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The ability to successfully engage in social interactions requires social cognitive abilities, like emotion perception. The most prominent nonverbal cue used by humans to convey emotion is facial expressions, making facial affect recognition (FAR) an integral part of social interactions. Previous research has shown that compared to younger adults, older adults exhibit deficits in FAR. Since deficits in FAR are associated with impaired social functioning and social isolation, finding ways to preserve the FAR abilities of older adults is important for their health and quality of life. Physical activity has been shown to reduce cognitive declines associated with advancing age, but this research has only examined a subset of cognitive constructs, not including FAR. However, existing research provides evidence of several mechanisms through which physical activity may be positively associated with older adults' FAR abilities. Furthermore, previous research with other populations has provided evidence that physical activity can benefit FAR, while also demonstrating a positive relationship between resting heart rate variability (HRV) indices of vagal tone and FAR.

The purpose of this study was to collect cross-sectional data concerning the relationship between physical activity and FAR as well as resting HRV measures of vagal tone (root mean square of the successive differences, RMSSD; absolute power of the high-frequency band, HF power) and FAR in both younger and older adults. Younger adults (n=27) and older adults (n=16) self-reported their physical activity behavior using the Global Physical Activity Questionnaire (GPAQ), had their resting HRV measured using a Polar V800 chest monitor and receiver, and completed a FAR task using facial stimuli from the FACES database. RMANOVA revealed that the older adult group had a significantly slower overall response time compared to the younger adult group. Bivariate correlations were then conducted to investigate the relationship between physical activity, RMSSD, HF power, and FAR. Significant negative correlations between RMSSD, HF power, and response times were found, indicating that higher resting RMSSD and HF power were associated with faster response times. Finally, regression analyses were used with age category, physical activity and the interaction between age category and physical activity as predictors of FAR performance. Results revealed that neither physical activity or the interaction of age category and physical activity were significant predictors. Additional regression analyses were then conducted with age category RMSSD, HF power, and the interaction of age category with both RMSSD and HF power as predictors of FAR performance. Again, neither RMSSD, HF power, or the interaction of age category with either RMSSD or HF power were significant predictors of overall FAR performance. However, results revealed that HF power was a significant predictor of response time to angry facial stimuli. This study therefore provides preliminary evidence of relationships between physical activity, RMSSD, HF power, and FAR abilities. Since FAR deficits can negatively impact health and quality of life, future research is warranted to investigate the effect physical activity can have on the FAR abilities of older adults.

PHYSICAL ACTIVITY AND FACIAL AFFECT RECOGNITION IN

OLDER ADULTS VERSUS YOUNGER ADULTS

by

Samantha L. DuBois

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Committee Chair

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This thesis written by SAMANTHA L. DUBOIS has been approved by the following committee of the Faculty of The Graduate School at The University of North Carolina at Greensboro.

Committee Chair ______________________________

Committee Members ______________________________

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Date of Acceptance by Committee

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Date of Final Oral Examination

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CHAPTER I

INTRODUCTION

Social interactions are a fundamental and necessary part of the activities people engage in on a daily basis. Attending a meeting at work, playing on the playground at school, eating a family dinner, and shopping with friends, all require people to interact with others in social settings. However, in order to engage in these interpersonal interactions and effectively navigate the social world in which we live, individuals must be able to recognize a variety of social cues, such as facial expressions and body language. These social cues are an integral part of communication as they provide valuable insight into how other people are feeling, what they are thinking, and what their intentions are. The ability to quickly, easily, and accurately recognize social cues is therefore necessary when engaging in social interactions, as it helps individuals understand one another, make sense of their social environment, and know how to behave appropriately in different social situations.

Social cognition is the broad term used to describe the mental operations that underlie how people process information in social settings during interactions with other people (Frith, 2008; Green et al., 2008; Penn et al., 2008). These mental operations are what allow individuals to recognize different social cues and infer from them important information pertaining to the people they are interacting with and the social environments they are operating in. While recognizing social cues, like different facial expressions of emotion, may seem simple, it actually requires a number of different cognitive abilities. One of these cognitive abilities is emotion perception.

Emotion perception refers to the ability to identify the emotions displayed by others through their facial expressions, body language, and tone of voice (Penn et al., 2008). Smiling faces, slumped shoulders, and raised voices are all emotional displays used as social cues in everyday life to let others know how we are feeling and what we are thinking. As such, the ability to correctly discern the emotions conveyed by these social cues is critical to the communication that occurs during social interactions as well as overall social functioning. The most prominent nonverbal social cue used by humans to convey emotion is facial expressions (Neumann et al., 2014).

Facial expressions are a form of nonverbal emotion communication that provide information about someone's internal state, attitudes, opinions, and intentions before or even in the absence of language (Batty & Taylor, 2003). Early emotion perception research argued that facial expressions of six basic emotions (anger, disgust, fear, happiness, sadness, and surprise) were universal and recognizable across cultures (Ekman, 1992; Ekman & Friesen, 1971; Johnson-laird & Oatley, 1992). The assumption was that these emotions produced specific behavioral and physiological changes that all people were prewired to recognize (Ekman, 1992; Levenson et al., 1990). However, while this notion of universal emotions has been challenged by more recent research and models of emotion perception (Barrett, 2006; Elfenbein & Ambady, 2016), research has demonstrated that individuals of different cultures are able to recognize static facial expressions at a greater than chance level (Elfenbein & Ambady, 2002a, 2002b).

Known as facial affect recognition (FAR), the ability to quickly and correctly identify the emotional facial expressions of others is extremely important to any and all social interactions, as deficits in FAR have been linked to reduced social functioning and worse social outcomes (Addington et al., 2006; Couture et al., 2006; Harvey & Penn, 2010; Torres et al., 2015). While deficits in FAR have been observed in a number of different clinical populations (Bal et al., 2010; Csukly et al., 2009; Demenescu et al., 2010; Hargrave et al., 2002; Harvey & Penn, 2010; Neumann et al., 2014), individuals with clinical disorders are not the only ones to exhibit deficits in FAR. As with other areas of cognitive functioning that experience age-related declines, such as memory (Blazer et al., 2015; Salthouse, 2009), FAR has also been shown to decline with advancing age (Gonçalves et al., 2018; Ruffman et al., 2008). This decline may be particularly concerning for older adults because of its association with reduced social engagement, loneliness, and social isolation, all of which have been shown to have serious negative consequences for older adults' health and quality of life (Bath & Deeg, 2005; Cacioppo et al., 2014; Cornwell & Waite, 2009; Luo et al., 2012). Finding ways to preserve or improve the FAR abilities of older adults therefore has important implications for their overall level of social functioning, health, and quality of life.

A growing body of research has provided evidence that physical activity can reduce the risk of cognitive decline in older adults, as older adults who are more physically active experience less severe age-related cognitive declines compared to older adults who are less physically active (Angevaren, Aufdemkampe, Verhaar, Aleman, & Vanhees, 2008; Carvalho, Rea, Parimon, & Cusack, 2014; Colcombe & Kramer, 2003). However, this research investigating the relationship between physical activity and age-related cognitive decline has only examined a subset of cognitive constructs, such as executive function, memory, and processing speed. In contrast, little to no research has investigated the relationship between physical activity and social cognitive abilities, like FAR. It therefore remains unclear if physical activity also has a positive association with FAR and could potentially reduce the deficits commonly observed with advancing age.

Several mechanisms have been proposed to explain the relationship between physical activity and cognitive functioning in older adults, including the cognitive reserve hypothesis. The cognitive reserve hypothesis suggests that lifestyle factors, like physical activity, can increase individuals' cognitive reserves thus helping to preserve cognitive functioning and decrease the severity of age-related declines (Fratiglioni et al., 2004; Salthouse, 2013; Whalley et al., 2004). As age-related declines in FAR have been shown to be associated with declines in other cognitive abilities (Suzuki & Akiyama, 2013), physical activity's ability to reduce the severity of age-related declines in these other cognitive abilities may consequently also help to preserve the FAR abilities of older adults. Furthermore, research also indicates that physical activity may boost cognitive reserves by protecting brain structure and function from age-related changes (Kramer & Erickson, 2007). Physical activity may therefore also have the potential to benefit the FAR abilities of older adults by protecting brain structures and functions necessary for emotion perception from age-related changes. Therefore, while the relationship between physical activity and FAR in older adults has yet to be explored, existing research provides evidence of several mechanisms though which physical activity may be positively associated with FAR in older adults.

While there is currently no research investigating the relationship between physical activity and FAR in older adults, some research in this area has been conducted with other populations, including adults with schizophrenia, children with autism spectrum disorder, and healthy young adults (Bal et al., 2010; Behere et al., 2011; Quintana et al., 2012). And while this body of research is small, it has provided preliminary evidence that physical activity can improve FAR in certain populations. Furthermore, it has also provided evidence of a positive relationship between heart rate variability (HRV) indices of vagal tone and FAR, suggesting that regulation of the autonomic nervous system is associated with FAR. Since greater HRV is associated with higher physical activity levels (Soares-Miranda et al., 2014), physical activity may be positively related to FAR because of its association with more efficient regulation of the autonomic nervous system during social interactions. This small body of research therefore does provide evidence of a positive relationship between physical activity and or HRV and FAR in at least some clinical and non-clinical populations, making it possible that a positive relationship also exists in older adults.

Prior to investigating if and how physical activity can improve the FAR abilities of older adults, research first needs to be conducted to establish if a positive relationship exists between older adults' physical activity levels and FAR abilities. The purpose of this study was therefore to collect cross-sectional data concerning the relationship between physical activity and FAR in cognitively normal younger and older adults as a first step in pursuing this research question. Furthermore, given that FAR may be related to regulation of the autonomic nervous system, the relationship between younger and older adults' resting HRV indices of vagal tone and FAR were also assessed. Based on previous evidence demonstrating age differences in FAR, it was hypothesized that older adults would perform worse than younger adults on a FAR task. However, based on research concerning the relationship between physical activity and age-related cognitive declines, as well as research investigating the relationship between physical activity, resting HRV indices of vagal tone, and FAR in other populations, it was predicted that physical activity level and resting HRV indices of vagal tone would have positive relationships with FAR in both younger and older adults, with higher levels of physical activity and greater resting HRV indices of vagal tone associated with better performance on a FAR task.

CHAPTER II

REVIEW OF LITERATURE

Overview of Social Cognition

Humans are by nature social beings who live, work, and interact with other individuals on a daily basis. However, in order to engage in the social interactions and behaviors that permeate almost all aspects of human life, a unique set of cognitive abilities is required. Frequently grouped together under the umbrella term “social cognition”, these cognitive abilities are specific to social stimuli and social interactions (Frith & Blakemore, 2006). Broadly speaking, social cognition is concerned with how people come to understand the social world in which they live and their place in it (Augoustinos, Walker, & Donaghue, 1995). More specifically, it refers to the mental operations that underlie social interactions, including perceiving, interpreting, and responding to social stimuli that pertain to the intentions and behaviors of other people. Social cognitive abilities are therefore what allow humans to think about other people and make inferences about their beliefs and thoughts based on social stimuli (Green et al., 2008).

The human ability to process social stimuli and infer from them what other people are thinking, how they are feeling, and what their intentions are is possible because of a distinct set of neural systems that specialize in processing social stimuli (Adolphs, 2008; Frith & Blakemore, 2006; Phillips, Drevets, Rauch, & Lane, 2003). During social interactions, social stimuli, such as eye gaze, body posture, and facial expressions, operate as social cues that provide insight into other people's minds and signal to others how they should behave (Frith, 2008). For example, when someone points at an object, the neural systems that underlie social cognition allow people to perceive the gesture as a social cue indicating that the individual wants others to direct their attention to the object being pointed at. This ability to rapidly identify social stimuli and infer from them what is going on in the minds of others is possible because of social cognition (Adolphs, 2008).

Social cognition is commonly broken down into four domains: emotion perception, Theory of Mind, attributional style, and social knowledge (Harvey & Penn, 2010). Emotion perception refers to the ability to identify emotionally salient stimuli from the environment, including both verbal and non-verbal cues to the emotions of others (Mitchell & Phillips, 2015). Theory of Mind represents the ability to attribute mental states to others through the understanding that other people have thoughts, feelings, and perspectives that are separate and different from one's own (Mitchell & Phillips, 2015; Schaafsma et al., 2015). Attributional style refers to the tendencies people have for explaining the positive and negative events in their lives, specifically to who or what they attribute the cause of events (Harvey & Penn, 2010; Penn et al., 2008). These causal attributions are usually viewed in terms of their stability (transient versus not transient), pervasiveness (global versus specific), and point of control (internal versus external) (Liu & Bates, 2014; Peterson et al., 1982). Finally, social knowledge, sometimes also called social perception, involves the mental representations people possess for their social environments, which they then use to make sense of their social world and make decisions about how they should act in it (Adolphs, 2008; Penn et al., 2008). Social knowledge encompasses people's ability to not only perceive social stimuli as social cues but to make judgements about those stimuli based on their knowledge and awareness of the roles other people possess and the social rules that govern social interactions (Harvey, 2013). Together, emotion perception, Theory of Mind, attributional style, and social knowledge allow humans to be social beings who possess the cognitive abilities to recognize social cues, effectively engage in social interactions, and thrive in a social world.

Overview of Emotion Perception

As previously mentioned, emotion perception is a domain of social cognition that refers to the ability to identify emotionally salient stimuli in the environment in the form of facial expressions, body language, and tone of voice (Mitchell & Phillips, 2015; Penn et al., 2008). It therefore entails the ability to detect emotionally salient stimuli, recognize that these stimuli provide social cues about other people's internal states, and then sort this information into defined emotional categories (Mitchell & Phillips, 2015; Schirmer & Adolphs, 2017). Emotion perception plays a crucial role in everyday life because emotional displays are an important mode of nonverbal communication that people use to convey their thoughts and feelings to others. The ability to correctly identify the emotions of others is therefore extremely important during social interactions, as it allows people to understand one another and determine how to appropriately respond to different social situations.

Without emotion perception, humans would struggle to make sense of their social environments and the social interactions they engage in each and every day. The necessity of emotion perception is evident when one considers the deficits in social functioning that occur when emotion recognition abilities are impaired. Impaired emotion recognition is a hallmark of several clinical disorders, including autism spectrum disorder and schizophrenia, both of which are marked by profound deficits in social functioning and social competence (Harvey & Penn, 2010; Penn et al., 2008; Pilowsky et al., 2000; Pinkham et al., 2008). In autism, individuals often experience difficulty coordinating social cues, perceiving the feelings of others, and anticipating other people's behaviors (Bal et al., 2010). Similarly, individuals with schizophrenia struggle with emotion recognition and frequently display inappropriate affect and unsuitable social behaviors (Mueser et al., 1991; Penn et al., 2008). In both of these clinical populations, as well as other populations that exhibit impaired emotion perception, research has shown that deficits in emotion recognition are associated with reduced social functioning, including difficulty communicating with others, maintaining employment, living independently, forming personal relationships, and functioning in the community (Carton et al., 1999; Couture et al., 2006; Green et al., 2008; Harvey & Penn, 2010; Penn et al., 2008; Ruffman, Sullivan et al., 2009). Emotion perception is therefore not only essential to successful social interactions but also to overall social functioning and quality of life.

Facial Affect Recognition

During social interactions, faces are arguably the most important social stimuli as they provide information about other people's identity as well as their emotional state, and consequently set the tone for the social interaction (Posamentier & Abdi, 2003). Furthermore, while there are many modes for conveying emotion to others, facial expressions are considered to be the most prominent nonverbal cue used by humans to communicate emotions (Neumann et al., 2014). Moreover, facial expressions can provide information about someone's internal state, thoughts, feelings, beliefs, and intentions more rapidly than language (Batty & Taylor, 2003). Facial expressions can therefore offer insight into other people's feelings before they have even explicitly stated them.

Historically, facial expressions of six emotions (anger, disgust, fear, happiness, sadness, and surprise) have been thought to be recognizable across cultures, suggesting that facial expressions are a universal mode of emotion communication that can be used to convey information even when people are unable to verbally communicate with one another (Ekman, 1992, 1993; Ekman & Friesen, 1971). Each of these emotions was assumed to exist as a separate entity, each with its own unique internal mechanism that produced specific changes in sensory, motor, and physiological functions that all people were inherently able to recognize (Ekman & Friesen, 1971; Ortony & Turner, 1990). However, more recent research and models of emotion perception have cast doubt upon this concept of universal emotions. While research has demonstrated that different cultures recognize emotional facial expressions at a level significantly greater than chance, it has also shown that accuracy is influenced by an in-group advantage whereby individuals who belong to the same cultural group as the individual depicting the emotion are more accurate than individuals who belong to a different cultural group (Elfenbein & Ambady, 2002a, 2002b). Furthermore, research has also shown that while the six basic emotions exist in many cultures, they do not exist in all cultures (Barrett, 2016). Therefore, while facial expressions of emotion may not be truly universal, the ability to quickly, easily, and accurately recognize the facial expressions of others is still extremely important during social interactions as it allows individuals to identify what is going on in the minds of others before explicit verbal communication has occurred. This initial insight can then help people anticipate the behaviors of others, thus facilitating effective interpersonal communication and potentially avoiding socially inappropriate behaviors.

As with deficits in overall emotion perception previously discussed, deficits in FAR specifically have been observed in a number of different clinical disorders, including autism spectrum disorder, schizophrenia, Alzheimer's Disease, depression, anxiety, and individuals who have suffered a traumatic brain injury (Babbage et al., 2011; Bal et al., 2010; Csukly et al., 2009; Demenescu et al., 2010; Hargrave et al., 2002; Harvey & Penn, 2010; Neumann et al., 2014). Within these different clinical populations, deficits in FAR have also been associated with reduced social functioning and worse social outcomes (Addington et al., 2006; Bal et al., 2010; Harvey & Penn, 2010; Shimokawa et al., 2001). Furthermore, these deficits in FAR often persist even when other symptoms of clinical psychopathology have seen improvements. These lingering FAR deficits can in turn make it difficult for people to return to the level of functioning they maintained prior to the onset of their disorder, thus highlighting the importance of FAR for people's ability to function in a social world (Penn et al., 2008).

Facial Affect Recognition in Older Adults. Deficits in FAR are not just exclusive to clinical populations, but have also been shown to exist in healthy, cognitively normal older adults (Gonçalves et al., 2018; Isaacowitz et al., 2007; Ruffman et al., 2008; Sullivan & Ruffman, 2004). That is, even though older adults have a lifetime of experience engaging in social interactions and identifying the emotions of others, they still experience a decline in FAR as a result of normal aging. Cognitive aging is defined as a lifelong process of ongoing cognitive decline that occurs as people get older (Blazer et al., 2015). These age-related cognitive declines are a normal part of the aging process and have been well documented in a variety of cognitive domains, including memory, processing speed, and executive function (Borella et al., 2008, 2011, 2017; Buckner, 2004; Burton et al., 2006; Gazzaley et al., 2005; Hedden & Gabrieli, 2004). Social cognitive abilities, like emotion perception and FAR specifically, may therefore also decline with increasing age as a normal part of cognitive aging.

While age-related deficits in FAR may be a normal part of cognitive aging, it is also possible that age-related decrements in other cognitive abilities are associated with declines in FAR, as emotion perception requires other cognitive abilities in order to detect and evaluate emotionally salient stimuli. Previous research has supported this hypothesis as age-related deficits in other cognitive abilities including processing speed (Orgeta & Phillips, 2007), executive function (MacPherson et al., 2002), and fluid intelligence (Ruffman, Halberstadt, et al., 2009; Suzuki et al., 2007) have all been associated with the FAR declines observed in older adults. Furthermore, a study by Suzuki and Akiyama (2013) found that age-related deficits in the recognition of facial expressions of fear, happiness, sadness, and surprise were statistically explained by older adults' processing speed and fluid intelligence, indicating that age-related declines in other cognitive abilities may be associated with deficits in FAR.

In addition to general cognitive decline due to cognitive aging, several other mechanisms have been proposed to explain why declines in FAR may occur with advancing age. The first suggests that deficits in identifying emotions may coincide with age-related changes within neural systems involved in FAR (Calder et al., 2003; Gonçalves et al., 2018; Isaacowitz et al., 2007; Ruffman et al., 2008; Sullivan & Ruffman, 2004; Suzuki et al., 2007). Specifically, frontal and temporal regions of the brain, which are thought to play an important role in emotion recognition and the labeling of emotional facial expressions, have been shown to experience reductions in volume with advancing age (Allen, Bruss, Brown, & Damasio, 2005; Bartzokis et al., 2001; Raz et al., 2005; West, 2000). In addition to changes in brain structure, it has also been proposed that age-related changes in neurotransmitter levels may contribute to deficits in FAR (Ruffman et al., 2008). Research with both animal models and humans has shown that with increasing age, certain emotion processing areas of the brain, like the amygdala and orbital frontal cortex, experience declines in dopamine and norepinephrine levels (Kaasinen et al., 2000; Míguez et al., 1999; Mukherjee et al., 2002). These age-related brain changes in regions associated with emotion processing may therefore also contribute to age-related deficits in FAR.

In an attempt to further elucidate these proposed mechanisms, research has sought to specify if older adults have an overall impairment in FAR or if these deficits are exclusive to the identification of certain facial expressions of emotion. However, the results from research have not been consistent. For example, in a 2007 study conducted by Isaacowitz and colleagues, older adults (n=78, mean age=71.90 years) were significantly less accurate at identifying facial expressions of anger, disgust, fear, and happiness compared to younger adults (n=189, mean age=27.05 years). However, in another study, older adults (n=34, mean age=69.7 years) were worse at identifying facial expressions of sadness but better at recognizing facial expressions of disgust compared to younger adults (n=34, mean age=20.6 years).

In an effort to clarify inconsistent findings in the literature, Ruffman and colleagues (2008) conducted a meta-analysis with 28 data sets from 15 studies in which the FAR abilities of older adults (n=705, mean age=70.2 years) were compared to younger adults (n=962, mean age=23.9 years). Results indicated that compared to younger adults, older adults were significantly worse at identifying facial expressions of anger, sadness, fear, surprise, and happiness, with the most severe deficits present for anger, sadness, and fear. Mean effect sizes were small ranging from .07 for surprise to 0.34 for anger and sadness. In contrast to the other facial expressions of emotion, older adults tended to be better at identifying facial expressions of disgust compared to younger adults, although this trend did not reach significance. Additionally, this meta-analysis also compared younger and older adults' ability to match facial and vocal expressions of emotion, and found that older adults were significantly worse at matching all emotions with small mean effect sizes ranging from .19 for surprise to .49 for sadness (Ruffman et al., 2008).

However, since the meta-analysis by Ruffman and colleagues was published, more research concerning the FAR abilities of older adults has been published. As such, Gonçalves and colleagues (2018) published a more recent meta-analysis that included 24 studies published after 2008 in which older adults (n=1,033, mean age≥55 years) were compared to younger adults (n=1,135, 20 years≤mean age≤35 years). Results revealed that overall older adults were significantly less accurate at identifying facial expressions of emotion with a large effect size of 1.80. After controlling for differences in sex and years of education between younger and older adults as well as stimulus features, older adults remained significantly worse at identifying facial expressions of anger, sadness, fear, surprise, and happiness with mean effect sizes ranging from small for happiness (.19) to medium for anger (.61) and fear (.62). The only facial expression of emotion that was not significantly different between younger and older adults was disgust (Gonçalves et al., 2018). Therefore, this more recent meta-analysis conducted by Gonçalves and colleagues (2018) supported the findings of the previous meta-analysis conducted by Ruffman and colleagues (2008) but found much larger effect sizes.

While the two previously discussed meta-analyses highlight how older adults' FAR abilities vary for different emotional expressions, other research has examined if the difficulty of the FAR task may influence age-related deficits. The intensity of emotional facial stimuli can vary from low/subtle to high/obvious, thus making some stimuli more or less challenging to accurately identify. Interested in determining if an intensity threshold existed at which older adults exhibited impaired FAR, Orgeta and Phillips (2007) examined how stimulus intensity influenced older adults' (n=40, mean age=69.83 years) FAR abilities compared to younger adults (n=40, mean age=20.08 years). Findings indicated that older adults were significantly worse at recognizing expressions of sadness, anger, and fear at all stimulus intensities, but that no differences existed for happiness, disgust, or surprise regardless of intensity (Orgeta & Phillips, 2007). These findings therefore suggest that an intensity threshold does not exist at which older adults have more difficulty identifying facial expressions of emotions compared to younger adults. Furthermore, similar to the two meta-analyses, older adults appear to have a particular difficulty identifying the negatively valanced facial expressions of sadness, anger, and fear.

However, the intensity of the facial stimuli is not the only aspect of a FAR task that can impact overall difficulty, as the number of available emotional labels to choose from can also make the task more or less challenging. To assess this, Orgeta (2010) used a forced choice recognition task in which participants were presented with either 2, 4, or 6 emotional labels to choose from. Results revealed that compared to younger adults (n=40, mean age=22.35 years) older adults (n=40, mean age=69.73 years) had more difficulty identifying fearful and sad facial expressions when 4 or 6 emotional labels were provided, as well as more difficulty identifying surprised expressions but only during the 4-label condition (Orgeta, 2010).

While most research on FAR has relied on the use of tasks in which participants are presented with still images of different facial expressions, some research has investigated how other stimuli formats may influence the emotion recognition of older adults. In a recent study conducted by Grainger and colleagues (2015), the researchers hypothesized that older adults would perform better on a FAR task with dynamic stimuli compared to still stimuli as these would be more life-like and therefore hold their attention better than still stimuli. However, while older adults (n=39, mean age=74.0 years) did indeed perform better with the dynamic stimuli compared to the still stimuli, they were still worse than both middle aged adults (n=42, mean age=54.4 years) and younger adults (n=42, mean age=26.0 years) on overall FAR with both still and dynamic stimuli (Grainger et al., 2015). However, in contrast, two other studies found few age differences in FAR when dynamic stimuli were used. Krendl and Ambady (2010) found that older adults did not display any FAR deficits when presented with dynamic facial images. Similarly, Holland and colleagues (2019) found that compared to younger adults, older adults only displayed deficits with the identification of angry facial expressions when dynamic stimuli were used. This research therefore indicates that age-related declines in FAR may be more pronounced when static stimuli are used, but that the use of dynamic stimuli may still not be enough to overcome all the FAR deficits experienced by older adults.

Finally, most research comparing the FAR abilities of younger and older adults have only used young facial stimuli and have not varied the ages of the models making the facial expressions. However, similar to research that has shown a cultural in-group advantage when identifying emotional facial expressions (Elfenbein & Ambady, 2002a, 2002b), some research has also shown that an own-age advantage may also exist, whereby individuals are more accurate and faster when identifying faces from their own age category as opposed to a different age category (Bäckman, 1991; Lamont et al., 2005). Yet other research has shown that, an own-age advantage does not exist, as regardless of the age of the viewer, individuals are more accurate in identifying facial expressions of young adults due to a young face preference or increased difficulty in identifying older faces because of age-related changes in facial features (Ebner & Johnson, 2009). This research suggests that considering the age of the facial stimuli in relation to the age of participants is also important.

Taken together, the previously discussed literature provides evidence that older adults have impaired FAR abilities, with meta-analyses indicating that these deficits exist specifically for facial expressions of anger, sadness, fear, surprise, and happiness. Furthermore, the literature suggests that these deficits may be particularly severe for the negatively valanced emotions of anger, sadness, and fear, while the identification of disgust appears to remain intact with advancing age. These behavioral findings provide support for the hypothesis that older adults' FAR impairments are the result of age-related changes in brain structure and function, as brain regions specifically involved in the identification of anger (orbitofrontal cortex), fear (amygdala), and sadness (anterior cingulate cortex) have all been shown to experience volume reductions with age, while areas associated with the recognition of disgust (basal ganglia) experience less decrements with age (Ruffman et al., 2008).

The impairment in FAR observed in older adults is particularly concerning because of the negative implications it has for older adults' health and quality of life. Social engagement later in life has been positively associated with both physical and mental health as well as overall quality of life (Bath & Deeg, 2005). However, as previously discussed, deficits in emotion perception, including FAR, have been associated with impaired social functioning in the form of reduced social competence, diminished social interest, poor interpersonal communication skills, and inappropriate social behaviors, all of which are associated with social isolation and loneliness and can consequently negatively impact the health and quality of life of older adults (Cacioppo et al., 2014; Carton et al., 1999; Cornwell & Waite, 2009; Luo et al., 2012; Ruffman, Sullivan, et al., 2009; Shimokawa et al., 2001). Finding ways to preserve or improve the FAR abilities of older adults therefore has important implications for not only improving their social functioning but also their overall health and quality of life.

Physical Activity and Cognition in Older Adults

One strategy that has been shown to prevent or reduce cognitive declines with advancing age is physical activity. Physical activity is defined as any bodily movement produced by skeletal muscles that results in energy expenditure above resting levels (Caspersen et al., 1985). Previous research has shown that older adults who are physically active are at a lower risk of experiencing age-related cognitive declines compared to those who are inactive (Angevaren et al., 2008; Carvalho et al., 2014; Clarkson-Smith & Hartley, 1989; S. Colcombe & Kramer, 2003; Weuve et al., 2004; Yaffe et al., 2001). In a cross-sectional study conducted by Clarkson-Smith and colleagues (1989), physically active older adults (n=62, mean age=67.13 years) performed better on cognitive tasks of reasoning, working memory, and reaction time compared to sedentary older adults (n=62, mean age=72.34 years). Furthermore, two prospective studies with older women have found that more physically active individuals are less likely to experience cognitive declines later in life (Weuve et al., 2004; Yaffe et al., 2001). In the first study conducted by Yaffe and colleagues (2001), older women (n=5,925, age≥65 years) who were more physically active at baseline were less likely to experience cognitive declines 6-8 years later. Similarly, Weuve and colleagues (2004) found that for older women (n=16,466, age≥70years) being regularly physically active was associated with less cognitive decline with advancing age.

In an effort to summarize the literature concerning physical activity and cognitive aging, several meta-analyses and systematic reviews have been conducted. A meta-analysis conducted by Colcombe and Kramer (2003), included 18 studies that investigated how aerobic exercise training impacted the cognitive functioning of older adults (age≥55years). Results showed that exercise training does enhance the cognitive functioning of older adults with an overall moderate effect of 0.478. Furthermore, a more recent-meta-analysis by Angevaren and colleagues (2008) that included 11 studies, investigated the effect that physical activity had on the cognitive functioning of older adults (age≥55 years). Again, the authors found positive effects, with the largest effect sizes observed for motor function (1.17), auditory attention (0.50), visual attention (0.26), and processing speed (0.26). Finally, a recent systematic-review that looked at research concerning physical activity later in life and age-related cognitive decline in cognitively normal older adults, concluded that there was overwhelming evidence to show that increased levels of physical activity attenuate cognitive declines associated with advancing age (Carvalho et al., 2014). These reviews therefore provide evidence that physical activity is associated with less severe cognitive aging, suggesting that physical activity may protect against cognitive declines that occur with advancing age.

While research provides considerable evidence for the beneficial relationship between physical activity and cognitive functioning later in life, less is known about the mechanisms underlying this association. One of the predominant hypotheses used to explain this beneficial relationship is the cognitive reserve hypothesis, which posits that individuals have cognitive reserves that are crucial to their cognitive functioning and these reserves can be increased by lifestyle factors, like physical activity, and decreased by other factors, such as advancing age (Whalley et al., 2004). Engaging in physical activity may therefore be positively associated with the cognitive functioning of older adults because it augments their cognitive reserves and thus lessens the cognitive declines that come with advancing age (Fratiglioni et al., 2004; Salthouse, 2013; Whalley et al., 2004).

One way in which physical activity may increase cognitive reserves is by preserving brain structure from normal age-related decrements, as total brain volume has been shown to decline with advancing age (Raz et al., 2005; Raz & Rodrigue, 2006). More specifically, research has shown that individuals who are physically active at midlife display greater total brain volume and greater gray matter volume later in life compared to those who were sedentary at midlife. Furthermore, this less severe reduction in gray matter volume was mainly found in the frontal lobe, an area of the brain that is important to cognitive functioning (Rovio et al., 2010) as well as emotion perception (Phillips et al., 2003).

In addition to maintaining brain structure, physical activity may also increase cognitive reserves by preserving normal neural activation and functional connectivity in the brain. The brain consists of networks that are comprised of separate brain regions that although spatially distinct are related functionally and therefore exhibit co-activation during specific tasks. However, neural activation and connectivity between and within brain networks have been shown to change with advancing age, indicating less efficiency, (Reuter-Lorenz & Cappell, 2008; Tsvetanov et al., 2016). These changes in activation and connectivity may therefore also contribute to cognitive declines with increasing age. However, research utilizing neuroimaging techniques has provided evidence that physical activity and physical fitness are positively associated with neural activation and functional connectivity, such that neural activation and functional connectivity are better preserved in more physically active/higher fit older adults (Colcombe et al., 2004; Kawagoe, Onoda, & Yamaguchi, 2017).

Mechanisms through which Physical Activity may Benefit Facial Affect Recognition

While no research has specifically examined the relationship between physical activity and FAR in older adults, research surrounding the relationship between physical activity and other age-related cognitive declines suggests that there are several potential mechanisms through which physical activity may help to preserve the FAR abilities of older adults. As previously discussed, research indicates that the FAR abilities of older adults are associated with other cognitive abilities, including processing speed, executive function, and fluid intelligence (MacPherson et al., 2002; Suzuki & Akiyama, 2013). Given that older adults who are more physically active experience less severe cognitive declines in these cognitive abilities, preservation of these cognitive abilities may consequently be associated with less severe age-related declines in FAR (Blondell et al., 2014; Sofi et al., 2011).

Another mechanism through which physical activity may reduce age-related deficits in FAR involves the neuroprotective effect physical activity has on brain structure and function throughout the aging process (Kramer & Erickson, 2007). Research indicates that frontal and temporal regions of the brain that play an important role in emotion recognition, including the amygdala, orbitofrontal cortex, and prefrontal cortex, all experience volume reductions with advancing age (Allen et al., 2005; Convit et al., 2001; Lamar & Resnick, 2004; Raz et al., 1997). However, since individuals who are more physically active tend to have greater overall brain volume and gray matter volume as well as more efficient functional connectivity later in life, especially in the frontal lobe

(Rovio et al., 2010; Tsvetanov et al., 2016), physical activity may help to decrease neurodegeneration in brain regions vital to emotion recognition, thus better preserving the FAR abilities of more physically active older adults.

Finally, a third mechanism through which physical activity may impact the FAR abilities of older adults involves the association between physical activity and the autonomic nervous system. According to polyvagal theory (Porges, 2003), the autonomic nervous system plays an important role in human social interactions through its influence on the body's normal physiological responses to social stimuli. The vagus nerve, which is the main nerve of the parasympathetic branch of the autonomic nervous system, innervates the sinoatrial node (pacemaker) of the heart and works as a brake to slow the heart's intrinsic rate. This activity of the vagus nerve is known as vagal tone. In the environment, stimuli, like facial expressions of emotion, that are perceived as threatening or negative will release the vagal brake and reduce vagal tone to increase heart rate, while stimuli that are viewed as safe or pleasant will activate the vagal brake to maintain vagal tone and decrease heart rate. Individuals with high vagal tone have better control over the vagal brake and can therefore better attenuate the body's naturally occurring physiological response to social stimuli (Bal et al., 2010; Porges, 2003; Quintana et al., 2012). However, research has shown that vagal modulation decreases with advancing age, but that higher physical activity levels are associated with more favorable indicators of autonomic function (Soares-Miranda et al., 2014). Older adults who are more physically active may therefore have better regulation of the autonomic nervous system during social interactions, while less physically active older adults have poorer regulation of the autonomic nervous system and less efficient control of the vagal brake during social interactions, thus impairing their FAR abilities (Porges, 2003). More physically active older adults may therefore have better FAR abilities because of more efficient autonomic nervous system functioning and higher vagal tone.

Physical Activity/Heart Rate Variability and Facial Affect Recognition in Other Populations

While no research has examined the relationship between older adults' physical activity levels and FAR abilities, a very small body of preliminary research has investigated the relationship between physical activity, vagal tone, and FAR abilities in other populations, including both clinical populations with impaired FAR abilities and non-clinical populations without impairment. Within this existing body of research three studies have been conducted, one with adults diagnosed with schizophrenia, another with children diagnosed with autism, and finally a third with healthy young adults (Bal et al., 2010; Behere et al., 2011; Quintana et al., 2012)

In the study conducted with adults diagnosed with schizophrenia, the researchers were interested in investigating the effects of yoga participation on FAR abilities. Adults diagnosed with schizophrenia were randomly assigned to either a yoga intervention group (n=27), exercise intervention group (n=17), or a waitlist control group (n=22). Both the yoga and exercise intervention groups received one-month of trained instruction and were then encouraged to continue engaging in either yoga or exercise for the next two months on their own. The FAR abilities of all participants were assessed using the Tool for

Recognition of Emotions in Neuropsychiatric Disorders (TRENDS) at baseline, one-month following the intervention, and again four months after the initial baseline assessment. Results indicated that participants who received the yoga intervention significantly improved their overall performance on the TRENDS from baseline to both the one-month and four-month follow-up assessments. In contrast, participants in the exercise intervention and control groups did not demonstrate improvements in FAR from baseline to either of the follow-up assessments (Behere et al., 2011). While this study has limitations, including a lack of description of what type of physical activity the exercise group engaged in as well as the absence of self-report or objective measures of participants' physical activity levels in the months following the intervention, it does provide initial evidence that some forms of physical activity may be able to improve the FAR abilities of adults with schizophrenia.

In addition to this research examining the effects of different types of physical activity on the FAR abilities of adults diagnosed with schizophrenia, research has also been conducted to examine the relationship between vagal tone and FAR in specific populations. Vagal tone can be measured non-invasively through HRV measures. HRV refers to the fluctuation in the time interval between consecutive heartbeats due to autonomic neural regulation of the heart by the parasympathetic autonomic nervous system and is therefore an indirect index of vagal tone (Acharya et al., 2006; Shaffer et al., 2014; Shaffer & Ginsberg, 2017). The beat to beat fluctuations of the heart are not monotonous, but are extremely complex and variable. In healthy individuals, higher HRV therefore reflects higher vagal tone (Shaffer et al., 2014). Specific HRV variables are thought to best reflect vagal tone. One of these is respiratory sinus arrythmia (RSA), which assess the normal variations in the time interval in between heartbeats that occurs during the respiratory cycle, such that the interbeat interval is longer during expiration and shorter during inspiration (Yasuma & Hayano, 2004). The amplitude of RSA can therefore be used to assess vagal tone (Porges, 2007). Interested in how RSA was related to FAR in children with autism, Bal and colleagues (2010) conducted a study in which children with autism (n=17, mean age=10.30 years) were compared to typically developing children (n=36, mean age=11.16 years) on performance on the Dynamic Affect Recognition Evaluation (DARE) task as well as RSA at rest. Children with low RSA, indicating poor control of the vagal brake and low vagal tone were hypothesized to perform worse on the FAR task as they would be less able to attenuate the naturally occurring physiological responses to social interactions and would therefore view them as more stressful. In support of this hypothesis, the researchers found that children with autism had significantly lower RSA than typically developing children and were also slower in emotion recognition while making more errors for angry facial stimuli. Furthermore, within the autism group, RSA was negatively correlated with response times, as higher RSA was associated with faster response times when identifying facial expressions of emotion (Bal et al., 2010).

Another study interested in the relationship between vagal tone and FAR was conducted with healthy young adults (n=65, mean age=20.91 years). In this study, the relationship between young adults' performance on the Reading the Mind in the Eyes Test (RMET), a task that assesses an individual's ability to identify the mental states of others based on images of just the eye region of the face, and resting high frequency HRV (HF HRV) was examined. HRV frequency domain measures filter the heart's electrical signal into different frequency bands, with each frequency band reflecting a different physiological origin. HF HRV reflects parasympathetic activity and vagal tone as it corresponds to fluctuations in the interbeat interval that are associated with the breathing cycle (Laborde et al., 2017; Shaffer & Ginsberg, 2017). The authors of this study therefore hypothesized that higher HF HRV would be associated with better performance on the RMET. Results indicated that there was a positive relationship between resting HF HRV and performance on the RMET, indicating that higher HF HRV was associated with better FAR performance (Quintana et al., 2012). Therefore, this study with healthy young adults and the study and conducted by Bal and colleagues (2010) that compared typically developing children to children with autism, both found positive associations between HRV indices of vagal tone and performance on FAR tasks. It is therefore plausible that a positive relationship between HRV indices of vagal tone and FAR also exists in healthy, cognitively normal older adults. However, research investigating this relationship is needed.

Literature Review Summary

This literature review highlights the importance of social cognition, emotion perception, and FAR to overall social functioning, health, and quality of life. The deficits in FAR observed in older adults is concerning and warrants research to find strategies to help preserve the FAR abilities that decline with advancing age. One such strategy may be physical activity, as previous research provides evidence that physical activity can reduce the risk of age-related cognitive declines. While this existing body of literature has not examined the relationship between physical activity and social cognitive abilities like FAR, research regarding the mechanisms that underlie the beneficial relationship between physical activity and cognition in older adults suggests that physical activity may also be able to help preserve older adults' FAR abilities. Furthermore, a small body of research has provided preliminary evidence that physical activity and HRV indices of vagal tone may be associated with FAR in specific populations. Establishing if a positive relationship exists between physical activity and or HRV measures of vagal tone and FAR in older adults will therefore help to further our understanding of the utility of physical activity as a strategy for preserving older adults' FAR abilities.

CHAPTER III

METHODS

Overview of Research Design

The purpose of this study was to investigate the relationship between physical activity and FAR as well as resting HRV indices of vagal tone and FAR in both younger and older adults. Cognitively normal younger and older adults with varying levels of physical activity were recruited to participate in this study. Cross-sectional data from a self-report measure of physical activity, objectively measured resting HRV, and performance on a FAR task were collected. Younger and older adults' FAR task performance were compared and the relationships between physical activity, resting HRV measures of vagal tone, and FAR were examined.

Participants

Younger adults aged 18-35 years and older adults aged 55-75 years were recruited from the local community to participate in this study via flyers, email announcements, and databases of younger and older adults who had previously participated in research and agreed to be contacted regarding future research opportunities. These age ranges for categorizing younger and older adults were selected in order to be consistent with previous research comparing the FAR abilities of younger and older adults (Goncalves et al., 2018; Ruffman et al., 2008) as well as to match the age range for which the self-report measure of physical activity used in this study was valid (Bull et al., 2009).

Individuals who expressed an interest in the study were screened to determine if they were eligible to participate. Eligibility criteria included being within the designated age ranges, having no diagnosed neurological or psychiatric disorders, and not self-reporting any clinical cognitive impairments. In order to recruit a sample of younger and older adults with varying levels of physical activity, no criteria were established for how physically active participants needed to be. Neurological or psychiatric disorders and clinical cognitive impairments were included as exclusion criteria to eliminate participants who may be experiencing deficits in FAR due to clinical psychopathology. Furthermore, prior to completing any study tasks, the Montreal Cognitive Assessment (MoCA) was administered to all participants to further assess cognitive normality. The MoCA is a brief cognitive screening tool that has been shown to be both highly sensitive and specific for detecting mild cognitive impairment in adults age 55-85 years. A 30-point test, the MoCA assesses short-term memory, visuospatial abilities, executive function, attention, concentration, working memory, language, and orientation (Nasreddine et al., 2005). Individuals who score at or above the cutoff of 26 on the MoCA are considered cognitively normal.

General Procedures

All testing took place during one in-person visit to the Physical Activity and Cognition Laboratory at the University of North Carolina at Greensboro or at a public facility that was easier for the participant to travel to. Prior to their study visit, participants were instructed to follow their normal daily routine but to not engage in any physical activity 24-hours prior to the testing session in order to reduce the potential effect of acute physical activity on cognitive functioning. Upon arrival to the testing session, participants were consented to the study. Following the consent process, the MoCA was administered to assess cognitive normality. Regardless of score on the MoCA, all participants proceeded with the rest of the study visit. During data analysis, all participants who scored below the cutoff score of 26 on the MoCA were removed from statistical analyses.

After the consent process and administration of the MoCA, participants completed a series of questionnaires, including a general demographic questionnaire and physical activity questionnaire. Once all questionnaires were completed, participants were fitted with a polar heart rate chest monitor and 7 minutes of resting HRV data was collected. After 7 minutes, participants then completed the FAR task on a computer. Upon completion of this task, the testing session was concluded, and participants were thanked for their participation in the study.

Measures

General Demographic Questionnaire. Participants completed a general demographic questionnaire that included information concerning their age, sex, race, ethnicity, level of education, and socioeconomic status. Also, due to the potential effects caffeine consumption and exercise can have on cognitive functioning, participants were asked if they had consumed any caffeine that day or if they had exercised on the day of the study visit. A copy of the general demographic questionnaire can be found in Appendix A Measures.

Physical Activity Questionnaire. The Global Physical Activity Questionnaire (GPAQ) version 2 was used to measure participants' physical activity levels. The GPAQ is a self-report measure of physical activity that was selected for use in this study because it is a reliable and valid self-report measure of physical activity for adults age 18-75 years, thus spanning the entire age range of participants recruited for this study. Developed by the World Health Organization as part of the STEPwise Approach to Chronic Disease Risk Factor Surveillance (STEPS), the GPAQ is comprised of 19-items that assess time spent performing moderate and vigorous intensity physical activity in three domains, work, travel, and recreational activities, as well as time spent engaging in sedentary behavior during a typical week (Bull et al., 2009). Data collected from the GPAQ regarding physical activity intensity and time can be used to calculate an individual's Metabolic Equivalent minutes per week (MET-mins/week), thus allowing for the quantification of total physical activity in a week. Reliability of the GPAQ is moderate to strong with kappa statistics ranging from 0.67 to 0.73 across the three domains of physical activity. Concurrent validity assessed by comparing the GPAQ to a previously validated and widely used self-report measure of physical activity, the International Physical Activity Questionnaire-short form (Lee et al., 2011), is moderate with Spearman's rho coefficients ranging from 0.45 for moderate physical activity, to 0.57 for vigorous physical activity, and 0.65 for sedentary behavior. Finally, criterion validity of the GPAQ, measured by examining the association between GPAQ MET-mins/week and objective measures of physical activity (pedometers and accelerometers), is comparable to other self-report measures of physical activity with Spearman's rho coefficients ranging from 0.06 to 0.35 (Bull et al., 2009).

In this study, the GPAQ was administered in a semi-structured interview format in which the researcher asked participants each question, provided examples of the types of physical activity that fell into each domain, and asked follow-up questions to clarify participants' answers regarding how much time and at what intensity they completed each type of physical activity they reported. A copy of the GPAQ can be found in Appendix A Measures.

Resting Heart Rate Variability. To assess the relationship between HRV indices of vagal tone and FAR, resting HRV data was recorded for each participant using a Polar V800 chest monitor and receiver. After completing all questionnaires, participants were fitted with the polar heart rate monitor just below the sternum. Participants were then instructed to sit quietly with their eyes closed, feet flat on the floor, and hands in their lap for 7 minutes. To measure HRV, R to R intervals were recorded for the 7 minutes of seated rest. Raw heart rate data from the polar monitor was extracted as a text file and imported into Kubios HRV Standard 3.3 (Tarvainen et al., 2014). For each participant, 5 minutes of continuous data was selected for analysis. The first minute of recording time was always excluded, and 5 minutes of continuous data was then selected from the remaining recording time based on data quality. Each participant's heart rate data was visually inspected for artifacts and, if necessary, an automatic filter was applied to correct for any artifacts in the data. A very low automatic filter was first applied, and if artifacts still persisted, then a low automatic filter was applied. If artifacts still remained after applying the low automatic filter, then that participant's HRV data was excluded from data analysis due to low quality.

Kubios was then used to calculate time domain and frequency domain indices of HRV. Time domain indices quantify the variability in the time period between successive heartbeats, while frequency domain analysis uses Fast Fourier Transformation modeling to determine the distribution of power of the heart's electrical signal into four frequency bands, ultra-low frequency (≤0.003 Hz), very-low frequency (0.0033–0.04 Hz), low-frequency (0.04–0.15 Hz), and high frequency (0.15–0.40 Hz), where power is the signal energy within each frequency band (Shaffer & Ginsberg, 2017). The time domain variable of interest was the root mean square of successive differences (RMSSD), which is calculated by taking the time difference between successive heartbeats, squaring each value, averaging the results, and then taking the square root of the total. RMSSD therefore indicates variance in the interbeat interval and is the primary time-domain variable to reflect vagal tone (Laborde et al., 2017; Shaffer et al., 2014). Time domain variables of mean heart rate and mean R to R interval were also calculated in order to describe the younger and older adult samples. The frequency domain variable of interest was high frequency power (HF power), which is the absolute power of the high frequency band, also known as the respiratory band because it corresponds to variations in heart rate related to the respiratory cycle. HF power is highly correlated with RMSSD and is also thought to reflect vagal tone (Laborde et al., 2017; Shaffer & Ginsberg, 2017).

Frequency domain variables of low frequency power (LF power), which represents a mixture of both sympathetic and parasympathetic activity, and the low frequency to high frequency ratio (LF/HF ratio) were also calculated in order to characterize the samples.

Facial Affect Recognition Task. FAR was assessed through a computerized task developed using facial stimuli from the FACES database (Ebner et al., 2010) and administered using E-Prime 3.0 software (Psychology Software Tools, Pittsburgh, PA). FACES is a validated set of facial images of 171 Caucasian male and female adults, consisting of younger (n=58), middle-aged (n=56), and older (n=57) adults each displaying six facial expressions: neutral, anger, disgust, fear, happiness, and sadness. The dataset consists of two pictures of each facial expression per model, for a total of 2,052 facial stimuli. Models received training on how to make each facial expression from an experienced research assistant based on a manual developed by Ekman and Friesen (2003). Feedback and instructions were also provided to models during image acquisition (Ebner et al., 2010). For the purposes of this study and to balance the number of male and female stimuli, images of only 56 younger adults (female=28) and 56 older adults (female=28) displaying five facial expressions (anger, disgust, fear, happiness, and sadness) were used, resulting in a total of 560 unique facial images. Examples of the facial stimuli used in this study's FAR task can be found in Appendix A Measures.

The FAR task was a forced choice recognition task in which participants were required to choose from five emotional labels (anger, disgust, fear, happiness, or sadness) when identifying facial expressions. Based on previous research demonstrating that older adults display more difficulty identifying certain facial expressions when a greater number of emotional labels are provided (Orgeta, 2010), five emotional labels were included to make the task as challenging as possible. At the start of the task, participants completed a practice session in which they familiarized themselves with the keys on the keyboard that correspond with each emotional label. This practice session consisted of 15 trials (3 per emotion), during which an emotion label appeared on the screen and participants had to select the key that corresponded with that emotion. Participants were provided with feedback during this practice session to ensure they learned which keys correspond with each emotion. Following this familiarization practice session, participants completed a practice session of the actual FAR task. During this practice session, a facial image appeared on the screen and participants had to choose the emotion label they believed best matched the facial expression displayed on the screen by selecting the key on the keyboard that corresponded with that emotion. This practice session consisted of 15 trials (3 per emotion) comprised of stimuli taken from the FACES database of models that did not appear in the actual task. No feedback was provided to participants during this practice session.

Once participants had completed the practice sessions, they proceeded to the actual FAR task. Prior to the start of the task, participants were instructed as follows, “During this task, a series of facial images will appear on the screen. It is your job to identify the emotion displayed by each facial image by pressing the key on the keyboard that corresponds with the emotion label you believe best matches the facial expression of the image on the screen. Please respond as quickly and accurately as possible with your gut reaction for each facial image". For each facial image, both response accuracy and response time were measured. The task was divided into two blocks, each consisting of 280 stimuli and comprised of no more than 3 images of each model per block. A break was offered between blocks to provide participants with a chance to relax before continuing with the task. Total task time, including the practice sessions, block 1, the break, and block 2, lasted approximately 25 minutes.

Statistical Analyses

Statistical analyses were performed using SPSS 26.0. Preliminary analyses were conducted on the demographic, physical activity, HRV, and FAR measures in order to provide descriptive statistics for the younger and older adult samples. Next, 2 X 2 mixed RMANOVAs were conducted to determine if task block and age category had an impact on overall FAR accuracy and response time. Task block was the within-subjects variable and was inspected in order to assess if task performance significantly differed from block 1 to block 2 due to fatigue or learning effects. Age category was the between-subjects variable and was examined in order to compare overall FAR accuracy and response time between the younger and older adult samples.

Bivariate correlations were then run to explore the associations between demographic, physical activity, RMSSD, HF power, and FAR measures. Finally, in order to assess the predictive relationships proposed in the hypotheses, hierarchical multiple regressions were conducted. If there were significant correlations between any demographic variables and FAR outcome measures, these variables were controlled for in model 1 of each regression. The first set of regressions investigated if physical activity, age category, and the interaction of physical activity and age category could be used to predict FAR performance. Two separate regressions were run with overall accuracy and response time as the criterion. Physical activity and age category were entered into the first model and the interaction of physical activity and age category were entered into the next model. Similarly, separate regressions with overall accuracy and response time as the criterion were conducted in which RMSSD and age category were entered into the first model and the interaction of RMSSD and age category was entered into the next model. Lastly, separate regressions were also conducted for overall accuracy and response time in which HF power and age category were entered into the first model and the interaction of HF power and age category were entered into the next model. Additional hierarchical multiple regressions were also conducted for each emotion's (anger, disgust, fear, happiness, and sadness) accuracy and response time in order to explore the specificity of the relationships.

CHAPTER IV

RESULTS

Descriptive Results

Demographic Information. Data was collected on 45 participants, which included 28 younger adults and 17 older adults. Of those 45 participants, 2 participants were excluded after data collection, one for not achieving a passing score on the MoCA and the other for a recent depression diagnosis. The final sample was therefore comprised of 43 participants, which included 27 younger adults ranging in ages from 18 to 33 years and 16 older adults ranging in ages from 57 to 74 years. Descriptive information is included in Table 1.

Physical Activity Information. Self-reported physical activity data collected using the GPAQ was used to calculate each participant's MET-minutes per week. Descriptive information for total MET-minutes per week, MET-minutes per week at moderate and vigorous intensities, MET-minutes per week across each domain of physical activity, and sedentary time per day is presented in Table 2. Overall, both the younger and older adult samples self-reported being extremely physically active. Individuals meeting weekly physical activity guidelines achieve 600 MET-minutes per week. Therefore, all participants in the younger adult sample exceeded physical activity guidelines, while only 2 older adult participants did not meet physical activity guidelines.

Table 1

Demographic Information

	Younger (n=27)		**Older (n=16)**	
	M	*SD*	*M*	*SD*
Age (years)	23.15	3.62	66.00	5.77
Education (years)	16.48	2.42	16.38	2.19
	Frequency	*%*	*Frequency*	*%*
Sex				
Female	24	88.9	9	56.3
Male	3	11.1	7	43.8
Race				
White	17	63.0	15	93.8
African American	7	25.9	1	6.3
Asian	2	7.4	0	0
Other	1	3.7	0	0
Income				
< $26,000	9	33.3	2	12.5
$26,000-$51,999	4	14.8	1	6.3
$52,000-$74,999	2	7.4	3	18.8
$75,000-$100,999	3	11.1	3	18.8
>$101,000	4	14.8	6	37.5
Declined	5	18.5	1	6.3

Table 2

Physical Activity Information

	Younger (n=27)			**Older (n=16)**		
	M	*SD*	*Range*	*M*	*SD*	*Range*
MET-mins/week						
Total	5865.93	5329.09	680-21,840	4796.25	3216.03	240-11,880
Moderate Intensity	3003.70	2855.51	360-11,280	2096.25	2049.30	240-9,000
Vigorous Intensity	2862.22	3819.13	0-14,880	2700.00	2347.42	0-8,400
Work Domain	3206.67	4721.52	0-18,000	1267.50	1731.76	0-6,720
Transportation Domain	714.81	941.63	0-3,360	467.50	777.69	0-2,400
Recreation Domain	1933.33	1496.23	480-6,240	3061.25	2380.53	240-8,760
Sedentary Time Per Day (hours)	6.72	2.61	2.00-13.00	6.06	3.41	2.00-13.00

Heart Rate Variability Information. Resting heart rate data from 30 participants (21 younger and 9 older) was included in the final sample. Heart rate data was not collected on 5 participants due to technical difficulties during data collection, and 8 other participants were excluded during data analysis because of low quality data. Correlations and regressions for HRV variables and FAR outcome measures were run separately for this smaller sample (n=30). Descriptive information for HR data is included in Table 3.

Table 3

Heart Rate Information

	Younger (n=21)		Older (n=9)	
	M	*SD*	*M*	*SD*
HR (bpm)	72.71	9.91	69.00	11.82
RR (ms)	840.24	115.05	891.67	142.50
RMSSD (ms)	46.61	14.03	19.53	10.05
HF power (ms^2)	1001.95	706.72	148.56	152.84
LF power (ms^2)	1437.00	1773.51	175.22	115.46
LF/HF ratio	2.47	4.67	2.52	2.02

Note. HR = resting heart rate; RR = R to R interval; RMSSD = root mean square of the successive differences; HF power = relative power of the high frequency band; LF power = relative power of the low frequency band; LF/HF ratio = ratio of low frequency to high frequency

Facial Affect Recognition Performance. Descriptive information for the FAR outcome measures, including overall accuracy and response time, accuracy and response time for each emotion, and accuracy and response time for both young and old faces is provided in Table 4

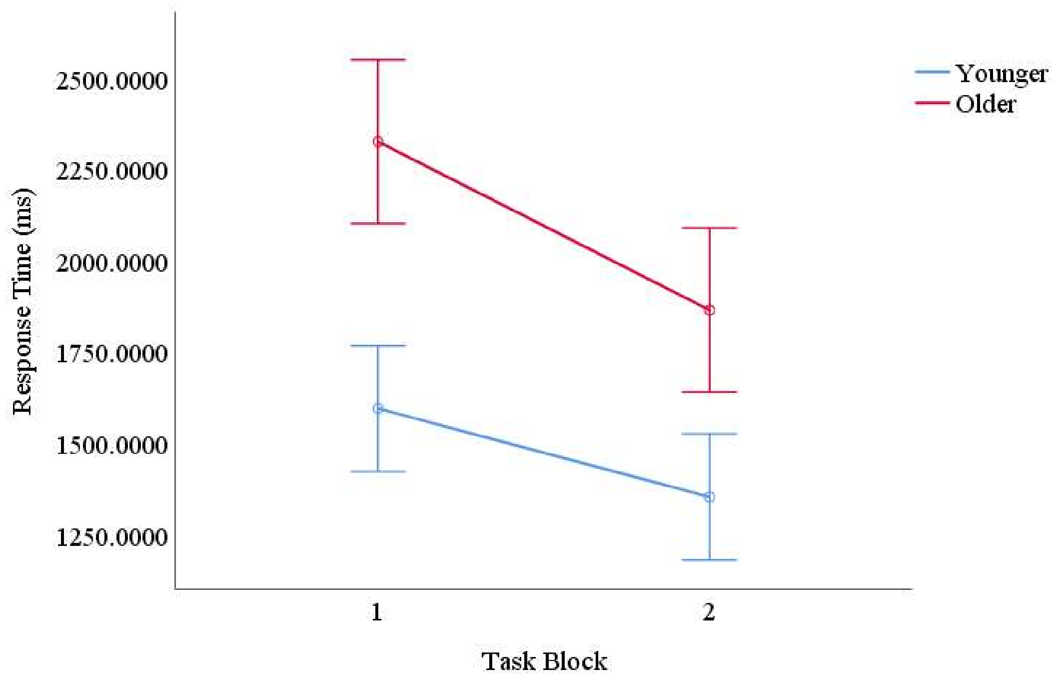
Table 4

Facial Affect Recognition Performance

	Younger (n=27)						Older (n=16)					
	Block 1		**Block 2**		**Overall**		**Block 1**		**Block 2**		**Overall**	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Accuracy												
Overall	0.82	0.06	0.84	0.07	0.83	0.06	0.84	0.11	0.84	0.11	0.84	0.11
Angry	0.77	0.16	0.77	0.16	0.77	0.15	0.77	0.15	0.78	0.16	0.78	0.15
Disgust	0.73	0.11	0.73	0.11	0.73	0.10	0.73	0.17	0.67	0.21	0.70	0.18
Fear	0.91	0.06	0.92	0.07	0.91	0.05	0.91	0.13	0.86	0.18	0.89	0.15
Happy	0.99	0.03	0.99	0.01	0.99	0.01	0.99	0.03	1.00	0.01	0.99	0.02
Sad	0.72	0.16	0.80	0.15	0.76	0.15	0.79	0.17	0.88	0.11	0.84	0.14
Young Faces	0.88	0.06	0.88	0.07	0.88	0.06	0.88	0.12	0.87	0.11	0.88	0.11
Old Faces	0.77	0.07	0.80	0.08	0.79	0.07	0.80	0.11	0.81	0.12	0.80	0.11
Response Time (ms)												
Overall	1593.40	279.90	1351.53	216.63	1472.47	232.08	2323.99	634.19	1863.15	677.71	2093. 57	647.99
Angry	1779.86	431.62	1514.16	269.83	1647.01	325.99	2508.87	633.01	1947.34	591.13	2228.10	594.45
Disgust	1692.74	373.23	1472.39	281.37	1582.56	309.36	2447.44	834.87	2142.28	827.21	2294.86	815.16
Fear	1558.14	291.89	1347.84	281.01	1452.99	260.69	2385.32	787.66	2033.04	1094.23	2209.18	933.12
Happy	1064.07	241.03	943.56	180.83	1003.81	199.61	1563.67	474.18	1211.72	293.34	1387.69	363.16
Sad	1872.20	436.25	1479.73	312.32	1675.96	353.93	2714.66	767.10	1981.38	741.36	2348.02	740.60
Young Faces	1493.74	269.26	1298.74	215.53	1396.24	226.06	2188.77	623.25	1733.05	626.05	1960.91	616.45
Old Faces	1693.05	305.41	1404.33	232.80	1548.69	249.31	2459.21	669.99	1993.25	753.76	2226.23	700.70

A 2 (block 1, block 2) X 2 (younger, older) mixed RMANOVA was conducted to examine if task block and age category had an effect on overall FAR accuracy. Results indicated that there was no main effect of task block ($F(1,41)=2.14$, $p=0.15$, $\eta_p^2=0.05$) and no main effect of age category ($F(1,41)=0.06$, $p=0.81$, $\eta_p^2<0.01$) on overall accuracy. There was also no interaction between task block and age category ($F(1,41)=0.84$, $p=0.37$, $\eta_p^2=0.02$). Similarly, a 2 (block 1, block 2) X 2 (younger, older) mixed RMANOVA was conducted to examine if task block and age category had an effect on overall FAR response time. Results showed that there was a significant main effect of task block ($F(1,41)=130.04$, $p<0.01$, $\eta_p^2=0.76$) with response time on block 2 faster than block 1. There was also a significant main effect of age category ($F(1,41)=20.64$, $p<0.01$, $\eta_p^2=0.34$) with younger adults performing faster than older adults. Additionally, there was a significant interaction between task block and age category ($F(1,41)=12.63$, $p<0.01$, $\eta_p^2=0.24$) with older adults exhibiting a greater reduction in response time from block 1 to block 2 compared to younger adults (see Figure 1).

Figure 1. Overall Response Time on Blocks 1 and 2 for Younger and Older Adults



Correlations

Association Between Demographic Variables and Facial Affect Recognition Measures. Bivariate correlations were conducted to examine the relationship between age, years of education, and FAR accuracy measures. There was a significant positive correlation between years of education and overall accuracy ($r=0.39$, $p<0.05$), fear accuracy ($r=0.36$, $p<0.05$), young faces accuracy ($r=0.35$, $p<0.05$), and old faces accuracy ($r=0.40$, $p<0.01$), indicating that a greater number of years of education was associated with higher accuracy on these specific FAR accuracy measures. There were no other significant correlations at the $p<0.05$ level (see Table 5 in Appendix B Tables).

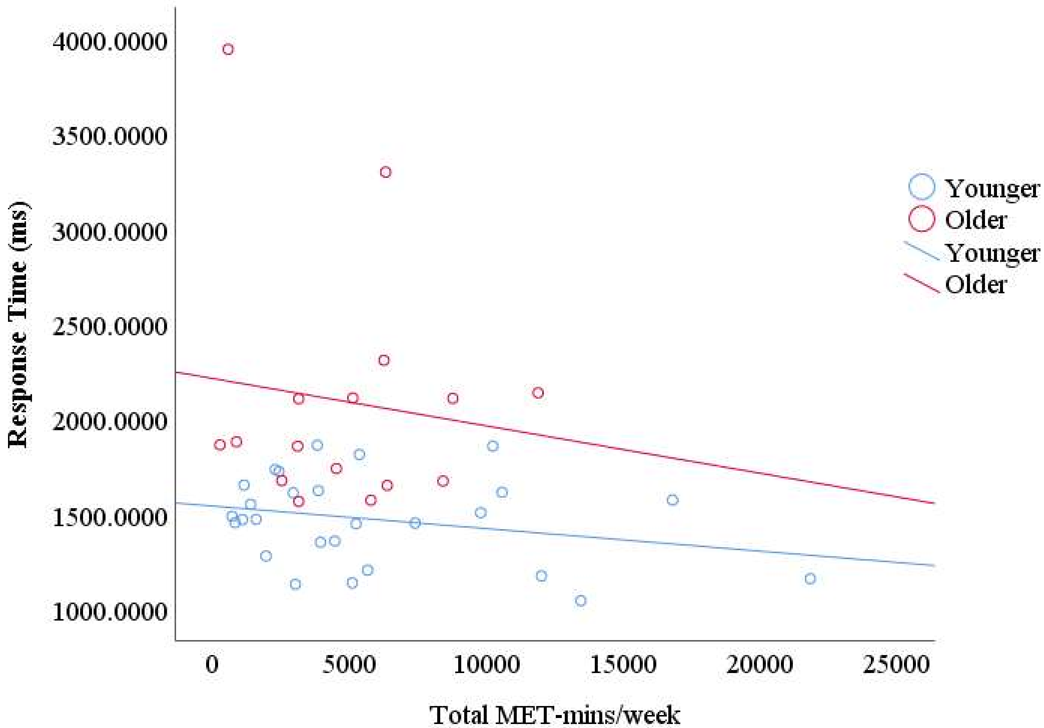
In order to examine the specificity of the relationships between demographic variables and FAR accuracy measures within each age group, separate correlations were run for the younger and older adult samples. For the younger adult sample, there were no significant correlations at the $p<0.05$ level. However, for the older adult sample, there were significant positive correlations between years of education and overall accuracy ($r=.61$, $p<0.05$), angry accuracy ($r=.58$, $p<0.05$), disgust accuracy ($r=.51$, $p<0.05$), fear accuracy ($r=.57$, $p<0.05$), young faces accuracy ($r=.57$, $p<0.05$), and old faces accuracy ($r=.63$, $p<0.01$), with a greater number of years of education associated with higher accuracy on these measures (see Table 6 in Appendix B Tables).

Bivariate correlations were also conducted for age, years of education, and FAR response time measures. There were significant positive correlations between age and overall response time ($r=0.58$, $p<0.01$), angry response time ($r=0.56$, $p<0.01$), disgust response time ($r=0.55$, $p<0.01$), fear response time ($r=0.52$, $p<0.01$), happy response time ($r=0.56$, $p<0.01$), sad response time ($r=0.52$, $p<0.01$), young faces response time ($r=0.56$, $p<0.01$), and old faces response time ($r=0.58$, $p<0.01$). Greater age was associated with slower response times. There were no significant correlations between years of education and any of the response time measures at the $p<0.05$ level (see Table 7 in Appendix B Tables). When examining these relationships for each age group separately, there was a significant positive correlation between age and angry response time in the younger adult sample ($r=.40$, $p<0.05$), with greater age associated with a slower response time to angry facial expressions. No other correlations were significant at the $p<0.05$ level for the younger adult sample. For the older adult sample, there was a significant negative correlation between years of education and fear response time ($r=-.53$, $p<0.05$), indicating that a greater number of years of education was associated with a faster response time to fearful facial expressions. No other correlations were significant at the $p<0.05$ level for the older adult sample (see Table 8 in Appendix B Tables).

Association Between Physical Activity Variables and Facial Affect Recognition Measures. Bivariate correlations were conducted for physical activity variables as measured by the GPAQ and FAR accuracy measures. There was a significant negative correlation between transportation MET-mins/week and happy accuracy ($r=-0.49$, $p<0.01$), indicating that more time spent engaging in physical activity in the transportation domain was associated with lower accuracy when identifying happy facial expressions. No other correlations were statistically significant at the $p<0.05$ level (see Table 9 in Appendix B Tables). Separate correlations for total physical activity level and FAR accuracy measures were then run for each age group, but no significant relationship at the $p<0.05$ level emerged in either the younger adult or older adult samples (see Table 10 in Appendix B Tables).

Bivariate correlations were also performed for physical activity variables and FAR response time measures. There were no significant correlations at the $p<0.05$ level (see Table 11 in Appendix B Tables). There were also no significant associations at the $p<0.05$ level when the correlations between total physical activity and FAR response time measures were run separately for each age group (see Table 12 in Appendix B Tables). Figure 2 shows the scatterplot of the relationship between overall response time and total physical activity level labeled by age category.

Figure 2. Scatterplot of the Relationship Between Overall Response Time and Physical Activity Level for Younger and Older Adults



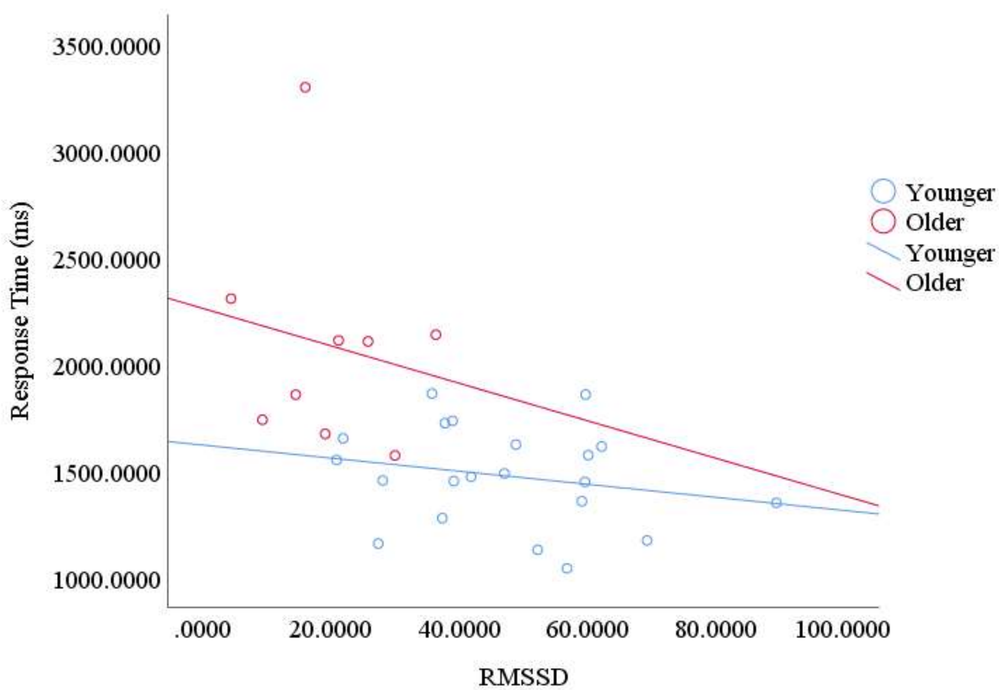
Association Between Heart Rate Variability Variables and Facial Affect Recognition Measures. Bivariate correlations were conducted for RMSSD, HF power, and FAR accuracy measures, but no correlations were significant at the $p<0.05$ level (see Table 13 in Appendix B Tables). When these correlations were run separately for each age group, no significant relationships emerged at the $p<0.05$ level (see Table 14 in Appendix B Tables).

The relationship between RMSSD and FAR response time measures was also examined with bivariate correlations. Results revealed significant negative correlations between RMSSD and overall response time ($r=-.52$, $p<0.01$), angry response time

($r=-.53$, $p<0.01$), disgust response time ($r=-.46$, $p<0.01$), fear response time ($r=-.47$, $p<0.01$), happy response time ($r=-.49$, $p<0.01$), sad response time ($r=-.40$, $p<0.05$), young faces response time ($r=-.53$, $p<0.01$), and old faces response time ($r=-.51$, $p<0.01$). Greater response time indicates slower performance, and a negative relationship between RMSSD and response time measures was expected (see Table 15 in Appendix B Tables).

The correlations between RMSSD and FAR response time measures were also run separately for each age group. However, there were no significant correlations at the $p<0.05$ level for either the younger adult or older adult samples (see Table 16 in Appendix B Tables). Figure 3 depicts the scatterplot of the relationship between overall response time and RMSSD labeled by age category.

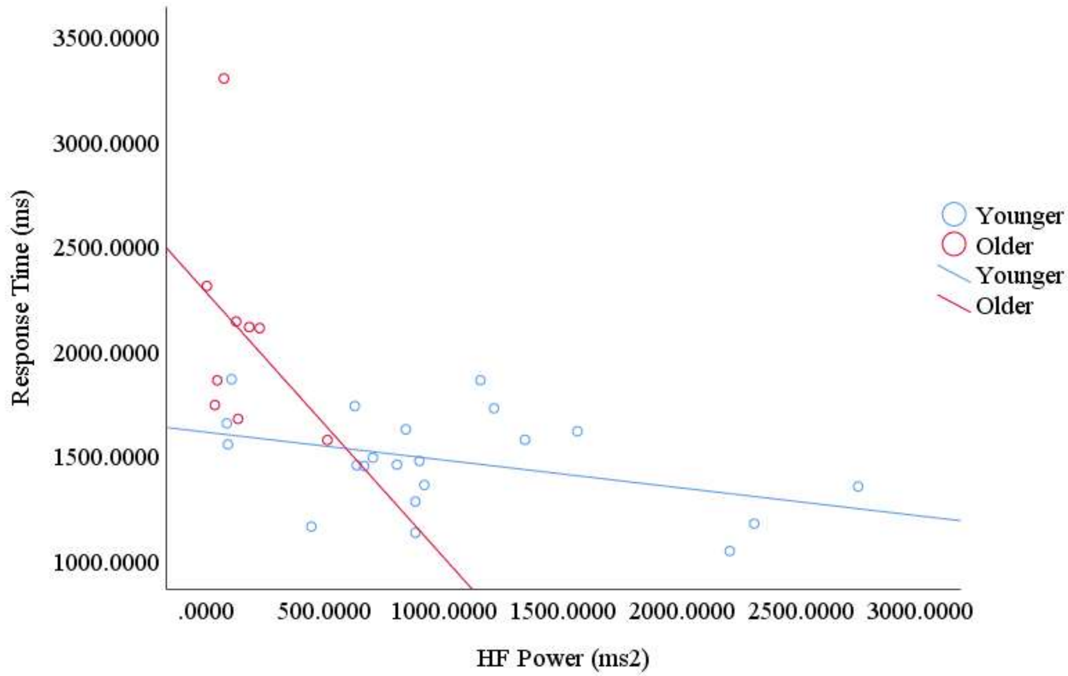
Figure 3. Scatterplot of the Relationship Between Overall Response Time and RMSSD for Younger and Older Adults



Similarly, the relationship between HF power and FAR response time measures was also assessed with bivariate correlations. Significant negative correlations were found between HF and overall response time ($r-.54$, $p<0.01$), angry response time ($r=-.57$, $p<0.01$), disgust response time ($r=-.52$, $p<0.01$), fear response time ($r=-.44$, $p<0.05$), happy response time ($r=-.54$, $p<0.01$), sad response time ($r=-.38$, $p<0.05$), young faces response time ($r=-.59$, $p<0.01$), and old faces response time ($r=-.49$, $p<0.01$). Again, greater response time indicates slower performance, and a negative relationship between HF power and response time measures was expected (see Table 15 in Appendix B Tables).

The relationship between HF power and FAR response time measures was then assessed for the younger and older adult samples separately. For the younger adults, there were significant negative correlations between HF power and angry response time ($r=-.50$, $p<0.05$) and young faces response time ($r=-.48$, $p<0.05$), indicating that higher HF power was associated with faster response times to angry and young faces. However, for the older adult sample no significant correlations at the $p<0.05$ level emerged (see Table 16 in Appendix B Tables). Figure 4 shows the scatterplot of the relationship between overall response time and HF power labeled by age category.

Figure 4. Scatterplot of the Relationship Between Overall Response Time and HF Power for Younger and Older Adults



Associations Between Physical Activity and Heart Rate Variability Variables. Since physical activity is associated with more favorable indicators of autonomic functioning (Soares-Miranda Luisa et al., 2014), the relationship between total physical activity level and both RMSSD and HF power was examined with bivariate correlations. There were no significant correlations between total MET-mins/week and RMSSD or HF power at the $p<0.05$ level. However, there was a significant positive correlation between RMSSD and HF power ($r=0.87$, $p<0.01$), such that higher resting RMSSD was associated with higher resting HF power (see Table 17 in Appendix B Tables).

Regression Analyses

Age Group and Physical Activity Level as Predictors. To test the hypothesis that age category, physical activity, and the interaction between age category and physical activity would be significant predictors of overall FAR accuracy, a hierarchical multiple regression was conducted. Since years of education was significantly correlated with overall accuracy, years of education was controlled for in model 1 of the regression The regression equation for model 1 was significant ($F(1,41)=7.16$, $p=0.01$, $R^2=0.15$) indicating that years of education was a significant predictor of overall accuracy, with 15% of the variance in FAR accuracy explained for by years of education. A greater number of years of education was associated with higher accuracy. The regression equations for model 2 ($\triangle F(2,39)=0.72$, $p=0.49$, $\triangle R^2=0.03$) and model 3 (($\triangle F(1,38)=0.63$, $p=0.43$, $\triangle R^2=0.01$) were both not significant, indicating that age category, total MET-mins/week, and the interaction between age category and total MET-mins/week were not significant predictors of overall FAR accuracy.

A hierarchical multiple regression was also performed to test the hypothesis that age category, physical activity, and the interaction between age category and physical activity level would be significant predictors of overall FAR response time. The regression equation for model 1 was significant ($F(2,40)=10.78$, $p<0.01$, $R^2=0.35$). The analysis showed that age category ($\beta=606.00$, $p<0.01$) was a significant predictor of overall response time, with older age associated with greater response time. Total MET-mins/week ($\beta=-0.01$, $p=0.34$) was not a significant predictor. The regression equation for model 2 ($\triangle F(1,39)=0.11$, $p=0.74$, $\triangle R^2=0.00$) was not significant indicating that the interaction between age category and total MET-mins/week was not a significant predictor of overall response time. A summary of the hierarchical regression analyses for physical activity level can be found in Appendix B Tables (Table 18).

Additional hierarchical multiple regressions were performed to examine if age category, physical activity, and the interaction of age category and physical activity would be significant predictors of overall FAR accuracy and response time for each emotion. None of the predictors were significant. A summary of the hierarchical regressions for each emotion can be found in Appendix B Tables.

Age Group and Heart Rate Variability as Predictors. To test the hypothesis that age category, RMSSD, and the interaction of age category and RMSSD would be significant predictors of overall FAR accuracy, a hierarchical multiple regression was performed. Since years of education was not significantly correlated with overall accuracy in the smaller sample for whom HRV data was available, years of education was not controlled for in the regression. The regression equation for model 1 ($F(2,27)=0.44$, $p=0.65$, $R^2=0.03$) was not significant, indicating that age category and RMSSD were not significant predictors of overall accuracy. The regression equation for model 2 ($\triangle F(1,26)=1.41$, $p=0.25$, $\triangle R^2=0.05$) was also not significant, indicating that the interaction of age category and RMSSD was also not a significant predictor of overall FAR accuracy.

A hierarchical multiple regression was then also performed to examine if age category, RMSSD, and the interaction of age category and RMSSD would be significant predictors of overall FAR response time. The regression equation for model 1 was significant ($F(2,27)=10.67$, $p<0.01$, $R^2=0.44$). Analysis indicated that age category ($\beta=508.73$, $p<0.01$) but not RMSSD ($\beta=-3.75$, $p=0.38$) was a significant predictor of overall response time, with older age associated with greater response time. The regression equation for model 2 was not significant ($\triangle F(1,26)=0.19$, $p=0.66$, $\triangle R^2=0.00$) indicating that the interaction between age category and RMSSD was not a significant predictor of overall response time. A summary of the hierarchical regression analyses for RMSSD can be found in Appendix B Tables (Table 19).

Additional hierarchical multiple regressions were performed to examine if age category, RMSSD, and the interaction of age category and RMSSD would be significant predictors of overall FAR accuracy and response time for each emotion. None of the predictors were significant. A summary of the hierarchical regressions for each emotion can be found in Appendix B Tables.

To test the hypothesis that age category, HF power, and the interaction of age category and HF power would be significant predictors of overall FAR accuracy, a hierarchical multiple regression was performed. Since years of education was not significantly correlated with overall accuracy in the smaller sample for whom HRV data was available, years of education was not controlled for in the regression. The regression equation for model 1 was not significant ($F(2,27)=0.37$, $p=0.69$, $R^2=0.03$) indicating that age category and HF power were not significant predictors of overall accuracy. The regression equation for model 2 ($\triangle F(1,26)=1.28$, $p=0.27$, $\triangle R^2=0.05$) was also not significant, indicating that the interaction of age category and HF power was not a significant predictor of overall FAR accuracy.

Finally, a hierarchical multiple regression was also conducted to examine if age category, HF power, and the interaction of age category and HF power were significant predictors of overall FAR response time. The regression equation for model 1 was significant ($F(2,27)=11.88$, $p<0.01$, $R^2=0.47$). Analysis revealed that age category ($\beta=481.09$, $p<0.01$) but not HF power ($\beta=-0.15$, $p=0.15$) was a significant predictor of overall response time, with older age associated with greater response time. The regression equation for model 2 was not significant ($\triangle F(1,2630)=2.26$, $p=0.15$, $\triangle R^2=0.04$), indicating that the interaction between age category and HF power was not a significant predictor of overall FAR response time. A summary of the hierarchical regression analyses for HF power can be found in Appendix B Tables (Table 20).

Additional hierarchical multiple regressions were performed to examine if age category, HF power, and the interaction of age category and HF power would be significant predictors of overall FAR accuracy and response time for each emotion. The regression equation for age category and HF power on angry response time revealed a significant effect ($F(2,27)=9.47$, $p<0.01$, $R^2=0.41$), as results showed that HF power was a significant predictor of angry response time ($\beta=-0.25$, $p<0.05$). A summary of the hierarchical regressions for each emotion can be found in Appendix B Tables.

CHAPTER V

DISCUSSION

Previous research has provided evidence that physical activity can prevent or reduce the severity of age-related cognitive declines. However, this research has primarily examined the relationship between physical activity and a subset of cognitive constructs, such as executive function, memory, and processing speed, with limited research on the relationship between physical activity and social cognitive constructs, like FAR. The purpose of this study was therefore to begin to describe the relationship between physical activity, resting HRV indices of vagal tone, and FAR in both younger and older adults.

Summary of Findings

Results partially supported the hypothesis that older adults would perform worse than younger adults on the FAR task, as the older adult sample had a significantly slower overall response time. Furthermore, age and response time were significantly correlated across all emotions as well as both young and old faces, indicating that older age was consistently associated with slower response times.

Physical activity, RMSSD, HF power, and the interaction of these variables with age category were not found to be significant predictors of overall FAR accuracy or response time. However, HF power was predictive of response time to angry facial expressions. Furthermore, the relationship of RMSSD and HF power with overall response time, response times for each emotion, and response times to both young and old faces were significant, with higher RMSSD and HF power associated with faster response times.

This study provides important insight into the relationships between physical activity, RMSSD, HF power, and FAR in both younger and older adults. Given the FAR deficits older adult frequently experience and the impact these deficits can have on social functioning, mental and physical health, and overall quality of life, the findings of this study have important implications. This study therefore provides preliminary evidence that there may be positive relationships between physical activity, resting HRV indices of vagal tone, and FAR abilities, and suggests that future research is needed in order to better understand these relationships and determine if physical activity can preserve or improve the FAR abilities of older adults.

Interpretation of Findings

Facial Affect Recognition in Younger Adults Versus Older Adults. Contrary to previous research in which older adults were less accurate at identifying facial expressions of emotion compared to younger adults (Gonçalves et al., 2018; Grainger et al., 2015; Isaacowitz et al., 2007; Orgeta, 2010; Orgeta & Phillips, 2007; Ruffman et al., 2008; Sullivan & Ruffman, 2004), there were no significant differences in overall accuracy, accuracy for each emotion, or accuracy for young or old faces between the younger and older adult samples in this study. The lack of significant differences in accuracy between the younger and older adults in this study could be due to the small sample size, which may have affected the power to detect significant differences. Another explanation for why differences in accuracy were not observed could be the use of an unlimited response window. While participants were instructed to respond as quickly as possible with their gut reaction to each facial expression, there was no time restriction placed on how long stimuli were presented before participants had to respond. This unlimited response window was necessary to measure response time, but may have made the task easier by allowing participants to view each stimulus for as long as they needed to. The older adults may have therefore been just as accurate as the younger adults because they had unlimited time to correctly identify each facial expression.

It is also possible that no accuracy differences were observed between the younger and older adult age groups because both young and old facial stimuli were included in the present study's FAR task. The vast majority of previous research that has found deficits in older adults FAR abilities has only used young facial stimuli. However, some research has shown that an own-age advantage may exist whereby older adults are more accurate when identifying older aged faces as opposed to younger aged faces (Bäckman, 1991; Lamont et al., 2005). Although not significant, the older adults in this study were more accurate than the younger adults at identifying older facial stimuli. However, both the younger and older adults were more accurate identifying the younger facial stimuli compared to the older facial stimuli. This higher accuracy in identifying younger facial stimuli falls in line with another body of previous research that suggests younger faces are easier to identify due to people's preference for younger faces, or perhaps because of an increased difficulty in identifying older facial expressions due to age-related changes in facial features (Ebner & Johnson, 2009).

While there were no differences in FAR accuracy observed between the younger and older age groups, the older adult group did exhibit a significantly slower overall response time. Furthermore, correlations revealed significant positive relationships between age and response time for each emotion as well as both young and old faces, indicating that older age was associated with slower response times irrespective of the age of the person providing the facial expression. This finding therefore suggests that while the younger and older adults were able to achieve similar levels of accuracy in identifying different facial expressions of emotion, the older adults took significantly more time to make those identifications. While most of the research on FAR has focused on accuracy rather than response time, a study by Sullivan and Ruffman (2004) also found that older adults were significantly slower at identifying facial expressions of emotion compared to younger adults. Slower response times in identifying facial expressions of emotion have important implications, as social situations in the real world are fast moving. Difficulties in quickly identifying emotional facial stimuli could therefore negatively impact older adults' social functioning and quality of life.

Physical Activity and Facial Affect Recognition. Physical activity was not a significant predictor of overall accuracy and the relationship between physical activity and overall accuracy was not significant. However, the relationship between physical activity and overall accuracy was in the expected direction, with greater total MET-mins/week tending to be associated with higher overall accuracy. This was also true when the relationship between overall accuracy and total MET-mins/week was examined for the younger and older adult samples separately. Furthermore, the relationships between physical activity and accuracy for each emotion, with the exception of happiness, as well as both young and old faces were also in the expected direction, with greater total MET-mins/week tending to be associated with higher accuracy. The consistency of these findings is promising, especially given the small sample size and low power to detect significant associations, as well as the lack of diversity in the physical activity levels of the participants in this study. While an effort was made to recruit participants of varying physical activity levels, the vast majority of participants in this study reported being very physically active, as only 2 participants' total MET-minutes/week did not meet physical activity guidelines. This lack of diversity in participants' self-reported physical activity levels could be why no significant relationships between physical activity and FAR performance emerged.

Physical activity level was also not a significant predictor of overall response time and the relationship between physical activity and overall response time was not significant. However, the relationships between physical activity overall response time, response time for each emotion, and response time to both young and old faces were all in the expected direction, with greater total MET-mins/week tending to be associated with a faster overall response time. Furthermore, the direction of these relationships was consistent for both the younger and older adult samples. Again, given the consistency of these correlations, the small sample size, low power, and lack of diversity in the self-reported physical activity levels of the participants in this study, these results are promising and could have important real-world implications for the slower FAR response times observed in the older adult sample.

Heart Rate Variability and Facial Affect Recognition. Neither RMSSD, HF power, or the interaction between age category and these HRV indices of vagal tone were significant predictors of overall accuracy. The relationships between RMSSD, HF power and overall accuracy, accuracy for each emotion, and accuracy for both younger and older faces were also not significant and were in the expected direction for some accuracy measures but not for others. However, when these relationships were examined in the older adult sample separately, the correlations were all in the expected direction, with higher resting RMSSD and HF power tending to be associated with higher accuracy scores. Since HRV data was only collected on 9 older adult participants, these findings are preliminary, but the consistency is promising and may suggest that HRV indices of vagal tone are associated with FAR accuracy in older adults but not younger adults. In previous research conducted with college-aged students, HF HRV was found to be a significant predictor of FAR accuracy (Quintana et al., 2012). However, the task used in that study only focused on the eye region of the face and provided participants with a variety of emotion labels to choose from, such as playful and pensive, instead of just the basic emotions. The FAR task used in that study was therefore very different from the one used in this study, making it difficult to draw comparisons.

While neither RMSSD, HF power, or the interaction between age category and these HRV indices of vagal tone were significant predictors of overall response time, HF power was a significant predictor of response time to angry facial stimuli. Additionally, there were significant negative correlations between RMSSD, HF power, overall response time, response times for each emotion, and response times for both young and old faces, with higher RMSSD and HF power associated with faster response times. When the older and younger adult samples were examined separately, the relationships between RMSSD, HF power, and FAR response time measures all remained in the expected direction. These findings are consistent with previous research in which the resting RSA of children with autism was negatively correlated with FAR response times, such that higher RSA was associated with faster response times. While children with autism are a different population from the healthy, cognitively normal younger and older adults that participated in this study, the present findings complement this earlier finding and suggest that vagal tone is associated with the speed in which facial expressions of emotion can be identified in populations with and without FAR deficits.

Research has shown that individuals who are physically active tend to have better autonomic functioning compared to individuals who are inactive or less physically active (Soares-Miranda Luisa et al., 2014). While total physical activity level was not significantly correlated with resting RMSSD or HF power in this study, these relationships were in the expected direction, with higher physical activity level tending to be associated with higher RMSSD and HF power. Since RMSSD and HF power were associated with faster FAR response times, this study provides preliminary support for the hypothesis that physical activity may be positively associated with FAR through its influence on autonomic nervous system functioning.

Limitations

The present study had several limitations. First, the findings of this study are based on a small sample size of younger and older adults, which may have impacted the power to detect statistically significant relationships between physical activity, RMSSD, HF power, and FAR. However, even with this low power, the relationships between physical activity, HRV indices of vagal tone, and FAR accuracy and response time were consistently in the expected directions for both the younger and older adult samples, with higher physical activity level and higher HRV indices of vagal tone tending to be associated with better FAR performance.

In addition to the small sample size and low power, the sample was also very homogenous in terms of biological sex (mostly female) and race (mostly white), which limits the generalizability of this study's findings to younger and older adult populations as a whole. Moreover, there was a lack of diversity in the physical activity levels of the individuals who participated in this study. According to calculations of participants' total MET-mins/week based on their self-reported physical activity behavior from the GPAQ, only 2 older adult participants did not meet weekly physical activity guidelines (600 MET/mins/week). Moreover, the average total MET-mins/week for the younger and older adult samples indicated that the vast majority of participants greatly exceeded weekly physical activity guidelines. The inability to successfully recruit individuals who were not regularly physically active to this study, may have therefore impacted the ability to detect significant relationships between physical activity and FAR, as almost all of the participants in this study were highly physically active people. Additionally, this lack of diversity in physical activity levels, limits the generalizability of this study's finding to highly physically active people and therefore may not be representative of the relationships between physical activity and FAR in less physically active or sedentary populations.

Another limitation of the present study was the use of a subjective self-report measure of physical activity behavior as the only method for quantifying participants' physical activity levels. While the GPAQ is a valid and reliable self-report measure of physical activity that is comparable to other commonly used self-report physical activity instruments (Bull et al., 2009), research has shown that self-report measures of physical activity are weakly associated with more objective measures of physical activity, like pedometers and accelerometers. There therefore could have been a large amount of error in the self-reported physical activity levels of the participants in this study. According to the Centers for Disease Control and Prevention (CDC), only 53.3% of adults over the age of 18 meet weekly physical activity guidelines for aerobic physical activity (CDC, 2019). Yet 95% of participants in this study did meet physical activity guidelines based on their self-reported physical activity behavior. While measuring people's physical activity behavior is difficult and always comes with some limitations as there is no gold standard of measurement, including both a subjective self-report measure of physical activity along with a more objective measure could have provided a more complete picture of participants' physical activity behavior in a typical week. The use of an objective measure of physical activity may therefore have reduced the error in participants' reported physical activity levels, thus increasing the reliability of the findings regarding the relationship between physical activity and FAR.

A final limitation of the present study was the loss of 8 participants' HRV data during data analysis due to low data quality. While using a polar heart rate monitor is quick, easy, and convenient during data collection, it does pose some limitations during data analysis. Specifically, unlike electrocardiogram (ECG) recordings where artifacts can individually be removed from heart rate data during analysis, 5 minutes of clean continuous recording is required for analysis of heart rate data collected from a polar monitor. Using ECG recordings to measure HRV indices of vagal tone may therefore have provided a larger sample of participants with HRV data in this study.

Future Directions

Overall, the findings of this study suggest that higher physical activity levels and higher resting HRV indices of vagal tone may be associated with better FAR abilities in both younger and older adults. However, future research is needed in order to address some of the limitations of the present study. First, a study with a larger sample of older and younger adult participants is needed so that adequate statistical power to detect potentially significant relationships between physical activity, HRV indices of vagal tone, and FAR can be achieved. Second, in order to truly examine the relationship between physical activity and FAR, a sample of participants from across the physical activity spectrum needs to be recruited. Future research should utilize both subjective and objective measures of physical activity in order to obtain a more accurate representation of participants' physical activity behavior. Additionally, future research should use ECG recordings to measure HRV so that less data is lost due to low quality.

While this study was a necessary first step in examining the relationships between physical activity, RMSSD, HF power, and FAR, future research aimed at investigating if physical activity can improve or preserve the FAR abilities of older adults is needed. Possible research directions include investigating if a chronic physical activity intervention program may benefit the FAR abilities of older adults. Previous research has demonstrated that physical activity interventions can benefit the cognitive functioning of older adults (Angevaren et al., 2008; Northey et al., 2018). While this body of research has not examined social cognitive abilities or FAR specifically, it does provide evidence that chronic physical activity interventions benefit older adults' cognitive functioning. Given the associations between deficits in FAR and impaired social functioning, reduced social engagement, and loneliness, determining if physical activity interventions are viable strategies for preserving or improving the FAR abilities of older adults is a necessary research direction with important implications for the health and quality of life.

Another potential future research direction would be to investigate the effect an acute bout of aerobic exercise can have on the FAR abilities of both younger and older adults. A growing body of literature has provided evidence that an acute bout of aerobic exercise can benefit cognitive functioning (Chang et al., 2012; Lambourne &

Tomporowski, 2010). However, this body of research has not examined what effect an acute bout of exercise has on FAR abilities. Future research investigating this question is needed, as it has important real-world applications for enhancing people's social cognitive functioning.

Finally, future research is also needed to begin investigating the potential mechanisms through which physical activity may benefit FAR. Research investigating physiological mechanisms through which physical activity may impact FAR, such as the preservation of brain structures and functions associated with emotion perception or other cognitive abilities is one interesting research direction. Another interesting direction could be to examine if the social setting in which physical activity occurs impacts FAR by facilitating social interactions and promoting increased social engagement.

In conclusion, this study found that compared to younger adults, older adults were significantly slower at recognizing different facial expressions of emotions. Results also indicate that higher physical activity levels tended to be associated with better FAR performance and resting HRV indices of vagal tone were negatively correlated with FAR response times, with higher resting RMSSD and HF power associated with faster response times. Given that social situations in the real-world are fast moving and older adults appear to be slower at recognizing different facial expressions of emotion, the findings of this study may have important real-world implications for preserving or improving the FAR abilities of older adults. However, more research is needed in order to better understand the relationships between physical activity, HRV indices of vagal tone, and FAR, as well as to investigate if physical activity is a useful intervention strategy for targeting the FAR deficits observed in older adults.

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APPENDIX A

MEASURES

General Demographic Questionnaire

General Demographic Questionnaire

Please answer the following demographic questions as accurately as possible.

1. What is your biological sex? ☐ Female ☐ Male

2. How old are you? ____________

3. What is your date of birth? ____________

4. What is your race? Please check all that apply.

☐ Asian ☐ American Indian or Alaska Native

☐ Black/African American ☐ Native Hawaiian or Pacific Islander

☐ White/Caucasian ☐ Other

5. What is your ethnicity? ☐ Hispanic or Latino ☐ Not Hispanic or Latino

6. How many years of education have you completed? ____________

7. What was your total household income last year? (If you are a dependent, please provide the income of your parent/guardian)

☐ $0-25,999 ☐ $26,000-51,999

☐ $52,000-74,999 ☐ $75,000-100,999

☐ More than $101,000 ☐ Don't know/Decline to say

8. Did you exercise today? ☐ Yes ☐ No

9. Have you consumed any caffeine today? ☐ Yes ☐ No

If yes, how much? ____

Global Physical Activity Questionnaire (GPAQ)

GPAQ

Physical Activity

Next I am going to ask you about the time you spend doing different types of physical activity in a typical week. Please answer these questions even if you do not consider yourself to be a physically active person.

Think first about the time you spend doing work. Think of work as the things that you have to do such as paid or unpaid work, study/training, household chores, harvesting food/crops, fishing or hunting for food, seeking employment. *[Insert other examples if needed]*. In answering the following questions 'vigorous-intensity activities' are activities that require hard physical effort and cause large increases in breathing or heart rate, 'moderate-intensity activities' are activities that require moderate physical effort and cause small increases in breathing or heart rate.

	Questions	Response	Code
Activity at work			
1	Does your work involve vigorous-intensity activity that causes large increases in breathing or heart rate like *[carrying or lifting heavy loads, digging or construction work]* for at least 10 minutes continuously? *[INSERT EXAMPLES] (USE SHOWCARD)*	Yes 1 No 2 *If No, go to P 4*	P1
2	In a typical week, on how many days do you do vigorous-intensity activities as part of your work?	Number of days └─┘	P2
3	How much time do you spend doing vigorous-intensity activities at work on a typical day?	Hours : minutes └─┴─┘:└─┴─┘ hrs mins	P3 (a-b)
4	Does your work involve moderate-intensity activity that causes small increases in breathing or heart rate such as brisk walking *[or carrying light loads]* for at least 10 minutes continuously? *[INSERT EXAMPLES] (USE SHOWCARD)*	Yes 1 No 2 *If No, go to P 7*	P4
5	In a typical week, on how many days do you do moderate-intensity activities as part of your work?	Number of days └─┘	P5
6	How much time do you spend doing moderate-intensity activities at work on a typical day?	Hours : minutes └─┴─┘:└─┴─┘ hrs mins	P6 (a-b)
Travel to and from places			
The next questions exclude the physical activities at work that you have already mentioned. Now I would like to ask you about the usual way you travel to and from places. For example to work, for shopping, to market, to place of worship. [insert other examples if needed]			
7	Do you walk or use a bicycle *(pedal cycle)* for at least 10 minutes continuously to get to and from places?	Yes 1 No 2 *If No, go to P 10*	P7
8	In a typical week, on how many days do you walk or bicycle for at least 10 minutes continuously to get to and from places?	Number of days └─┘	P8
9	How much time do you spend walking or bicycling for travel on a typical day?	Hours : minutes └─┴─┘:└─┴─┘ hrs mins	P9 (a-b)
Recreational activities			
The next questions exclude the work and transport activities that you have already mentioned. Now I would like to ask you about sports, fitness and recreational activities (leisure), [insert relevant terms].			
10	Do you do any vigorous-intensity sports, fitness or recreational *(leisure)* activities that cause large increases in breathing or heart rate like *[running or football,]* for at least 10 minutes continuously? *[INSERT EXAMPLES] (USE SHOWCARD)*	Yes 1 No 2 *If No, go to P 13*	P10
11	In a typical week, on how many days do you do vigorous-intensity sports, fitness or recreational *(leisure)* activities?	Number of days └─┘	P11
12	How much time do you spend doing vigorous-intensity sports, fitness or recreational activities on a typical day?	Hours : minutes └─┴─┘:└─┴─┘ hrs mins	P12 (a-b)

Continued on next page

GPAQ, Continued

Physical Activity (recreational activities) contd.			
Questions		**Response**	**Code**
13	Do you do any moderate-intensity sports, fitness or recreational *(leisure)* activities that causes a small increase in breathing or heart rate such as brisk walking,*(cycling, swimming, volleyball)*for at least 10 minutes continuously? *[INSERT EXAMPLES] (USE SHOWCARD)*	Yes 1 No 2 *If No, go to P16*	P13
14	In a typical week, on how many days do you do moderate-intensity sports, fitness or recreational *(leisure)* activities?	Number of days └─┘	P14
15	How much time do you spend doing moderate-intensity sports, fitness or recreational *(leisure)* activities on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs mins	P15 (a-b)
Sedentary behaviour			
The following question is about sitting or reclining at work, at home, getting to and from places, or with friends including time spent [sitting at a desk, sitting with friends, travelling in car, bus, train, reading, playing cards or watching television], but do not include time spent sleeping. *[INSERT EXAMPLES] (USE SHOWCARD)*			
16	How much time do you usually spend sitting or reclining on a typical day?	Hours : minutes └─┴─┘ : └─┴─┘ hrs min s	P16 (a-b)

Facial Stimuli from the FACES Database for Younger Models (top 5 pictures) and Older Models (bottom 5 pictures)

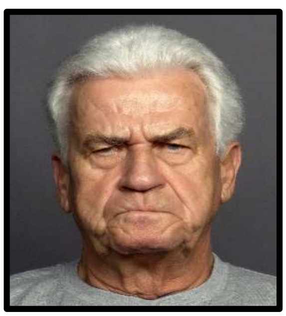

Angry

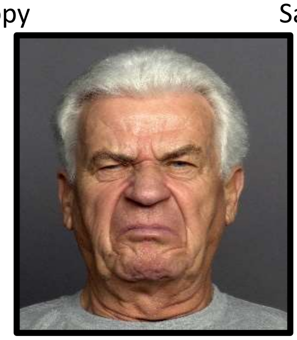

Disgust

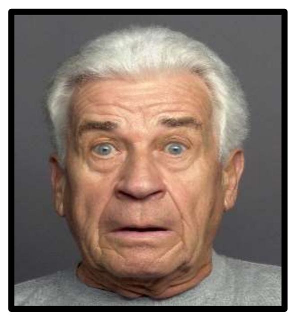

Fear

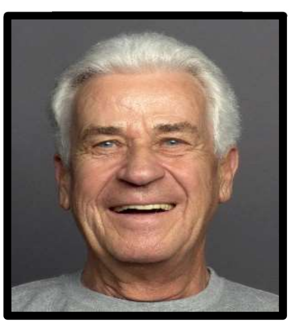

Happy

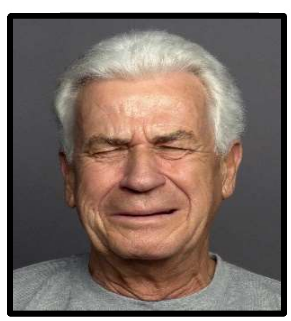

Sad


Angry


Disgust


Fear


Happy


Sad

APPENDIX B

TABLES

Table 5

Correlation Matrix for Demographic Variables and FAR Accuracy Measures (N=43)

Measure	1	2	3	4	5	6	7	8	9	10
1. Age	--									
2. Years Education	.03	--								
3. Overall Accuracy	.00	.39*	--							
4. Angry Accuracy	.01	.28	.81**	--						
5. Disgust Accuracy	-.14	.30	.70**	.47**	--					
6. Fear Accuracy	-.16	.36*	.87**	.61**	.58**	--				
7. Happy Accuracy	.08	.15	.25	.12	.18	.25	--			
8. Sad Accuracy	.24	.26	.69**	.38*	.14	.55**	.15	--		
9. Young Accuracy	-.04	.35*	.97**	.79**	.66**	.88**	.28	.65**	--	
10. Old Accuracy	.04	.40**	.97**	.78**	.70**	.81**	.22	.69**	.89**	--

Note. * p<.05 ** p<.01

Table 6

Correlation Matrix for Demographic Variables and FAR Accuracy Measures in Younger Adults (n=27) and Older Adults (n=16)

	Younger Adults										Older Adults									
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. Age	--										--									
2. Years Education	.73**	--									-.33	--								
3. Overall Accuracy	.17	.22	--								-.39	.61*	--							
4. Angry Accuracy	-.06	.12	.83**	--							-.23	.58*	.85**	--						
5. Disgust Accuracy	.06	.13	.40*	.23	--						-.39	.51*	.88**	.75**	--					
6. Fear Accuracy	.12	.19	.79**	.72**	.06	--					-.32	.57*	.94**	.69**	.75**	--				
7. Happy Accuracy	.18	.11	.06	.04	.02	.16	--				-.38	.23	.45	.26	.36	.38	--			
8. Sad Accuracy	.31	.18	.70**	.33	-.09	.51**	-.07	--			-.35	.45	.79**	.48	.46	.82**	.47	--		
9. Young Accuracy	.20	.18	.95**	.80**	.31	.82**	.21	.66**	--		-.36	.57*	.98**	.87**	.84**	.93**	.37	.77**	--	
10. Old Accuracy	.13	.26	.97**	.80**	.43*	.70**	-.06	.68**	.84**	--	-.40	.63**	.98**	.79**	.88**	.92**	.52*	.77**	.93**	--

Note. *p<.05 **p<.01

Table 7

Correlation Matrix for Demographic Variables and FAR Response Time Measures (N=43)

Measure	1	2	3	4	5	6	7	8	9	10
1. Age	--									
2. Years Education	.03	--								
3. Overall RT	.58**	-.22	--							
4. Angry RT	.55**	-.06	.92**	--						
5. Disgust RT	.55**	-.15	.97**	.91**	--					
6. Fear RT	.52**	-.30	.95**	.83**	.89**	--				
7. Happy RT	.56**	-.27	.90**	.81**	.84**	.84**	--			
8. Sad RT	.52**	-.25	.91**	.75**	.85**	.82**	.77**	--		
9. Young RT	.56**	-.19	.99**	.92**	.97**	.92**	.92**	.88**	--	
10. Old RT	.58**	-.24	.99**	.91**	.95**	.95**	.85**	.92**	.95**	--

Note. RT= response time (lower RT indicates better performance); ** p<.01

Table 8

Correlation Matrix for Demographic Variables and FAR Response Time Measures in Younger Adults (n=27) and Older Adults (n=16)

	Younger Adults										Older Adults									
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. Age	--										--									
2. Years Education	.73**	--									-.33	--								
3. Overall RT	.17	-.05	--								.01	-.46	--							
4. Angry RT	.40*	.21	.85**	--							-.12	-.35	.93**	--						
5. Disgust RT	.37	.13	.87**	.84**	--						.04	-.41	.98**	.91**	--					
6. Fear RT	-.01	-.21	.80**	.54**	.60**	--					.02	-.53*	.95**	.87**	.89**	--				
7. Happy RT	-.21	-.27	.75**	.49**	.48*	.80**	--				.07	-.41	.90**	.84**	.88**	.79**	--			
8. Sad RT	-.01	-.16	.73**	.45*	.50**	.40*	.42*	--			.04	-.42	.92**	.74**	.89**	.84**	.78**	--		
9. Young RT	.15	-.02	.97**	.83**	.84**	.83**	.80**	.63**	--		.05	-.42	.98**	.92**	.98**	.90**	.94**	.89**	--	
10. Old RT	.18	-.07	.98**	.82**	.86**	.73**	.67**	.79**	.91**	--	-.02	-.49	.99**	.90**	.95**	.97**	.83**	.92**	.94**	--

Note. RT= response time (lower RT indicates better performance); *$p<.05$ **$p<.01$

Table 9

Correlation Matrix for Physical Activity Variables and FAR Accuracy Measures (N=43)

Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1. Total MET	--														
2. Moderate MET	.72**	--													
3. Vigorous MET	.84**	.22	--												
4. Work MET	.88**	.71**	.68**	--											
5. Transportation MET	.35*	.40**	.17	.15	--										
6. Recreation MET	.43**	.08	.54**	.00	.08	--									
7. Sedentary Time	-.45**	-.27	-.42**	-.42**	.06	-.26	--								
8. Overall Accuracy	.12	.10	.09	.14	-.19	.09	-.10	--							
9. Angry Accuracy	.15	.06	.16	.13	-.11	.13	-.12	.81**	--						
10. Disgust Accuracy	.06	.11	.00	.06	-.02	.03	.05	.70**	.47**	--					
11. Fear Accuracy	.01	.02	.00	.09	-.27	-.05	.07	.87**	.61**	.58**	--				
12. Happy Accuracy	-.12	-.17	-.04	-.10	-.49**	.14	-.24	.25	.12	.18	.25	--			
13. Sad Accuracy	.13	.11	.09	.14	-.19	.10	-.24	.69**	.38*	.14	.55**	.15	--		
14. Young Accuracy	.11	.09	.08	.12	-.23	.11	-.08	.97**	.79**	.66**	.88**	.28	.65**	--	
15. Old Accuracy	.12	.11	.09	.15	-.17	.05	-.11	.97**	.78**	.70**	.81**	.22	.69**	.89**	--

Note. MET= MET-mins/week; Sedentary Time= time spent sitting per day. ** p<.01

Table 10

Correlation Matrix for Total Physical Activity and FAR Accuracy Measures in Younger Adults (n=27) and Older Adults (n=16)

	Younger Adults									Older Adults								
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Total MET	--									--								
2. Overall Accuracy	.15	--								.13	--							
3. Angry Accuracy	.10	.83**	--							.33	.85**	--						
4. Disgust Accuracy	.10	.40*	.23	--						.00	.88**	.75**	--					
5. Fear Accuracy	.00	.79**	.72**	.06	--					-.01	.94**	.69**	.75**	--				
6. Happy Accuracy	-.15	.06	.04	.02	.16	--				-.01	.45	.26	.36	.38	--			
7. Sad Accuracy	.16	.70**	.33	-.09	.51**	-.07	--			.16	.79**	.48	.46	.82**	.47	--		
8. Young Accuracy	.11	.95**	.80**	.31	.82**	.21	.66**	--		.15	.98**	.87**	.84**	.93**	.37	.77**	--	
9. Old Accuracy	.17	.97**	.80**	.43*	.70**	-.06	.68**	.84**	--	.10	.98**	.79**	.88**	.92**	.52*	.77**	.93**	--

Note. MET= MET-mins/week; *p<.05 **p<.01

Table 11

Correlation Matrix for Physical Activity Variables and FAR Response Time Measures (N=43)

Measure	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Total MET	--														
2. Moderate MET	.72**	--													
3. Vigorous MET	.84**	.22	--												
4. Work MET	.88**	.71**	.68**	--											
5. Transportation MET	.35*	.40**	.17	.15	--										
6. Recreation MET	.43**	.08	.54**	.00	.08	--									
7. Sedentary Time	-.45**	-.27	-.42**	-.42**	.06	-.26	--								
8. Overall RT	-.19	-.22	-.09	-.25	-.19	.14	-.21	--							
9. Angry RT	-.23	-.28	-.11	-.29	-.21	.14	-.08	.92**	--						
10. Disgust RT	-.17	-.22	-.07	-.22	-.24	.17	-.23	.97**	.91**	--					
11. Fear RT	-.10	-.14	-.03	-.19	-.08	.20	-.23	.95**	.83**	.89**	--				
12. Happy RT	-.12	-.10	-.10	-.15	-.06	.05	-.27	.90**	.81**	.84**	.84**	--			
13. Sad RT	-.25	-.28	-.13	-.26	-.27	.06	-.18	.91**	.75**	.85**	.82**	.77**	--		
14. Young RT	-.18	-.19	-.10	-.23	-.18	.13	-.21	.99**	.92**	.97**	.92**	.92**	.88**	--	
15. Old RT	-.20	-.25	-.08	-.26	-.20	.15	-.21	.99**	.91**	.95**	.95**	.85**	.92**	.95**	--

Note. MET= MET-mins/week; Sedentary Time= time spent sitting per day; RT= response time (lower RT indicates better performance); ** p<.01

Table 12

Correlation Matrix for Total Physical Activity and FAR Response Time Measures in Younger Adults (n=27) and Older Adults (n=16)

	Younger Adults									Older Adults								
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
1. Total MET	--									--								
2. Overall RT	-.27	--								-.12	--							
3. Angry RT	-.28	.85**	--							-.17	.93**	--						
4. Disgust RT	-.25	.87**	.84**	--						-.07	.98**	.91**	--					
5. Fear RT	-.09	.80**	.54**	.60**	--					-.04	.95**	.87**	.89**	--				
6. Happy RT	-.04	.75**	.49**	.48*	.80**	--				-.15	.90**	.84**	.88**	.79**	--			
7. Sad RT	-.33	.73**	.45*	.50**	.40*	.42*	--			-.20	.92**	.74**	.89**	.84**	.78**	--		
8. Young RT	-.24	.97**	.83**	.84**	.83**	.80**	.63**	--		-.12	.98**	.92**	.98**	.90**	.94**	.90**	--	
9. Old RT	-.29	.98**	.82**	.86**	.73**	.67**	.79**	.91**	--	-.13	.99**	.90**	.95**	.97**	.83**	.92**	.94**	--

Note. MET= MET-mins/week; RT= response time (lower RT indicates better performance); **p*<.05 ***p*<.01

Table 13

Correlation Matrix for HRV Variables and FAR Accuracy Measures (N=30)

Measure	1	2	3	4	5	6	7	8	9	10
1. RMSSD	--									
2. HF (ms^2)	.87**	--								
3. Overall Accuracy	.05	.06	--							
4. Angry Accuracy	.00	.04	.79**	--						
5. Disgust Accuracy	.24	.22	.58**	.34	--					
6. Fear Accuracy	.16	.10	.85**	.55**	.46**	--				
7. Happy Accuracy	-.13	-.10	.46*	.31	.40*	.46*	--			
8. Sad Accuracy	-.14	-.12	.73**	.43*	.03	.57**	.17	--		
9. Young Accuracy	.06	.06	.98**	.81**	.51**	.84**	.51**	.71**	--	
10. Old Accuracy	.05	.05	.98**	.75**	.63**	.82**	.41*	.71**	.92**	--

Note. * *p*<.05 ** *p*<.01

Table 14

Correlation Matrix for HRV Variables and FAR Accuracy Measures in Younger Adults (n=21) and Older Adults (n=9)

	Younger Adults										Older Adults									
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. RMSSD	--										--									
2. HF (ms^2)	.83**	--									.66	--								
3. Overall Accuracy	.09	.15	--								.36	.32	--							
4. Angry Accuracy	.06	.14	.83**	--							.38	.30	.85**	--						
5. Disgust Accuracy	.30	.33	.40*	.23	--						.39	.32	.88**	.75**	--					
6. Fear Accuracy	-.01	-.02	.79**	.72**	.06	--					.28	.27	.94**	.69**	.75**	--				
7. Happy Accuracy	-.12	-.03	.06	.04	.02	.16	--				.27	.19	.45	.26	.36	.38	--			
8. Sad Accuracy	-.04	-.02	.70**	.33	-.09	.51**	-.07	--			.20	.22	.79**	.48	.46	.82**	.47	--		
9. Young Accuracy	.09	.14	.95**	.80**	.31	.82**	.21	.66**	--		.31	.28	.98**	.87**	.84**	.93**	.37	.77**	--	
10. Old Accuracy	.07	.15	.97**	.80**	.43*	.70**	-.06	.68**	.84**	--	.41	.34	.98**	.79**	.88**	.92**	.52*	.77**	.93**	--

Note. *p<.05 **p<0.01

Table 15

Correlation Matrix for HRV Variables and FAR Response Time Measures (N=30)

Measure	1	2	3	4	5	6	7	8	9	10
1. RMSSD	--									
2. HF (ms^2)	.87**	--								
3. Overall RT	-.52**	-.54**	--							
4. Angry RT	-.53**	-.57**	.89**	--						
5. Disgust RT	-.46**	-.52**	.94**	.87**	--					
6. Fear RT	-.47**	-.44*	.92**	.76**	.82**	--				
7. Happy RT	-.49**	-.54**	.83**	.72**	.72**	.74**	--			
8. Sad RT	-.40*	-.38*	.86**	.63**	.75**	.74**	.65**	--		
9. Young RT	-.53**	-.59**	.99**	.90**	.93**	.88**	.88**	.81**	--	
10. Old RT	-.51**	-.49**	.99**	.86**	.92**	.94**	.77**	.87**	.94**	--

Note. RT= response time (lower RT indicates better performance); * p<.05 ** p<.01

Table 16

Correlation Matrix for HRV Variables and FAR Response Time Measures in Younger Adults (n=21) and Older Adults (n=9)

	Younger Adults										Older Adults									
Measure	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1. RMSSD	--										--									
2. HF (ms^2)	.83**	--									.66	--								
3. Overall RT	-.23	-.41	--								-.17	-.38	--							
4. Angry RT	-.33	-.50*	.85**	--							-.20	-.27	.93**	--						
5. Disgust RT	-.27	-.43	.87**	.84**	--						.12	-.15	.98**	.91**	--					
6. Fear RT	-.07	-.29	.80**	.54**	.60**	--					-.36	-.42	.95**	.87**	.89**	--				
7. Happy RT	-.08	-.28	.75**	.49**	.48*	.80**	--				-.12	-.41	.90**	.84**	.88**	.79**	--			
8. Sad RT	-.08	-.10	.73**	.45*	.50**	.40*	.42*	--			-.10	-.45	.92**	.74**	.89**	.84**	.78**	--		
9. Young RT	-.26	-.48*	.97**	.83**	.84**	.83**	.80**	.63**	--		-.06	-.38	.98**	.92**	.98**	.90**	.94**	.89**	--	
10. Old RT	-.19	-.32	.98**	.82**	.86**	.73**	.67**	.79**	.91**	--	-.24	-.36	.99**	.90**	.95**	.97**	.83**	.92**	.94**	--

Note. RT= response time (lower RT indicates better performance); *p<.05 **p<.01

Table 17

Correlation Matrix for Physical Activity and HRV Variables (N=30)

Measure	**1**	**2**	**3**
1. Total MET	--		
2. RMSDD	0.21	--	
3. HF	0.26	0.87**	--

Note. MET= MET-mins/week; ** p<.01

Table 18

Summary of Hierarchical Regression Analyses for Physical Activity Predicting FAR Performance (N=43)

	Overall Accuracy@									Overall Response Time^					
	Model 1			Model 2			Model 3			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Years Education	0.01*	0.01	0.39	0.01**	0.01	0.41	0.02*	0.01	0.46	--	--	--	--	--	--
Age Category	--	--	--	0.01	0.02	0.07	0.04	0.04	0.24	606.00**	137.68	0.57	671.01**	237.93	0.63
MET-mins/week	--	--	--	0.00	0.00	0.17	0.00	0.00	0.23	-0.01	0.02	-0.13	-0.01	0.02	-0.11
Age Category X MET-mins/week	--	--	--	--	--	--	0.00	0.00	-0.22	--	--	--	-0.01	0.04	-0.08
R^2	0.15			0.18			0.19			0.35			0.35		
F for change in R^2	7.16*			0.72			0.63			10.78**			0.11		

Note. @ = years of education entered in model 1, main effects entered in model 2, interaction entered in model 3; ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 19

Summary of Hierarchical Regression Analyses for RMSSD Predicting FAR Performance (N=30)

	Overall Accuracy^						Overall Response Time^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.04	0.04	0.22	-0.04	0.08	-0.26	508.73**	177.90	0.54	639.29	347.12	0.68
RMSSD	0.00	0.00	0.20	0.00	0.00	0.09	-3.75	4.17	-0.17	-3.06	4.51	-0.14
Age Category X RMSSD	--	--	--	0.00	0.00	0.48	--	--	--	-5.70	12.94	-0.14
R^2	0.03			0.08			0.44			0.45		
F for change in R^2	0.44			1.41			10.67**			0.19		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ** $p<0.01$

Table 20

Summary of Hierarchical Regression Analyses for HF Power Predicting FAR Performance (N=30)

	Overall Accuracy^						**Overall Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.03	0.04	0.19	0.00	0.05	-0.02	481.09**	158.97	0.51	667.58**	198.90	0.71
HF power	0.00	0.00	0.16	0.00	0.00	0.13	-0.15	0.10	-0.25	-0.13	0.10	-0.22
Age Category X HF power	--	--	--	0.00	0.00	0.29	--	--	--	-1.14	0.76	-0.28
R^2	0.03			0.07			0.47			0.51		
F for change in R^2	0.37			1.28			11.88**			2.26		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ***p*<0.01

Table 21

Summary of Hierarchical Regression Analyses for Physical Activity Predicting Angry Accuracy and Response Time (N=43)

	Angry Accuracy^						**Angry Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.02	0.05	0.06	-0.05	0.08	-0.15	560.01 **	139.46	0.52	629.00**	240.97	0.59
MET-mins/week	0.00	0.00	0.15	0.00	0.00	0.09	-0.02	0.02	-0.18	-0.02	0.02	-0.15
Age Category X MET-mins/week	--	--	--	0.00	0.00	0.26	--	--	--	-0.01	0.04	-0.08
R^2	0.03			0.05			0.33			0.33		
F for change in R^2	0.51			0.91			9.69**			0.13		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ***p*<0.01

Table 22

Summary of Hierarchical Regression Analyses for RMSSD Predicting Angry Accuracy and Response Time (N=30)

	Angry Accuracy^						**Angry Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.07	0.08	0.23	-0.03	0.15	-0.09	373.09	203.97	0.37	458.75	398.98	0.45
RMSSD	0.00	0.00	0.14	0.00	0.00	0.07	-6.97	4.78	-0.29	-6.51	5.19	-0.28
Age Category X RMSSD	--	--	--	0.00	0.01	0.31	--	--	--	-3.74	14.87	-0.08
R^2	0.03			0.05			0.36			0.37		
F for change in R^2	0.43			0.58			7.73**			0.06		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ** $p<0.01$

Table 23

Summary of Hierarchical Regression Analyses for HF Power Predicting Angry Accuracy and Response Time (N=30)

	Angry Accuracy^						**Angry Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.07	0.07	0.23	0.03	0.09	0.11	353.71	179.58	0.35	464.54	231.63	0.46
HF power	0.00	0.00	0.17	0.00	0.00	0.15	-0.25*	0.12	-0.38	-0.24	0.12	-0.36
Age Category X HF power	--	--	--	0.00	0.00	0.16	--	--	--	-0.68	0.88	-0.15
R^2	0.04			0.05			0.41			0.43		
F for change in R^2	0.52			0.40			9.47**			0.59		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 24

Summary of Hierarchical Regression Analyses for Physical Activity Predicting Disgust Accuracy and Response Time (N=43)

	Disgust Accuracy^						**Disgust Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	-0.03	0.04	-0.09	-0.02	0.07	-0.06	696.08**	175.72	0.53	715.45**	304.98	0.54
MET-mins/week	0.00	0.00	0.05	0.00	0.00	0.06	-0.02	0.02	-0.11	-0.01	0.02	-0.10
Age Category X MET-mins/week	--	--	--	0.00	0.00	0.05	--	--	--	0.00	0.05	-0.02
R^2	0.01			0.01			0.30			0.30		
F for change in R^2	0.25			0.03			8.66**			0.01		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ***p*<0.01

Table 25

Summary of Hierarchical Regression Analyses for RMSSD Predicting Disgust Accuracy and Response Time (N=30)

	Disgust Accuracy^						**Disgust Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.06	0.06	0.22	-0.06	0.12	-0.24	580.24*	228.26	0.51	299.42	442.37	0.26
RMSSD	0.00	0.00	0.38	0.00	0.00	0.27	-3.49	5.35	-0.13	-4.98	5.75	-0.19
Age Category X RMSSD	--	--	--	0.01	0.00	0.45	--	--	--	12.26	16.49	0.24
R^2	0.08			0.13			0.37			0.38		
F for change in R^2	1.22			1.33			7.822**			0.55		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * *p*<0.05 ***p*<0.01

Table 26

Summary of Hierarchical Regression Analyses for HF Power Predicting Disgust Accuracy and Response Time (N=30)

	Disgust Accuracy^						Disgust Response Time^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.03	0.06	0.13	-0.02	0.07	-0.07	506.57*	202.29	0.45	573.31*	263.03	0.51
HF power	0.00	0.00	0.29	0.00	0.00	0.26	-0.20	0.13	-0.27	-0.19	0.14	-0.26
Age Category X HF power	--	--	--	0.00	0.00	0.28	--	--	--	-0.41	1.00	-0.08
R^2	0.06			0.10			0.41			0.41		
F for change in R^2	0.84			1.32			9.27**			0.17		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 27

Summary of Hierarchical Regression Analyses for Physical Activity Predicting Fear Accuracy and Response Time (N=43)

	Fear Accuracy@									Fear Response Time^					
	Model 1			Model 2			Model 3			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Years Education	0.02*	0.01	0.36	0.02*	0.01	0.36	0.02*	0.01	0.43	--	--	--	--	--	--
Age Category	--	--	--	-0.02	0.03	-0.11	0.03	0.06	0.13	750.19**	193.14	0.52	791.39*	334.15	0.55
MET-mins/week	--	--	--	0.00	0.00	0.04	0.00	0.00	0.12	-0.01	0.02	-0.04	0.00	0.02	-0.03
Age Category X MET-mins/week	--	--	--	--	--	--	0.00	0.00	-0.30	--	--	--	-0.01	0.05	-0.04
R^2	0.13			0.14			0.17			0.28			0.28		
F for change in R^2	6.03*			0.34			1.18			7.80**			0.02		

Note. @ = years of education entered in model 1, main effects entered in model 2, interaction entered in model 3; ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 28

Summary of Hierarchical Regression Analyses for RMSSD Predicting Fear Accuracy and Response Time (N=30)

	Fear Accuracy ^						**Fear Response Time ^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	-0.02	0.05	-0.08	-0.12	0.10	-0.58	671.13*	281.87	0.49	1398.07*	526.18	1.01
RMSSD	0.00	0.00	0.11	0.00	0.00	-0.01	-4.89	6.60	-0.15	-1.03	6.84	-0.03
Age Category X RMSSD	--	--	--	0.00	0.00	0.49	--	--	--	-31.73	19.62	-0.52
R^2	0.03			0.08			0.35			0.41		
F for change in R^2	0.41			1.47			7.36**			2.62		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 29

Summary of Hierarchical Regression Analyses for HF Power Predicting Fear Accuracy and Response Time (N=30)

	Fear Accuracy ^						**Fear Response Time ^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	-0.03	0.05	-0.14	-0.07	0.06	-0.36	682.12*	257.16	0.49	1079.44**	311.33	0.78
HF power	0.00	0.00	0.03	0.00	0.00	-0.01	-0.15	0.17	-0.16	-0.01	0.16	-0.11
Age Category X HF power	--	--	--	0.00	0.00	0.31	--	--	--	-2.42	1.18	-0.40
R^2	0.02			0.08			0.36			0.45		
F for change in R^2	0.32			1.52			7.52**			4.18		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 30

Summary of Hierarchical Regression Analyses for Physical Activity Predicting Happy Accuracy and Response Time (N=43)

	Happy Accuracy^						**Happy Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.00	0.01	0.09	0.00	0.01	0.03	379.32^{**}	86.93	0.57	454.34^{**}	149.71	0.68
MET-mins/week	0.00	0.00	-0.11	0.00	0.00	-0.13	0.00	0.01	-0.06	0.00	0.01	-0.02
Age Category X MET-mins/week	--	--	--	0.00	0.00	0.08	--	--	--	-0.02	0.02	-0.14
R^2	0.02			0.03			0.33			0.34		
F for change in R^2	0.48			0.08			9.99^{**}			0.38		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ***p*<0.01

Table 31

Summary of Hierarchical Regression Analyses for RMSSD Predicting Happy Accuracy and Response Time (N=30)

	Happy Accuracy^						**Happy Response Time^**					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.01	0.01	0.14	-0.01	0.02	-0.26	362.09^{**}	108.06	0.62	396.30	211.49	0.68
RMSSD	0.00	0.00	-0.04	0.00	0.00	-0.13	-1.10	2.53	-0.08	-0.92	2.75	-0.07
Age Category X RMSSD	--	--	--	0.00	0.00	0.39	--	--	--	-1.49	7.88	-0.06
R^2	0.03			0.06			0.46			0.46		
F for change in R^2	0.39			0.93			11.52^{**}			0.04		

Note. ^ = main effects entered in model 1, interaction entered in model 2; ***p*<0.01

Table 32

Summary of Hierarchical Regression Analyses for HF Power Predicting Happy Accuracy and Response Time (N=30)

	Happy Accuracy^						**Happy Response Time**^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.01	0.01	0.16	0.00	0.01	0.05	316.58**	95.77	0.55	393.93**	122.53	0.68
HF power	0.00	0.00	-0.01	0.00	0.00	-0.03	-0.09	0.06	-0.24	-0.08	0.06	-0.21
Age Category X HF power	--	--	--	0.00	0.00	0.16	--	--	--	-0.47	0.47	-0.18
R^2	0.03			0.04			0.50			0.51		
F for change in R^2	0.37			0.37			13.21**			1.02		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 33

Summary of Hierarchical Regression Analyses for Physical Activity Predicting Sad Accuracy and Response Time (N=43)

	Sad Accuracy^						**Sad Response Time**^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.08	0.05	0.26	0.07	0.08	0.22	644.43**	165.66	0.51	764.86*	285.71	0.61
MET-mins/week	0.00	0.00	0.16	0.00	0.00	0.14	-0.03	0.02	-0.19	-0.02	0.02	-0.16
Age Category X MET-mins/week	--	--	--	0.00	0.00	0.05	--	--	--	-0.02	0.05	-0.12
R^2	0.08			0.08			0.32			0.33		
F for change in R^2	1.82			0.04			9.43**			0.27		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 34

Summary of Hierarchical Regression Analyses for RMSSD Predicting Sad Accuracy and Response Time (N=30)

	Sad Accuracy^						Sad Response Time^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.08	0.08	0.22	-0.01	0.16	-0.02	557.10*	241.53	0.49	643.90	472.60	0.56
RMSSD	0.00	0.00	0.00	0.00	0.00	-0.05	-2.30	5.66	-0.09	-1.84	6.15	-0.07
Age Category X RMSSD	--	--	--	0.00	0.01	0.23	--	--	--	-3.79	17.62	-0.08
R^2	0.05			0.06			0.30			0.30		
F for change in R^2	0.67			0.34			5.80**			0.05		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$

Table 35

Summary of Hierarchical Regression Analyses for HF Power Predicting Sad Accuracy and Response Time (N=30)

	Sad Accuracy^						Sad Response Time^					
	Model 1			Model 2			Model 1			Model 2		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Age Category	0.07	0.08	0.22	0.04	0.10	0.11	546.46*	220.36	0.48	826.68**	273.62	0.73
HF power	0.00	0.00	0.00	0.00	0.00	-0.02	-0.09	0.14	-0.12	-0.06	0.14	-0.08
Age Category X HF power	--	--	--	0.00	0.00	0.16	--	--	--	-1.71	1.04	-0.34
R^2	0.05			0.06			0.31			0.37		
F for change in R^2	0.67			0.38			5.94**			2.69		

Note. ^ = main effects entered in model 1, interaction entered in model 2; * $p<0.05$ ** $p<0.01$