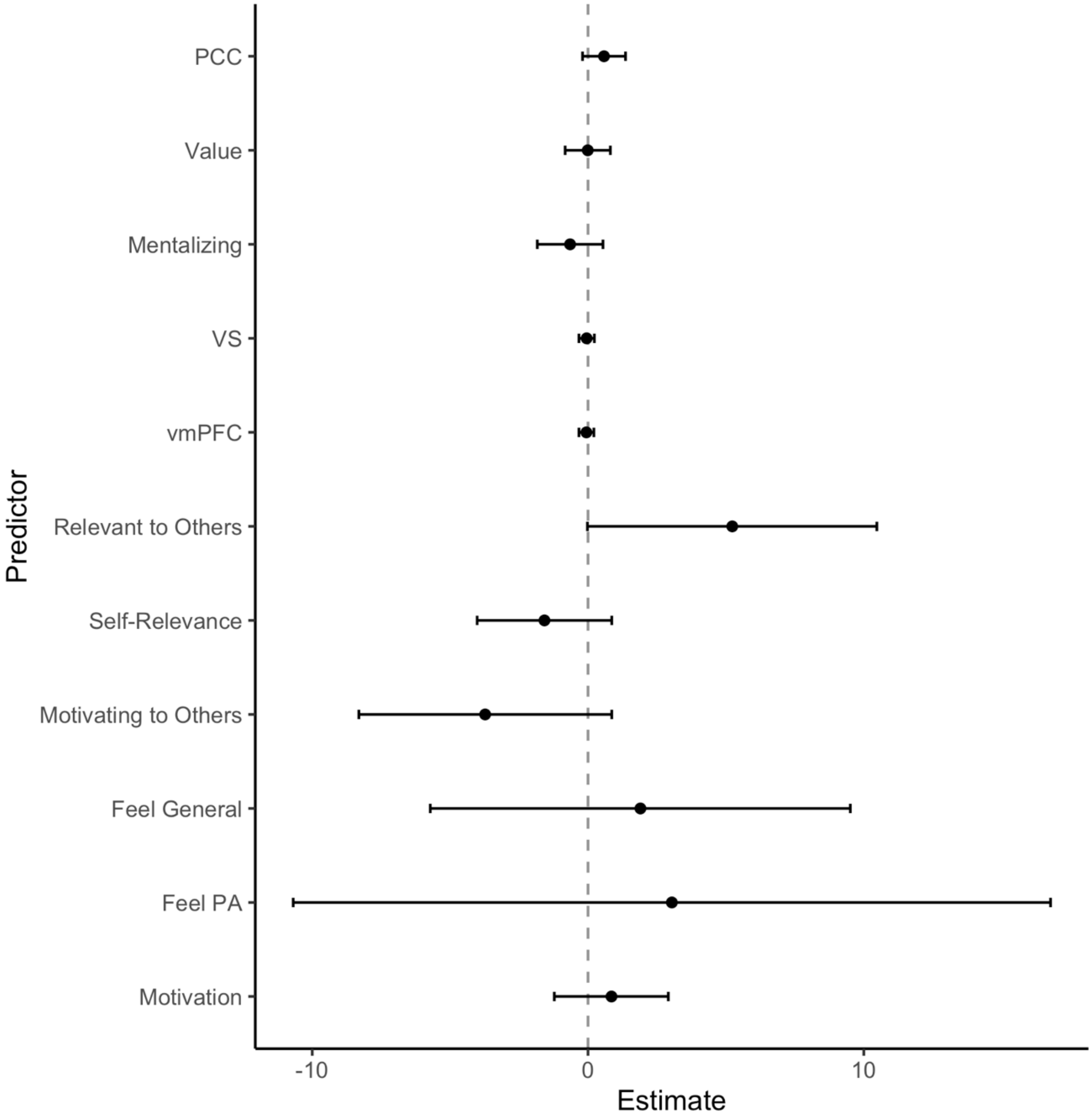

Figure 9: Self-report and Neural Predictors of Moderately Active Minutes (Model 4)

Table 6: Regression Results for Model 5 and Model 6 using Lightly Active Minutes as the Criterion

Model 5				**Model 6**			
Predictor	**Estimate**	**95% CI**		**Predictor**	**Estimate**	**95% CI**	
		LL	***UL***			***LL***	***UL***
Intercept	224.62***	180.71	268.54	*Intercept*	236.13	189.17	283.08
Motivation	1.08	-1.89	4.06	*Motivation*	0.52	-2.40	3.44
Feel PA	-24.21	-59.28	10.85	*Feel PA*	-29.28	-64.03	5.48
Feel General	-20.29*	-40.26	-0.32	*Feel General*	-16.37	-35.88	3.15
Motivating to Others	-2.67	-17.19	11.84	*Motivating to Others*	-5.72	-15.32	3.88
Self Relevance	2.75	-3.53	9.02	*Self Relevance*	2.79	-3.65	9.23
Relevant to Others	13.76	-2.70	30.22	*Relevant to Others*	16.21**	5.58	26.83
				vmPFC	0.25	-0.13	0.63
				VS	-0.23	-0.74	0.29
				Mentalizing	-1.81	-4.41	0.78
				Value	0.63	-0.81	2.07
				PCC	1.65	-0.50	3.81

*Note. Feel PA is participant's rating of how the message makes them feel towards physical activity. * indicates p < 0.05, ** indicates p < 0.01, *** indicates p < 0.001*

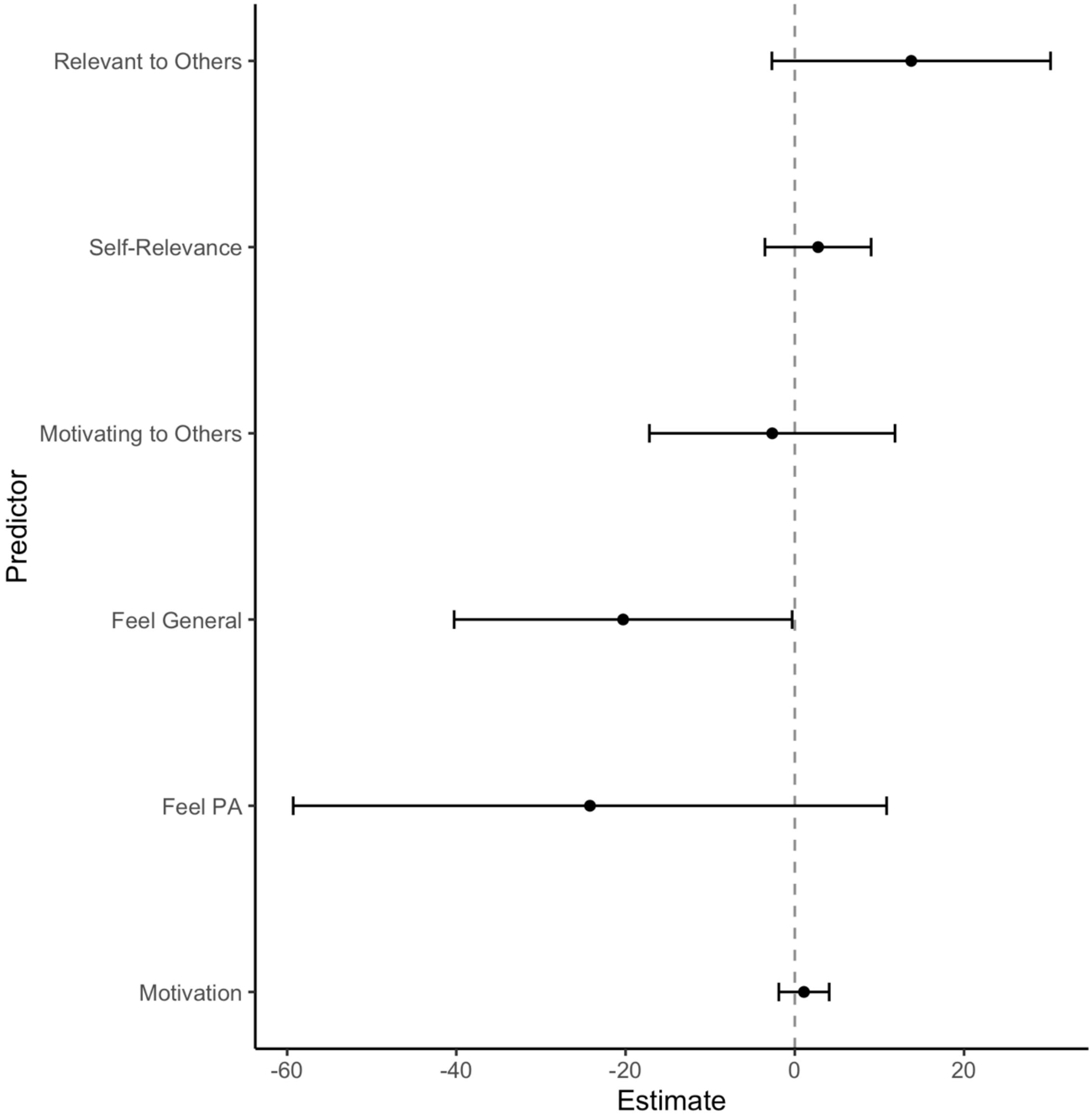

Figure 10: Self-report Predictors of Lightly Active Minutes (Model 5)

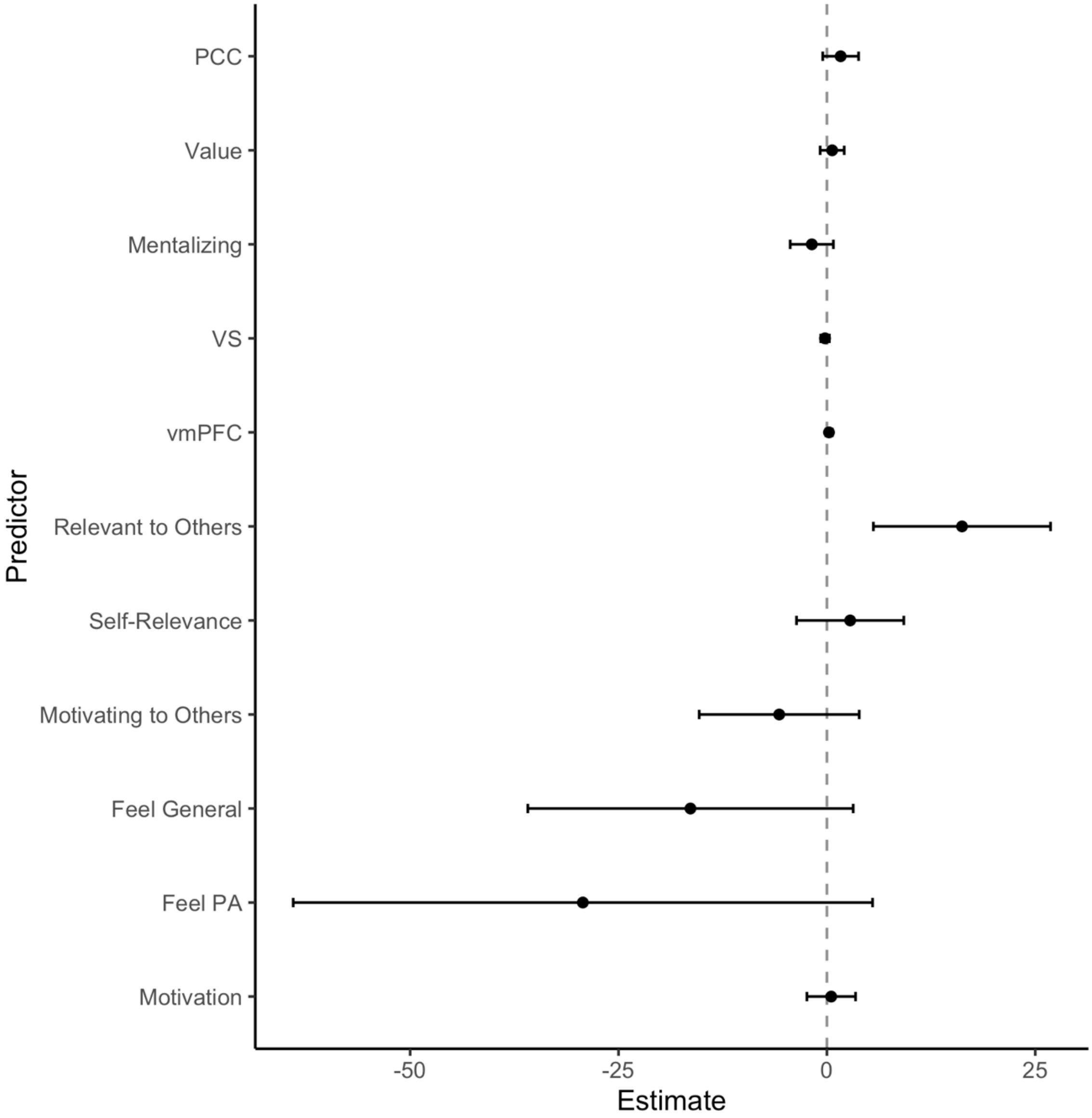

Figure 11: Self-report and Neural Predictors of Lightly Active Minutes (Model 6)

3.4 Discussion

The overarching goal of the present study was to investigate whether we could utilize self-report and neural activity to predict the effectiveness of different types of health messages on physical activity. By combining self-reported evaluations of messages, functional neural activity, and wearable fitness tracker data, we attempted to identify whether using brain imaging could provide additional predictive power in identifying the most effective messages to deliver in a mobile health intervention.

Participants in the study rated each message on multiple dimensions related to how relevant and motivating the messages were to themselves and others and how the messages made them feel. We expected several of these ratings to be positively correlated with message effectiveness (e.g., daily steps). For example, we expected a message rated by an individual participant as highly motivating or highly relevant to elicit more physical activity when they received that message in their everyday life weeks or months later. However, only one of the self-report ratings was significantly correlated with message effectiveness. How relevant to others the messages were rated was a consistent significant positive predictor in all models utilizing brain data even across variations in the dependent variable (e.g., total daily steps, moderately active minutes, lightly active minutes), suggesting a small, but robust association. How motivating to others the messages were rated was also a significant predictor in one model, but the effect was not robust to variations in covariates. Interestingly, participants own perceptions of their own self-relevance or motivation was not associated with levels of physical activity when delivered in everyday life. There seems to be some sort of disconnect between what people think is motivating and relevant to themselves versus others. It is possible that individuals are taking a more generalized approach when asked to rate a message based on its motivation or relevance to others, thus discounting their idiosyncratic preferences and leading to a more robust effect. Notably, the effect sizes are small. These ratings based on others should be replicated in an independent sample.

Functional neural activity across a range of a priori regions of interest selected for their role in motivation and self-relevance did not significantly predict message effectiveness. Previous research across a range of disciplines has demonstrated that in some situations there might be "hidden information" in the brain related to individuals' likelihood to engage in a specific activity or make a particular choice. More specifically, adding in neural measures explained additional variance compared to models only including self-report or behavioral measures. However, the magnitude of these effects is varied. For example, some studies have found relatively large changes in variance explained (Falk, Berkman, Mann, & Harrison, 2010; Falk, Berkman, Whalen, & Lieberman, 2011), while others have found small amounts (Kuhnen & Knutson, 2005). It is also possible that other studies that didn't find any additional predictive power weren't written or published due to publication bias for positive effects.

Regarding message content, previous work has suggested that positively framed messages have greater positive effects on physical activity behavior than negatively framed messages (Gallagher & Updegraff, 2012; Latimer, Brawley, & Bassett, 2010; van 't Riet, Ruiter, Werrij & de Vries, 2010). Contrary to previous work, we did not see a significant difference between positively and negatively framed messages effects on total daily steps. Based on previous findings suggesting a role for socially based rewards in motivating behavior change (Mayr & Freund, 2020; Raposo et al., 2021), we predicted that socially based messages would be more effective for increasing daily step count than non-socially based messages. However, we saw no difference between the two types of messages on physical activity. One reason for this discrepancy could be due to previous research focusing on older adults while the present work including participants across adulthood.

One limitation of the present work is that participants had repeated exposure to the messages from the scanner task and post-scanner rating task. Previous work has found that repeated exposure to messages can lead to diminished effectiveness (Cacioppo & Petty, 1979) and in some cases result in lower motivation (Schumann, Petty, & Clemons, 1990). A future study could collect ratings at a period after the intervention or collect the ratings from a different sample of participants.

Another limitation was that participants had a fairly high baseline total daily steps at the beginning of the intervention before messaging had begun. One reason for this could be a generally physically active sample. Another reason could be due to the effect of wearing the fitness tracker. The novelty of having the ability to track daily steps could cause individuals to strive to be more active. Future studies could screen for more sedentary participants and/or utilize a pedometer or accelerometer without the ability to see total steps taken.

A third and final limitation is the relatively small sample size. A small sample size can make it difficult to detect meaningful differences or relationships between variables. Physical activity based interventions often have small effect sizes (Foster, Hillsdon, Thorogood, Kaur, & Wedatilake, 2005). The current study is underpowered to detect small effect sizes. Additionally, small sample size can lead to low power, meaning that the study may have a low probability of detecting a true effect if one exists. To address this limitation, a future study could be done with a larger sample size.

Based on the present study's limitations, there are multiple directions for future work. For example, futures studies using similar approaches could avoid the effects of repeated message exposure by having participants rate the messages motivational aspects after the SMS intervention component. Future work could also benefit from collecting a larger sample. Finally, targeted recruitment for more sedentary adults would be beneficial for studies taking a similar approach to the current study. Based on the findings of the present study suggesting that participants' ratings of messages for others may be more revealing than ratings for themselves, future work could consider having participants rate messages for the average population rather than rating them for themselves.

4. Conclusion

The principal aim of this dissertation was to examine the role of neural and behavioral determinants of physical activity behavior change. In the first chapter, I reviewed two prominent theoretical approaches to physical activity behavior, social cognitive theory and dual process theory, and highlighted how integrating neuroimaging techniques can help inform gaps in both theoretical and applied knowledge of physical activity. In the second chapter, I explored whether there are brain regions correlated with physical activity behavior change. The third chapter focused on neural and self-report responses to different types of health messages and their ability to predict physical activity behavior change. Overall, this dissertation provides examples of how emerging multidisciplinary psychological and neuroscience research may be able to optimize physical health interventions used in everyday life.

Using functional neuroimaging, chapter two revealed that brain activation in the posterior cingulate cortex (PCC)/precuneus and lateral and medial frontal cortex in response to health messages about walking was associated with greater increases in average daily steps. The PCC/precuneus region has been associated with self-referential processing, which concerns stimuli that are strongly experienced as relating to one's own self (Chua et al., 2011; Northoff et al., 2006). This finding is consistent with theoretical models emphasizing the role of self-relevance in persuasion (Chua et al., 2009) and provides further support for this hypothesis in the context of health messages and walking behavior. The frontopolar cortex is broadly implicated in cognitive control, motivation, and goal directed behavior (Koechlin, Ody, & Kouneiher, 2003). This region has been found to play a role in pre-commitment, a self-control strategy where people anticipate self-control failures and prospectively restrict access to tempting alternative choices (Ariely & Wertenbroch, 2002). It is possible that participants in the study presented in Chapter 2 were exercising some type of pre-commitment to increasing their daily steps. Chapter 3 expanded on the previous chapter by integrating the neural findings from Chapter 2 along with self-report responses to health messages to predict the efficacy of different messages to produce physical activity behavior change. We found that the only consistent significant predictor of message effectiveness was how relevant to others the message was rated. Interestingly, participants own perceptions of how relevant the messages were to themselves was not associated with levels of physical activity when delivered in everyday life. There seems to be disconnect between what people think is relevant to themselves versus others. Although Chapter 2 suggests that we can localize brain regions involved in physical activity, when we utilized the findings to predict changes in physical activity, the brain regions that we focused on did not significantly predict behavior change. The study suffered from many limitations (detailed in Chapter 3) that could be addressed in future research. Although our first attempt at identifying how neuroimaging data might be useful in optimizing physical activity interventions across adulthood had limited success, the study generated a number of ideas that could be tested in future research to better evaluate the general utility of this type of approach.

The theories discussed at the start of the present work focused on traits of the individual such as self-efficacy and implicit motivation. While these theoretical frameworks have been dominant in the field, this approach has been criticized because it may overemphasize the individual and fail to consider the context within which a behavior takes place (McLeroy, Bibeau, Steckler, & Glanz, 1988; Stokols, 1992). Considering this, some work has begun to examine an approach that integrates factors beyond the individual, or the social ecological model. The social ecological model is a multi-dimensional approach that proposes that behavior is affected by not only individual characteristics, but also by variables on the broader social, physical, and policy environmental levels (McLeroy et al., 1988).

Studies identifying correlates of physical activity at all levels of the social ecological model can provide an empirical basis for intervention design. While few studies have concurrently evaluated factors at all levels, there is evidence suggesting the utility of the framework. Regarding the social environmental level, neighborhood social cohesion was found to be significant variable affecting the physical activity of older adults (Kim et al., 2020). At the physical environmental level, the architectural and urban environment of the community has shown to influence physical activity (Sun et al., 2020). Further, a study in older adults found correlates of physical activity at all social-ecological model levels of variables (Thornton et al., 2017).

Considering the evidence above, the social ecological framework is a promising approach to studying physical activity behavior. While our first attempt at identifying how neuroimaging data might be useful in optimizing physical health interventions had limited success, research on the effects of the social and physical environment on the brain suggest that integrating brain imaging into the broader social ecological framework could be a promising future direction. For example, neighborhood socioeconomic disadvantage is associated with altered brain development across adolescence highlighting the effects of the social environment on the brain (Whittle et al., 2017). The physical environment also has effects on the brain. For example, urban upbringing and city living have effects on the amygdala and anterior cingulate cortex affecting evaluative stress processing (Lederbogen et al., 2011). Considering that the social and physical environment can affect an individual's brain, it is logical to take into account a broader social ecological framework when studying behavior change. Using structural and functional brain imaging to assess the specific impact in an individual of social and physical environment could inform the design of individualized interventions. Some exploratory experimental work has begun to examine how physical environments affect neural responses in parts of the brain related to affect and motivation (Ariely & Berns, 2010; Eberhard, 2009; Higuera-Trujillo, Llinares, & Macagno, 2021). However, research in this area is very limited so far. It's unclear how to integrate this approach into physical activity interventions. It is likely that this research area is not far enough along to attempt to integrate the approach yet.

Getting adequate amounts of physical activity is extremely important for emotional, cognitive, and physical well-being (Pendo & Dahn, 2005; Rhodes, Janssen, Bredin, Warburton, & Bauman, 2017). Despite this fact, many adults do not get significant amounts of daily physical activity (World Health Organization, 2022). An individual's engagement with physical activity is determined by many different psychological, social, and environmental factors suggesting that there are many reasons why people choose to engage in exercise or choose not to. The better we are able to understand the individual characteristics involved in physical activity behavior change and integrate them into a broader framework, the better we will be able to optimize future physical activity interventions to increase public health.

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