Modelling the Effects of Demographics and Lifestyle on Cognitive Performance

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Abstract

Human cognitive performance is ultimately the result of many factors. Previous inquiries note the contributions of demographic and lifestyle cognitive performance. I used a series of structural equation models and dimensionality reduction methods to identify how demographic and lifestyle measures simultaneously contribute to cognitive performance: a theory-driven model using combined measures of cognitive performance and latent variable structure; and a data-driven model using principal components analysis. Participants (N = 1141, M_{age} = 23.13 years) completed a battery of tasks and questionnaires measuring cognitive performance and collecting demographic and lifestyle measures. Overall, both models provided evidence that the inclusion of lifestyle measures over and above demographic measures accounted for and predicted cognitive performance. Further, the two models give rise to complementary but distinct insights into the basic components of cognitive performance. This work provides a methodology and evidence for accounting for difference in cognitive performance with demographic and lifestyle measures.

Dedication

This is now the second thesis I have completed, both of which my father, Arnold Park, did not get to read. My father was endlessly proud of everything I have and would accomplish. He was kind, compassionate, and intelligent. I strive to be like him in the very best of ways. He was excited to hear about every step of my academic journey and I know he would have ecstatic about my graduate school career. As I move forward once again, I am grateful for everything he was and who I am because of him.

Dad, thank you for everything. *Once again*, this is for you. I love you.

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Chapter 1: Introduction and Literature Review

Every interaction we have with our environment or with other people is a complex process. Even the simplest and seemingly mundane tasks require the extraordinary coordination of several neural mechanisms. Our environment is dynamic, and it follows that human functioning is contingent on our ability to be adaptive to our environment. This adaptability and flexibility are the core and foundation of human cognition.

Cognition has varying definitions based on discipline and perspective. In psychological inquiry, *cognition* encompasses the mental processes by which information is acquired, stored, and transformed (Eysenck & Brysbeart, 2018). In the general sense, cognition concerns the entirety and complexity of human experience. The model for input to behaviour is such that sensory information is received by the brain from the receptors of the peripheral nervous system. The brain processes this information by the means of cognition, this then drives a motor response (e.g., speaking, moving). This motor output is characterized as behaviour. The mechanisms underlying cognition have been heavily presented, disputed, and reconceptualized. For this reason, while there are some distinct functions with notable neural underpinnings, there exists simultaneously considerable overlap.

An Experience-driven Perspective on Cognition

People and their cognitive processes exist within their environment, which is determined and shaped by their experiences. The real world is complex and dynamic. There is familiarity and it allows for responsiveness. Consequently, our experience can have long-term implications on our cognition. The complement is that there are attributes of ourselves that affect our cognition and the environment. This can be understood in theory, but how can this be represented in the statistical analyses that we conduct? One approach to understanding the factors that affect cognition is through statistical modelling. Structural Equation Modelling is a technique being used to try and mathematically define this relationship.

For my thesis, I will be investigating how our experiences can affect cognitive performance. I will use demographic and lifestyle information as a smaller scale representation of life experience and measure cognitive performance through tasks assessing working memory, attention, and response inhibition. The analyses will be conducted using a series of Structural Equation Models to uncover a factor structure and allow for the simultaneous effects of lifestyle and demographics on cognitive performance. While only a scaled model, this series of analyses will garner a greater insight into how cognitive performance is determined in part by a person's experiences.

Structural Equation Modelling

Structural Equation Modelling (SEM) is a statistical approach that is used to make inferences surrounding, and statistically test, cause-effect relationships (Karimi & Meyer, 2014). SEMs have two primary elements in the model: (1) measured or observed variables, and (2) unobserved variables, more commonly called latent factors or latent variables (LVs). Latent variables are explained by measured variables, such as using several measures of physical ability to give an overall index of physical fitness. In the cognition context, we can think of cognition itself as a latent construct and all our measures as the observed variables. Within the SEM framework, there are specific uses and goals to their use. Factor structures, and the constructs they represent, can be uncovered, or imposed and subsequently tested. The former is an exploratory factor analyses (EFA), and the latter is a confirmatory factor analysis (CFA). Both are widely used and serve distinct purposes, and often applied in succession.

Within the context of cognition, there is a large body of research employing SEM methods. Lemes and colleagues (2017) defined an SEM to explore how the relationship between physical fitness and cognition is mediated by other health-related lifestyle factors (age, sleep, quality of life, school vulnerability [measure of socioeconomic status], physical activity, and weight) in children aged 10 to 14 years. The authors wanted to simultaneously explore all their factors of interest, which is possible using an SEM approach. As alluded to above, physical fitness was a LV composed of three measures of fitness, and cognitive performance was a LV composed of eight neurocognitive assessments. For specific measures, please refer to Lemes et al (2017). In short, Lemes et al. found that fitness was predictive of cognitive performance and that age, sleep, and quality of life were not associated with fitness. Quality of life was only predictive of cognitive performance in the male sample. Further, socioeconomic status was the greatest predictor of cognitive performance in their sample. This analysis that considered many other known correlates of cognitive performance and fitness was possible using the SEM framework.

The study by Lemes et al. (2017), highlights another feature of SEM analyses in psychology and cognitive psychology in particular. Recall, that SEM allows for multiple relationships to be explored simultaneously and how many predictors (measured or observed variables) measure the same constructs (unmeasured or LVs), and any relationships between these measured and LVs. Lemes et al. (2017), were able to appropriately model the complexity and multi-deterministic nature of performance, garnering insights which may have otherwise been unobserved or discarded as error or variance using other methods.

Measures of Cognitive Performance

A wide array of tasks have been developed and validated in an to attempt to isolate certain cognitive processes. These processes underlie our ability to function and engage cognitive control. For certain aspects of cognition, there are tasks developed to measure it, such as response inhibition, attention, and working memory. While each task is meant to probe specific processes related to cognition, there is undeniably overlap among these processes. That is, it is ultimately the coordination of many networks and processes that give rise to cognitive performance.

Response Inhibition

Also referred to as impulse inhibition, *response inhibition* is the ability to suppress or withhold a response (Wright et al., 2014). The active control required to withhold a speeded motor response, or to stop it once it has been initiated, is a functional and adaptive process underlying healthy cognition. Miller and Cohen (2001), note response inhibition is necessary to support cognitive processes such as executive or cognitive control. Healthy and adaptive behaviour necessitates control. Several pathologies are hallmarked by the inability to exert control over impulses, as deficits can be detrimental. Attention Deficit Hyperactivity Disorder (ADHD), substance use disorders, and classes of personality disorders are often associated with control over impulses, and the lack thereof (Wright et al., 2014).

Go/No-go. The Go/No-go task is among the most common and validated tasks to measure response inhibition (Wright et al., 2014). Participants are presented with one of two cues, a go or no-go, and must make a speeded response. When a cue appears from a blank screen, participants are motivated to quickly make a response, such as a keyboard press. However, they must engage restraint and withhold the impulse to immediately respond and first decide if the cue is “go” or “no-go” before acting.

Of note is that the Go/No-go procedure should not be confused with a similar forced two-choice procedure where a response is required for both types of stimuli. In a two-choice task, the discrimination is made by two different responses, such as two different keys as opposed to withholding and acting. However, work by Gomez et al., (2017) shows that even though a Go/No-go only provides one measured response, that the action of withholding marks a similar discrimination as would be observed in two-choice task where both responses are measured.

Attention

Broadly, *attention* describes the series of process that allow information in the environment to be selected, filtered, and processed. What we attend to determines the information we are processing which has direct limiting effect on our decisions and subsequent behaviour. There is a class of disorders that are marked by deficits and misattribution of attention, where the misattribution of attention underlies maladaptive behaviours (Mahone & Denckla, 2017).

The literature covers a broad array of evidence with support for various theories on what exactly comprises attention, how attention facilitates cognition, and on what principles attention relies. While this debate remains and new evidence continues to be garnered and implications explored, there are dominating theories and properties that are well-supported in the literature. Petersen and Posner (2012), suggest a tripartite framework to describe attention being comprised of networks, each of which facilitate a specific function. In brief, the authors identify and describe three networks: alerting, orienting, executive control. The *alerting network* concerns arousal and has often been referred to as vigilance (Ocasio, 2011). The *orienting network* supports the ability to select the sensory input to attend to, and not to be confused with executive control (Petersen & Posner, 2012). Once selected, the attenuation to a target is underpinned by the *executive control* network. While these networks are long supported by, and originally conceptualized using, behavioural findings, they continue to be supported in conjunction with contemporary and evolving methods such as neuroimaging and physiological.

In addition to the networks and functions attention serves, the operating principles have an equally well-supported framework: the top-down versus bottom-up processes. *Top-down processes* are those in which our perception is affected by our cognition (Sarter et al., 2001); wherein our previous experience has a tangible impact on how we perceive stimuli. Top-down accounts, or goal-driven accounts, generally posit that behaviour is attributable to the influences of cognition, such as prior beliefs or priming on attention etc. The converse are *bottom-up processes*, whereby our perception is a product of the sensory input from a stimulus. How likely our bottom-up attention is captured is described as stimulus salience. Here, what we attend to is driven by the properties of the stimulus itself. Consequently, bottom-up attention is also referred to as stimulus-driven in the literature. The top-down versus bottom-up distinction can also be thought of as attention being directed (top-down) versus drawn (bottom-up) (Wolfe & Horowitz, 2017). The general consensus in the research is that attention cannot be described as relying purely on top-down or bottom-up processes, but rather our attention functions using a combination of these two processes. The mechanism of top-down user driven guidance and bottom-up stimulus salience interact to drive attention, the determination of the information entering memory.

Visual Attention. Attention as described is a complex process to filter sensory input to be processed by the finite cognitive resources at our disposal at any given moment. Given the prevalence of visual information, a proportionally large body of the literature on attention concerns specifically visual attention.

Visual Search Task. The visual search task is a validated measure of visual attention whereby participants must scan an array to identify a target among other stimuli, distractors.

Inquiries and investigations on attention using the visual search task focuses on the bottom-up mechanisms. The salience of items in the array, target or distractors, can impede or improve the participant's ability to correctly identify the presence of a target. Salience, generally, is the extent that an object is attended to; the more salient an object is, the more it draws attention. Bottom-up attention, and how it can be manipulated, greatly impacts performance on a visual search task. When a target is more salient than the distractors, it is easier to identify, target-distractor heterogeneity (Wolfe & Horowitz, 2017). The presence of any distractors slows participant response to a target (van Doest & Zonk, 2004). However, if a distractor is salient, response time is further slowed, and even slower if the target is less salient that any distractors.

The process of holding the memory a target to search for functions based on a top-down process as it is goal directed. This process can also be described as feature guidance (Wolfe & Horowitz, 2017). When the distractors are similar to a target, response time is slowed (van Doest & Zonk, 2004), This finding is not explained by purely bottom-up accounts, as the goal and knowledge of the target affects search behaviour. The cohesion of the bottom-up and top-down processes is ultimately the best account for the visual search task, as is the case for attention more generally.

Attention Shifting. Shifting the focus and goals of our attention is an imperative function. When completing a composite task, as are real-world tasks, we need to attend to several things, each with different demands. As is the case for attention more generally, this is an adaptive process, but it is not immune to error (Monsell, 2003).

Task Switching Task. The task switching task assesses the ability to direct attention differently conditional a set of rules. It is a well-validated and widely used measure of attention shifting. Each task condition requires the participant to attend to a different attribute of the stimulus, such as colour, size, orientation, or components (Monsell, 2003). When the task demands changes from, the following trial is a switch trial, whereas when the demands do not change between trials, that trial is a non-switch trial. Switch trials are more difficult for the participant and incur a switch cost (Monsell, 2003). Behaviourally, the shift cost is the slowing of responses and increase in incorrect responses, or errors. When participants are provided with cues that a switch trial is approaching, the cost is reduced, but not eliminated.

Trail Making Test (B). Trail Making Test (TMT) as a whole is a commonly administered neuropsychological assessment aimed at assessing attention, specifically both visual attention and attention shifting. Participants are to connect a series of scattered letters (Test A), or letters and numbers, in sequential order (i.e., A-B-C… and 1-A-2-B-3-C…) (Test B). The latter task, called Trail Making Test B (TMT-B) is the more difficult of the two as it requires participant to orient their visual attention and shift between the numbers and letters (Reitan & Wolfson, 1985 as cited in Tombaugh, 2003).

Working Memory

One facet of cognition is working memory, often presented with Baddeley and Hitch's (1974) theory of working memory. They describe *working memory* as a component within the larger memory system that controls the temporary storage of information. Further inquiry by Baddeley (1983) proposes a refinement of this model that introduces more specific components to describe how working memory supports memory and cognition. This model defines working memory as being a Central Executive being supported by the Visuospatial Sketchpad and the Phonological Loop (Baddeley, 1983). The *Central Executive* controls and coordinates the information being processed by these two supporting systems. Working memory has been studied extensively and shown to be a predictor of overall cognitive ability, educational achievement, cognitive flexibility, and health outcomes (Cowan, 2014).

N-Back Task. The N-Back task, first presented by Kircher in 1958, is robust and well-validated assessment of working memory. Since then, it has been used widely in experimental paradigms to assess working memory as a greater proxy of overall cognitive performance. In this task, participants are presented with a series of visual stimuli and are asked to report is the stimulus presented is the same as presented *N* trials, or stimuli, before. An *N*-level of 3, referred to as a 3-back, requires participants to compare the current stimulus to the one presented three trials earlier (Gajewski et al., 2018). The stimuli used are heavily spatial in nature, often stimuli are different locations of a target in an array. This task requires the participant to hold the visuospatial information of each stimulus, maintaining and updating constantly with each trial and subsequent stimulus presented. A participant must use their working memory to make a constant comparison between stimuli, keep track of which stimuli they are comparing, and then use this information to make an appropriate decision and produce a response. Even a seemingly simple task, especially compared to those taken on outside of the laboratory, demands the coordination of several cognitive mechanisms.

The N-Back task is shown to be sensitive to varying cognitive states and processes including both or normal and pathological aging and other disease (Gajewski et al., 2018). Behavioural findings have been supported with concurrent evidence from neuroimaging and physiological measures (Lamichhane et al., 2020; Missonnier et al., 2003).

Tunneling Task. The Tunneling task assess broadly visuomotor function. It recruits visuospatial working memory among other cognitive faculties, such as motor planning and coordination (Mirdamadi & Block, 2020). In a computerized task, participants are required to navigate a cursor through a “tunnel” created by visual boundaries from a starting point to an ending point. The complexity of the track is aimed to measure the speed-accuracy trade-off, the reduction in speed with increase in accuracy and vice versa, in participants.

Mirdamadi and Block (2020) employed the tunneling task in their investigation into motor skill learning and proprioception. In their original procedure, participants grasped a handle to manipulate a robotic manipulandum (BKIN; see Fig. 1A in Mirdamadi and Block) with vision of their shoulder, arm, and hand obscured. Using the handle, participants navigated their cursor through a series of tunnel tracks. Improved speed-accuracy trade-off (i.e., reduction in speed without a reduction in accuracy) was seen for all participants with practice. Concurrent measures of sensorimotor integration found that motor skill learning, as measured by the tunneling task, was correlated with increased sensorimotor integration.

Construct Overlap Between Attention and Working Memory

While often categorized as measuring different facets, each of the aforementioned tasks represent overlap in the processes they are attributed to. Aside from the broad construct of cognition, any of these tasks or components cannot measure any construct in isolation. Attention and working memory are two distinct constructs but are nearly inextricable in measurement. Attention is conceptualized as a filter to information that can enter working memory and subsequent processing (Han & Kim, 2009).

To form a decision or make a discrimination and then produce a response requires both attention and working memory in sequence. You must attend to the stimuli, such as a target, for it to be processed. This information is then manipulated in our working memory and used to make a response. Thus, in the grander schema, there is a serial processing sequence of attention to processing in memory to decision to response generation. Consequently, overlap is expected. There is some measurement of attention in a working memory task and vice versa. This exact overlap, or more operationally, statistical redundancy poses a challenge and consideration with many statistical models. This issue with construct overlap, measurement, and analysis is not unique and holds true for many other constructs measured, especially in the case of behaviour.

Relationships between Cognition and Demographic and Lifestyle Determinants

Cognition is not an independent process, both internally within the supporting processes, and with respect to the effect of external factors. Many approaches to study psychology are limited and explore only a few main effects. In reality, cognitive performance is shaped by many aspects including demographic attributes such as age or sex and gender (Gajewski et al., 2018; Hyde, 2016; Smittenaar et al., 2015). While also being subject to lifestyle factors such as sleep, stress, affect, and physical fitness (Frenda & Fenn, 2016; Schoofs et al., 2008; Yang et al., 2013). Our behaviour is a result of our cognition, and our cognition is also affected by many aspects of our lifestyle which are related to demographics attributes. From this view, we can construct statistical models to show these relationships. It follows that demographic and lifestyle factors affect cognition, which ultimately give rise to behaviour. Each of these proposed relationships have been, and continue to be, well-studied. The demographic attributes/background can account for differences in cognitive performance. This is equally true for the lifestyle of participants. The nature of these relationships remains a productive inquiry.

Demographics Account for Differences in Cognitive Performance

Among the earliest inquiries in psychology concern the study of *individual differences* (Goodwin, 2008). In that, how can we account for differences in behaviour? These individual differences were often explored in relation to demographic groups, including race, ethnicity/culture, sex/gender. The continued study of individual differences has brought forward competing findings.

Sex and Gender

There are many established beliefs regarding cognition and gender. Some include a male advantage on mathematical and visuospatial ability, and a female advantage in verbal ability (Hyde, 2016). Also, that males have superior cognitive processing and are more analytic in their reasoning. With evolutions in social climate and psychological methods, many of these gender differences are no longer supported, and nuances identified.

Working Memory. Studies have found memory ability to have systematic variance attributed to gender. Pauls and colleagues (2013) aimed to investigate how visual working memory performance was different between males and females. Using subtests of the WMS-IV (spatial addition, symbol span) to index spatial working memory, the authors found an overall significant effect of gender on spatial working memory, with males outperforming females (d = 0.34). This value is for a sample of males and females (N = 696, n_{female} = 366) with an age range of 16 to 69 years.

In contrast, using the N-Back task specifically as a measure of visuospatial ability, Schmidt et al. (2009), found no gender differences in behavioural performance nor in activation through fMRI. Through samples of males and females matched on age, education, and ethnicity, Schmidt et al., did not detect statistically significant difference between accuracy and response times attributable to gender. Subsequent fMRI data supports the lack of gender bifurcation in behavioural data. Schmidt et al., observed the activation between females and males to be "remarkably similar". The same regions are implicated between the female and male participants while undergoing fMRI scanning and completing the N-Back task. The authors note that they believe the incongruency with the trend of poorer female performance is due to their sampling methods. They boast a sample matched on each of age, education, and ethnicity, and larger sample compared to past studies.

In light of competing results, contemporary analysis methods, notably the meta-analysis, have been sought out by researchers to further probe the presence of gender differences in cognition. Hyde (2016) references a body of meta-analyses to illustrate the research on gender differences in cognition. The focus on visuospatial ability found gender effects, a male advantage, ranging d = 0.51 – 0.77. Importantly, these meta-analyses draw on results from a specific visuospatial task, the 3D rotation task where participants demonstrate their ability to manipulate and hold a mental image or representation of an object. Consequently, incongruent findings could be reduced to a measurement issue.

Works of Hyde (2016, 2005) on disentangling the literature proposes the *Gender Similarity Hypotheses* (GSH). In short, the GSH holds the conjecture that those of differing gender are more similar than they are distinct (Hyde, 2005). Variance within those of a shared gender are greater than those between distinct genders. Acknowledging the moderate male visuospatial advantage, Hyde (2016) proposes the domain of testing in visuospatial ability is unique. There is no formal education curriculum targeting visuospatial ability as there is for many other cognitive domains where there are little to no observed gender differences (verbal ability & mathematics). Males are more likely to engage in activities drawing on spatial ability such as sports activities and video games. An additional important factor is that spatial abilities can be improved through training intervention. In tandem, Hyde (2016) suggests that this difference in gender on visuospatial ability is less likely an innate ability but rather due to the activities and environment of males.

Attention. Research concerning gender and attention have competing findings. Similar to as observed in working memory. Given the intractability of attention from working memory as previously discussed, the same pattern in findings between working memory and attention is not surprising.

Selective visual attention shows distinct patterns of behaviours for male and female participants. In a cueing task, female participants' performance was worsened with an invalid cue compared to no cue (Merritt et al., 2007). In contrast, the male participants' performance was increased with an invalid cue compared to no cue. The validity of a cue, the knowledge of a stimulus being relevant to the task, draws on top-down attention rather than stimulus-driven bottom-up. Feng et al. (2011), present similar physiological findings corroborating the increased cueing effect on females. Event-related potential (ERP) data analysis found that female participants show a greater amplitude, meaning, they change in electrical potential of the scalp is greater. The authors offer the greater endogenous efforts of females as explanation for greater activation.

Focusing on a task-switching task (attention shifting), Hirsch et al. (2019) find no gender advantage in either of response time or accuracy. The authors report an effort to control for any gender difference in working memory, processing speed, and fluid intelligence. Moreover, of the ten attentional tasks aimed at evaluating multitasking abilities, none of them produced evidence for gender differences.

Response Inhibition. Li et al. (2006) explore response inhibition using a Go/No-go task in 20 male and 20 female age – and education – matched participants who also underwent fMRI imaging. The authors did not find evidence for gender differences in their behavioural analyses. Accuracy and reaction times for go and no-go trials did not differ, nor did self-reported frustration. However, the fMRI data did reveal that their male participants showed consistently higher level of cortical activation in their areas of interest than the female participants on no-go trials. On go trials, the two samples show different areas of activation. Li et al., describe this finding as male participants rely on motor networks whereas female participants relied on visual and learning networks when engaging in response inhibition. While there are differing neural correlates, the behaviour initiated by the males and females do not differ.

Age

Across the developmental lifespan, there are notable difference in working memory, attention, and response inhibition. Using an N-Back task, Gajewski et al. (2018) show that young adults (20 – 40 years) have greater working memory performance than middle aged (41 – 60 years) and older adults (61 – 80 years). This is indexed by reaction times slowing and decreased target detection with older age. Using concurrent psychometric testing, the authors suggest that the change in performance is driven by processing changes as we age. Younger adult performance was most related to executive functioning, whereas the older adults' performance correlated most to attention and working memory abilities. Older adults appear to use different strategies and rely on different processes than do younger adults. However, within age cohorts, performance is quite uniform. Thus, in participants from the same age group, we would not expect to see differences in attention and working memory attributable to age.

Age-related differences in response inhibition are a similar trend as to working memory attention, which is expected. Older adults are slower to respond to stimuli, however, the processes relied on are different than younger adults as is the case for attention and working memory (Smittenaar et al., 2015). Smittenaar et al. (2015), suggest that the case of reactive responding is distinct and relies on separate mechanisms than when responses are proactive, when we are prepared to make a response. In the proactive case, older adults do not show the same deterioration in response time. Further, this case has been argued to be more representative of the responses encountered in daily settings. As such, it is sensible that older adults would continue to react to these appropriately as this is adaptive and necessary for functioning. As with attention and working memory, performance on inhibition tasks is homogenous within an age cohort and observed differences are unlikely to be attributable to age alone.

Lifestyle Affects Cognitive Performance

The environment of a person is shaped by patterns of behaviour that culminates as their lifestyle. Given, that people exist within their environment, it follows that these factors would correspond to describable cognitive performance.

Sleep

Anecdotally, it is widely endorsed that proper sleep is a necessary component for daily functioning. Proper sleep is crucial to many aspects of cognitive processing from the neural level and the subsequent network activity that support and give rise to behaviour (Walker, 2009). Unsurprisingly, sleep deprivation results in poorer performance on an array of working memory and attention tasks (Frenda & Fenn, 2016). Response times and response accuracy are both comprised when a participant is sleep deprived. This can be seen in slowed responses, reduced accuracy, or both (Frenda & Fenn, 2016).

Further, inadequate sleep reduces response inhibition (van Peer et al., 2018). Using a Go/No-go paradigm, van Peer et al. (2018) show that participants deprived of sleep for three nights were significantly less accurate than the well-rested control group. The sleep deprived participants also report decreased attention and alertness in addition to a more negative affect. Drummond et al. (2006), show that while acute sleep-related detriments in cognitive performance are observed, they have the potential to be recovered. Depriving participants of sleep for two nights resulted in significant difficulty withholding responses, showing an increased response rate where a response should have been withheld. However, by restoring proper sleep for two more nights, participants can return to their baseline level of response inhibition.

Affect

Affect is the emotional state of a person at the time of interest (Kaufmann et al., 2020). Not to be confused with mood, which is used in a longer time frame, less transient than would be affect. Although often used synonymously, clinically and through psychological measurement, they address related but separate constructs about emotion. To further explain the distinction, Kauffman et al. (2020) describe mood as reported by a participant whereas affect can be reported but it is also observable. Affect is described by its valence, negative or positive.

When considering cognitive performance, affect is not a unique mental attribute. There exists a body of literature on the relationship between a person's affect and their cognitive performance on attributes such as working memory, attention, and response inhibition. Research by Yang and colleagues (2013) probed how the processing of information in working memory is related to positive affect. The authors manipulated the affect of their participants by experimentally inducing a positive affect in half of the sample, and then had all participants complete both a word-span and operation-span task. Those in the positive affect conditions performed better than those in the neutral condition on both span tasks, suggesting a working memory and attention benefit of positive affect. Further probing showed that this gain in attention and working memory was not solely accounted for by motivation. Another study using an N-Back task conducted by Brose et al. (2012) echo these findings using the converse: reduced working memory performance is correlated with negative affect. Of note is this investigation used correlational data and was not an experiment. Participants were from a larger longitudinal study and completed the same measures at multiple timepoints. The analyses revealed that sessions where N-Back performance was low, the participants tended to report a negative affect more often than not. Consequently, the authors draw a relationship between affect and working memory and attention.

On response inhibition, there is evidence to conjugate affect with response behaviour. Albert et al. (2010) had participants complete a Go/No-go task with stimuli present superimposed on emotionally (affectively) valanced images (see Albert et al. (2010) for materials). Electrophysiological data, ERP, were also recorded in their procedure to measure activation in networks associated with inhibitory control, the orbitofrontal cortex (OFC) and the anterior cingulate cortex (ACC). The researchers found greater ACC activation during trials using positively valanced images, implying that more inhibitory control must be exerted when stimuli are positive than neutral or negative. Albert and colleagues propose that this could be due to approach and withdrawal. In that approaching behaviour is related to positive affect and emotion, whereas withdrawing behaviour is related to negative affect and emotion. Taken together, in a positive affect, the increased effort required to inhibit responses may be due to approaching behaviour. Lending to participants initiating responses when they should withhold. Of note is that this inquiry concerns the affect and valence of the stimuli and not of the participant themselves. The underlying assumption is that positively valanced stimuli elicit positive affect in participants. However, this may not be the case invariably when considering affect.

Stress

Stress is well known to impact general cognitive functioning and performance on specific tasks. A prevailing theory surrounds the stress-performance curve, also known as the Yerkes-Dodson law (Yerkes & Dodson, 1908). This describes the concept that there exists some intermediate level of stress that drives peak performance. Further, that levels of stress that are too high or low result in poorer performance (Teigan, 1994). Consequently, when participants experience these extremes we expect, and observe, poorer task performance. In one example, Schoofs et al. (2008) show that performance on an N-Back task can be hindered by induced sufficient acute stress. Increased stress as measured by self-report and salivatory samples (cortisol, hormone & alpha-amylase, enzyme) correlated with increased negative affect and resulted in longer response latencies and lower accuracy in the N-Back task. Thus, increases in acute stress in reduce working memory performance.

Likewise, Janelle (2001) proposed that attention, specifically visual attention, is affected by stress. Increased stress can cause participants to use visual search strategies that are not effective and lend to worse performance as indexed by increased reaction times and lower accuracy. Qi et al (2018), support this with faster reaction times under stress, but lower accuracy rates in only one task. Thus, stress affects behavioural performance and modulates how attention is allocated. The impact of stress on performance has been further corroborated in tasks involving response inhibition. Inducing stress in participants concurrently affects response inhibition. Qi et al. (2017) induced stress and found that response inhibition was reduced, in that responses were made more quickly in a stress-induced condition than at baseline. However, response accuracy was not affected.

Fitness

Increased fitness, measured and self-reported, is consistently shown to have positive psychological and neurocognitive effects. An investigation by Basso et al. (2022) investigates the effects of increased aerobic exercise on an array of psychological and neurocognitive measures including affect and working memory. Half of the participants were instructed to maintain their current exercise regimen, control group, while the other increased their load over three months. Participants completed all assessments before and after the three months period. Increasing aerobic exercise resulted in in decreased negative affect and sadness. Working memory was measured using the N-Back task, the increased group outperformed the control group in accuracy but only for the 0-back condition. This was the only group-time interaction.

Acknowledging that aerobic exercise may not be the best measure for fitness and cognition, Gu et al. (2019) further delve into different types of fitness and exercise. Gu et al., argue that while much of the literature is concerned with advantages stemming from aerobic exercise, when considering neurocognitive effects, sports may be a better measure. Since, sports involve a higher cognitive demand. Through systematic review, they identify many findings and trends within the literature. Overall, sports requiring attention, active decision making, and cognitive flexibility (e.g., basketball, tennis) show greater benefits in cognitive functioning than sports that are more skill-based (e.g., running, swimming, cycling). However, all engagement in sports was shown to related to increased cognitive performance in the several domains including response inhibition, visuospatial attention, attention shifting, and working memory.

Lifestyle and Demographics Interact to Affect Cognitive Performance

The study of cognition and performance is far reaching. There are some competing results into how certain factors can account for our cognitive performance. Examining demographic factors, age has well-supported trends with aging. Younger adults tend to outperform older adults and rely on different mechanisms. However, performance within those age cohorts is homogenous. Sex and gender have less consistent results. Overall, male and female participants show equal performance with the exception of a slight male advantage in visuospatial working memory. Lifestyle factors also have tangible impacts on cognitive performance. Generally, cognitive performance worsens with decreased sleep and fitness, increased stress, and negative affect. Working memory and attention are affected in accord with each other, as is expected with the aforementioned construct overlap. Response inhibition tends to follow as well.

Factors pertaining to our lifestyle and demographic characteristics are not mutually exclusive, in that they are intrinsically tied. For example, gender differences in many cognitive and other outcomes are diminishing or have disappeared from statistical significance altogether. Since, what was measured as a difference attributable gender was ultimately accounting for many other contributing factors, such as education, socioeconomic status, and experience. This principle of non-unique attribution equally applies to other demographic and lifestyle indicators.

Are demographic factors such as gender or age uniquely and causally contributing to any patterns in cognitive performance? Or can any relationships be better explained by other factors? For example, the research on stress and cognitive performance also measures and reports on affect, given the stress and affect relationship (Qi et al., 2017; Qi et al., 2018; Schoofs, 2008). Is it stress driving the cognitive performance, or affect? Or some other causal chain. It is also known that decreased sleep and increased stress inhibit cognitive performance. Are these effects independent or causal? To acknowledge these more ecologically valid and complex questions, exploring multiple effects simultaneously is required.

Structural Equation Models for Modelling Cognition

To address the causality issues left by using single or limited predictors, SEM has been adopted by researchers to explore factors affecting cognitive performance. Recall, Lemes et al. (2017) used an SEM to determine how children’s physical fitness mediated the relationship between many known predictors of cognitive performance. This insight was possible by exploring all relationships of interest simultaneously.

A similar study by Padulo and colleagues (2019), also explored physical activity and fitness on school performance in children (M_{age} = 11 years, *SD* = 0.3 years). Here, school performance is thought of as a cognitive measure. Using their extensive inventory of measures, their final model comprised four LVs: family context, socio-demographics lifestyle, and school performance. The authors proposed an original model that included a latent factor for their measures of physical fitness of each participant, but their revised model did not include these measures. The SEM framework allowed for the metrics and ability to adjust their original hypotheses and create a revised model better suited to their data. In brief, school performance was predicted by family context, socio-demographics and lifestyle. Further, lifestyle fully moderated the relationship between family content and school performance. Padulo and colleagues demonstrate both how cognitive performance is impacted by many factors, how lifestyle can account for some of these relationships, and the utility of an SEM approach.

Within the domain of cognition, Fino et al. (2014), used SEM to confirm the theoretical constructs in in impulsive behaviour and inhibitory control in adolescents (M_{age} = 17 years, *SD* = 0.82 years). Executive function was predicted by control and impulsivity, and itself predicted task errors. Turning to older adults, Hull et al. (2008), investigated the factor structure underlying executive functioning in older adults. Using a Confirmatory Factor Analysis (CFA), they tested a proposed model of executive functioning comprised of three factors representing the constructs of: shifting, updating, and inhibition. Shifting referring to set shifting or (task switching, cognitive flexibility), updating being monitoring and updating information (attention and working memory), and inhibition representing response inhibition. However, their analyses revealed that a two-factor model using only shifting and updating to be the best fitting model.

Hull et al., suggest their findings support that updating abilities in older adults underlies age-related in executive functioning.

Using SEM, these authors were able to test complex hypotheses with several statistical relationships simultaneously. Moreover, to define models with several latent factors and to test the suitability of these models, allowing them to be refined. In context, Lemes et al. (2017) and Padulo et al. (2019) were able to show how cognitive performance was affected by several lifestyle factors and especially the importance of physical fitness. Fino et al. (2014) and Hull et al. (2008) created and refined models for executive functioning in adolescents and older adults, respectively. Testing hypotheses involving complex relationships is required to support the development of theories and models of cognition. Thus, the implementation of SEM in cognitive psychology in an essential advance.

Summary and Current Study

Cognition encompasses the mental processes that underlie how we attend to, store, and process information (Eysenck & Brysbeart, 2018). The mechanisms underlying cognition are subject to external influence, such as the environment that a person functions within. Disentangling these complex relationships is imperative to understanding the nature of cognition. Demographic attributes such as age and gender are shown to account for variance observed in cognitive performance. Additionally, characteristics of a person’s lifestyle is related to their cognitive performance. Understanding the nature of these relationships requires a simultaneous investigation of the influence of both demographic and lifestyle factors on cognitive performance. Testing theories of cognition requires a quantifiable means for evaluation and refinement. This is done using statistical modelling, which is facilitated through SEM. Research in cognitive psychology leverages SEM analyses to understand cognition at several levels on inquiry spanning networks of neural activity and behaviour.

The aim of the current study is to parse the relationships and influence exerted by demographic and lifestyle measures on cognitive performance, and how this ultimately drives behaviour. Using a battery of cognitive tasks and several questionnaires to collect demographic and lifestyle data, I will create statistical models using the SEM framework. All tasks were built in PsychoPy and hosted online via Pavlovia (Peirce et al., 2019). Questionnaires were hosted on Qualtrics (Provo, UT, USA).

I hypothesize that each of the measured cognitive variables will load onto one or more latent factors representing three aspects of cognitive task performance: (1) Cognitive control which will encompass processes such as response inhibition and general executive functioning; (2) visuospatial working memory and visual attention; and (3) visuomotor functioning as each cognitive task is visual in nature and requires motor responses. Further that demographic and lifestyle measures will account for variance in cognitive performance.

Chapter 2: Method

Participants

A total of 1141participants (n_{females} = 781, M_{age} = 23.13 years, *SD* = 7.38 years) were recruited from introductory psychology classes at York University and completed the study remotely. Participants received course credit for their participation.

Materials

The study was administered online, and participants used their own devices to complete the browser-based battery. All cognitive tasks and surveys are conducted online, consequently, all hardware is not standardized and are that of the participant. Participants were required to use a desktop or laptop computer. Visual stimuli presented on remote devices could vary based on the size of display used by each participant but was scaled proportionally. The study comprised a series of cognitive tasks built using PsychoPy software (Peirce et al., 2019) and hosted through on a server Pavlovia, and a series of questionnaires hosted through Qualtrics (Version: September 2020).

Participants completed eight cognitive tasks and an extensive questionnaire to collect demographic and lifestyle data. Only a subset of these tasks and measures were used and those will be described. A full list of tasks and measures can be found in Appendix A.

Cognitive Tasks

Participants completed questionnaires and eight tasks over two online sessions, each around 1.5 hours-long scheduled one week apart. These tasks are meant to assess varied facets of cognitive and a subset of four tasks are used in this analysis.

N-Back. The N-Back task assess visuospatial working memory. The current instantiation is adapted from that of Dores et al. (2015). The N-level corresponds to the number of positions, or trials, before the one currently presented that the participant must compare to. Increasing the *N*-level is a harder task for the participants as cognitive load increases with having to maintain information for each stimulus presented. Participants are presented a 3x3 grid on their screen and are asked to attend to a white square that will appear in one of the nine cells. See figure 1. In a 2-back block, participants must choose via a keyboard response (spacebar if correct position, no response if not) if the white square is in the same position (cell) that it was two trials (positions) prior; similar to one prior in a 1-back and three in a 3-back. Each participants completes three blocks of trials for each of the 1-, 2-, and 3-back conditions.

The outline of the grid changes from the default white to green for a correct response, and red for an incorrect response. For trials when the participant does not hit the spacebar, no feedback as

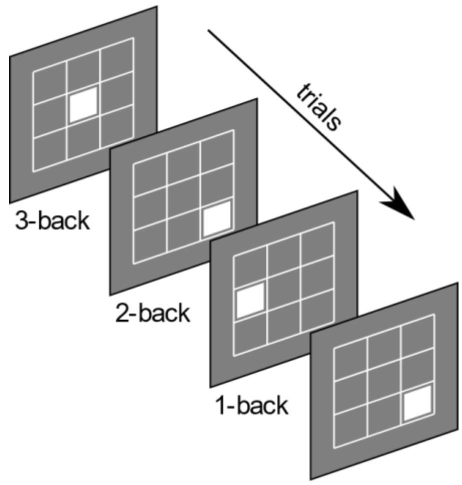

Figure 1. Procedure and Stimulus Example for the N-Back Task.

colour change appears. A response is not required in approximately 75% of trials. 180 trials (3 blocks of 60 trials each) are completed at 2000ms each, for an approximate time of 6mins. Response time and accuracy are recorded.

Task Switching. The task-switching task is a measure of cognitive flexibility (Monsell, 2003). The current instantiation is adapted from that of Stoet (2010). Participants are required to respond to a set of stimuli based on two different response rules in an alternating sequence. Participants are presented with a white 2x2 grid containing 4 cells. In each cell, a compound stimulus with a shape and filling (dots) attribute would appear. The shape could be either a square or a diamond (square rotated 90 degrees); the filling was small solid circles (dots) arranged vertically and could be either two or three. A grid with example stimuli is shown in Figure 2.

Each of the three blocks had different instructions. In all blocks participants made keyboard responses. In the first block, participants were instructed to respond to the shape attribute and ignore the figure attribute, whereby the ‘x’ key was for a diamond and ‘m’ key for the square shape. The second block had participants only respond to the filling and ignore the

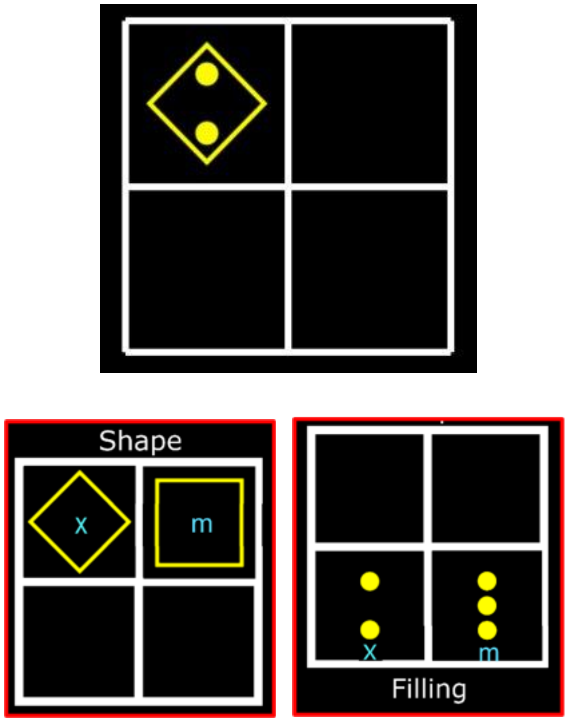

Figure 2. Stimulus Array in Grid for the Task Switching Task. Bottom two arrays display the shape and filling participants must attend to.

shape attribute of the stimulus; ‘x’ 3 dots and ‘m’ for 2 dots. The third block introduced the task-switching component, where the attribute to which the participated responded to would alternate every two trials (AABB) between the shape and dots. The stimuli would appear in the cells in the grid in a clockwise rotation (1,1 to 1,2 to 2,1 to 2,2) beginning with the (1,1) cell (first row, first column).

Trials advanced by participants making a keyboard response, or a set timeout of 10secs. Feedback was given by the colour of the grid, changing from white to green for correct responses, and white to red for incorrect. The first two blocks would reshow the instructions for keyboard responses on incorrect trials. Each participant completed 74 trials distributed across 3 blocks. The first two blocks consisted of 12 trials, and the third 50 trials. Response time and accuracy are recorded.

Visual Search. The visual search task measures visual attention and requires participant to locate an upright letter ‘T’ in an array of other distractors of similar shapes. This instantiation was adapted from Triesman and Gelade (1980) and Stoet (2010, 2017). An example of an example trial with stimulus array is shown in Figure 3.

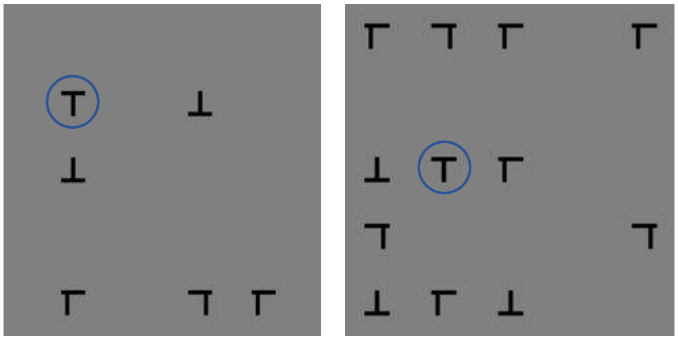

Figure 3. Example Trials for the Visual Search Task. The left example shows a size 6 array, and the right a size 12 array.

Participants must search the array for the target ‘T’ and make a keyboard response, “x” if the target is in the array (present) and “m” if it is not (absent). Each of the array items, target or distractors, can appear in one of 25 locations on the screen, these positions are randomized. The size of the array is either 6, 12, or 18 items; and the target is present 50% of the time. Trials are completed and advanced following the participant’s response. No feedback is given.

Each participants completes a total of 162 trials distributed evenly across three blocks (54 trials per block), with interleaved rest between blocks. In each block, each combination (6 unique) of array size (6, 12, 18) and corresponding target status (present or absent) occurs nine times. Response time and accuracy rates are recorded.

Go/No-go. The Go/No-go task assess impulse inhibition, the ability to ignore or withhold a response when not appropriate (Wright et al., 2014). Participants are required to make a speeded decision and simultaneously control the impulse to respond to the stimulus. This instantiation is adapted from Stoet (2010, 2017). Participants are presented with a circle containing a cue for either “go” where they must make a keyboard response, or “no-go” where they must refrain. As shown in Figure 5, all “go” cues are a blue circle with the text “go” in the centre, and all “no-go cues” are orange circles with the text “no go”. The task comprises three blocks of 100 trial each, with a 1:5 go to no-go ratio (20% go, 80% no-go). Reponses can be made at stimulus onset and was timed out at 2secs regardless of if a response was made. Response time and accuracy are recorded for go and no-go trials.

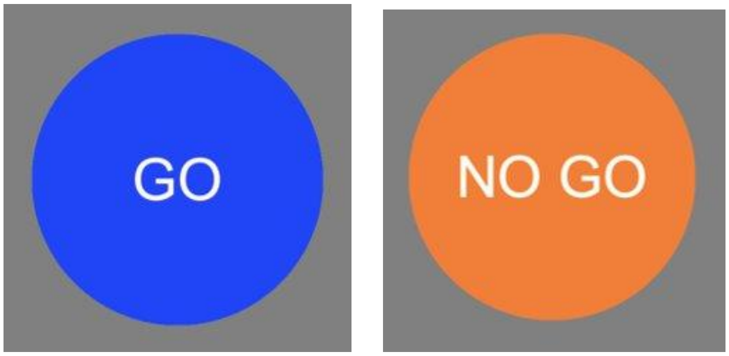

Figure 4. Go and No-go Stimuli.

Trail Making Test B (TMT-B). The Trail Making Test B (TMT-B) is the second part of the Trail Making Test (TMT), a neuropsychological assessment where participants must draw on visual attention and task switching to connect a series of circles containing letters and numbers (Reitan & Wolfson, 1993). The circles must be connected from 1 to A to 2 to B and so on, alternating ascending numbers and letters. This experiment used a shortened version that uses letters A-I and 1-9, as seen in Figure 5, as opposed to the original longer version extending to letter L and number 13. Participants were forced to complete the trials correctly as drawing a trail was contingent on the participant completing the previous trail correctly. Meaning, participants were forced to draw trails in the correct order. Time to completion, or movement time was recorded for each of the 5 trials of different mapping layouts.

Tunneling. The tunneling task is a visuomotor task requires participants to draw on motor acuity and goal directed processes to move their cursor through a bordered track (tunnel).

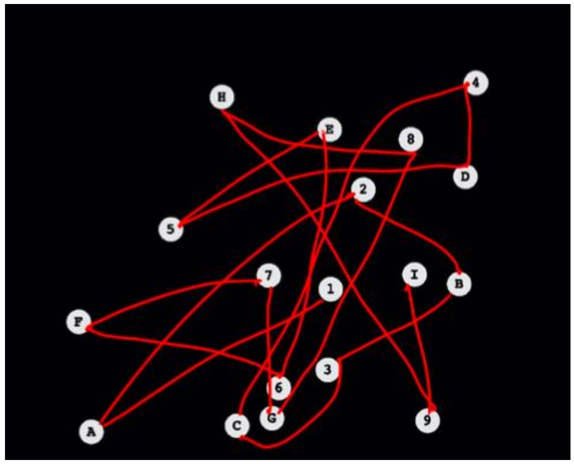

Figure 5. Example Completed Trail Making Trial.

The instantiation used is adapted from McGrath & Kantak (2015) and Mirdamadi & Block (2020). Participants to navigate their cursor through a series of 24 tunnels, as seen in Figure 6. Trials begin once the cursor is in the orange home position, and end once participants navigate to the blue target position and return to home. Tunnels are presented in a variety of conditions with varying scales (40%, 60%, 80%, and 100% - original scale) and orientation (original orientation or flipped 180°). Time to complete the track, movement time, and proportion of time within the track is recorded for each trial.

Figure 6. Example Tunneling Trials. Left is example of original size and orientation, right is flipped 180° and 40% scale.

Questionnaire Data

Demographic Information. The demographic information used are age, sex. Information concerning the lifestyle of participants was also collected.

Lifestyle Information. A subset of all lifestyle measures collected are used for analysis. A full list of all data collected from participants, tasks, and questionnaire, can be found in Appendix A.

Sleep. Self-reported sleep quality was assessed using the Pittsburgh Sleep Quality Index (PSQI) (Buysse et al., 1989). The PSQI asks participant to reflect on their sleep during the past month or the night before. The 10 questions represent seven component scores. Each response to a question is then contributed to a component score using the criteria outlined by Buyesse and colleagues. Each component score ranges from 0 to 3. Total scores range from 0 to 21, where higher scores are indicative of poorer sleep quality.

Affect. Affect was measured using the International Positive and Negative Affect Scale – Short Form (I-PANAS-SF) (Thompson, 2007). The I-PANAS-SF is a validated 10-item questionnaire that assess participant affect. The prompt "Thinking about yourself and how you normally feel, to what extent do you generally feel: __" is presented and participants rate 10 feelings on a 5-point Likert scale ranging from 1 (never) to 5 (always). The 10 items are divided evenly to form two subscales, (1) Positive Affect (PA) and (2) Negative Affect (NA); see Table 1. Higher summed scores across each subscale range from 5-25, where higher scores correspond to higher feelings of PA or NA.

Stress and Fitness. Participants self-reported their subjective levels of personal stress and fitness. Participants were asked "how stressed have you been feeling this week" and "how fit/physically active do you consider yourself?". Each of these items were answered on 7-point

Table 1

I-PANAS-SF Items with Affect Valence

Positive Affect	Negative Affect
Active	Afraid
Alert	Ashamed
Attentive	Hostile
Determined	Nervous
Inspired	Upset

Likert scale ranging from 1 (not at all) to 7 (extremely). The single-point measure is used for each participant.

Procedure

Following informed consent, participants respond to the questionnaire items and then proceed to the cognitive tasks. Due to the length of the study, full participation is split evenly across two parts. All demographic information (e.g., age and sex) was collected in part one alongside fitness, stress, sleep, and affect. The visual search, Go/No-go, and task switching tasks were also completed in part one. Part two comprised another measure of sleep, affect, stress; as well as the N-Back task. Since the parts are completed on different days, sleep, affect, and stress are in each part. This is because these measures ask participants about themselves and their state when they are completing the study. Within each part, the order of cognitive tasks is randomized. The order of questionnaire items is not randomized.

Analysis

The hypothesized model of cognitive performance includes the demographic and lifestyle measures as regressed onto LVs for cognition. Cognitive performance is measured through six cognitive tasks and each of these tasks has multiple response time (RT) and accuracy (Ac) measures per participant, 40 in total. Consequently, it is likely that many measures are redundant. Redundancy in data is handled through dimensionality reduction. Some techniques for dimensionality reduction rely on theory and frameworks in the literature, theory-driven approaches. The first step was to reduce the number of indicators per task.

Consider the visual search task, where there are three array sizes and conditions for when the target was absent and present for each, which is 6 indicators for one task. For this task, the proposed measure is to regress RT on array size for each participant. The slope of this regression represents the increase in RT with a one-unit increase in array size for each participant. A regression is performed, and slope calculated, for the each of the target absent and target present conditions.

For the N-Back task, d' ("d prime"), is used as a measure of sensitivity is used for each N-level. Similarly, d' is used for the Go/No-go task. The task-switching task uses switch-cost, which is defined as the difference in RT between trials when participants were required to switch from responding to the shape of the stimuli to instead responding to the dots. For the TMT-B and tunneling the mean movement time across paths/tracks is used. These combined measures of cognitive performance were used within the SEM analysis.

Chapter 3: Results

All analyses were conducted in R software (Version 3.6.1) using the Lavaan (Version 0.6.13), regSEM (Version 1.9.5), FactoMineR (Version 2.8), and missMDA (Version 1.18) packages.

Regularized SEM on Combined Indices of Cognitive Performance

As mentioned in the analysis section, data from all 45 indicators across each of the six tasks were reduced to 10 using a theory-driven approach (see Analysis). Descriptive data for all

10 measures can be found in Table 2.

Table 2

Descriptive Statistics for the Combined Measures Data

	Mean *(SD)*	Skew	Kurtosis
Nbk. 1-back d’	3.00 (*0.81*)	- 1.02	2.16
Nbk. 2-back d’	2.18 (*0.91*)	- 0.54	- 0.13
Nbk. 3-back d’	1.27 (*0.64*)	- 0.24	- 0.50
Vis. absent slope	0.21 (*0.10*)	- 0.83	2.33
Vis. present slope	0.14 (*0.07*)	0.51	0.94
Gng go d’	3.90 (*0.64*)	0.12	2.38
Tsw. Switch cost	0.58 (*0.48*)	1.20	2.85
Trl. Mean Movement Time	37.43 (*14.52*)	2.38	10.63
Tun. Mean Movement Time	4.69 (*2.05*)	1.05	2.31

Employing combined measures is the first theory-driven dimensionality reduction technique. The second step involves creating the SEM model, with the LV loadings hypothesized to represent cognitive processes underlying the combined behavioural measures. Three LVs were created: (1) cognitive control, (2) visuospatial working memory and visual attention, and (3) visuomotor functioning. This model was fitted along with the lifestyle and demographic measures. Descriptive data for the demographic and lifestyle measures can be found in Table 3.

The relationships between the cognitive LVs and the lifestyle and demographic measures were originally hypothesized to be directional, however, issues with missing data meant that this would not be possible. In the SEM framework, directional hypothesis and relationships require complete cases as it maps participants’ response across several items. Consequently, bidirectional relationships computed as covariances were used. Also note that all measures were scaled such that the estimated loadings were comparable. Each of the demographic and lifestyle

Table 3

Descriptive Statistics for the Demographic and Lifestyle Measures

	Mean *(SD)*	Skew	Kurtosis
Age (years)	23.13 (7.*38*)	2.28	5.04
Stress	4.57 (*1.65*)	- 0.43	- 0.57
Fitness	4.24 (*1.33*)	- 0.49	- 0.07
Sleep (PSQI)	6.59 (*3.36*)	0.52	0.09
Pos. Affect (PANAS-PA)	16.28 (*0.64*)	- 0.04	- 0.26
Neg, Affect (PANAS-NA)	12.25 (*3.83*)	0.33	- 0.36

Note. The Stress and Fitness can range from 1(not at all) to 7(extremely), PSQI scores can range from 0(no sleep difficulty) to 21(severe sleep difficulties), and Affect can range from 5(low affect) to 25(high affect).

measures were specified to covary with each of the LVs. Combined measures were specified to load onto any LVs representing its hypothesized cognitive construct. This model is presented in Figure 7.

The regularized structural equation model (regSEM) runs the initially specified SEM and iteratively applies a penalty score, regularization, to penalize large and complicated models and aims to a reduce to a simpler model with fewer indicators and connections. The initial model was specified with a penalty of $\lambda = 0$ and increased by .05 each iteration. Penalties were applied to the loadings of measured items onto LVs. The best model as selected through lowest BIC. The best model was the original model, the starting model with a penalty of $\lambda = 0.0$. This model with significant paths as presented in Figure 8 and loadings in Table 4. Holistically, the model fit is poor. Model fit indices presented in Table 5.

Cognitive Model

Looking first to the cognitive portion of the model, some hypothesized loadings are not

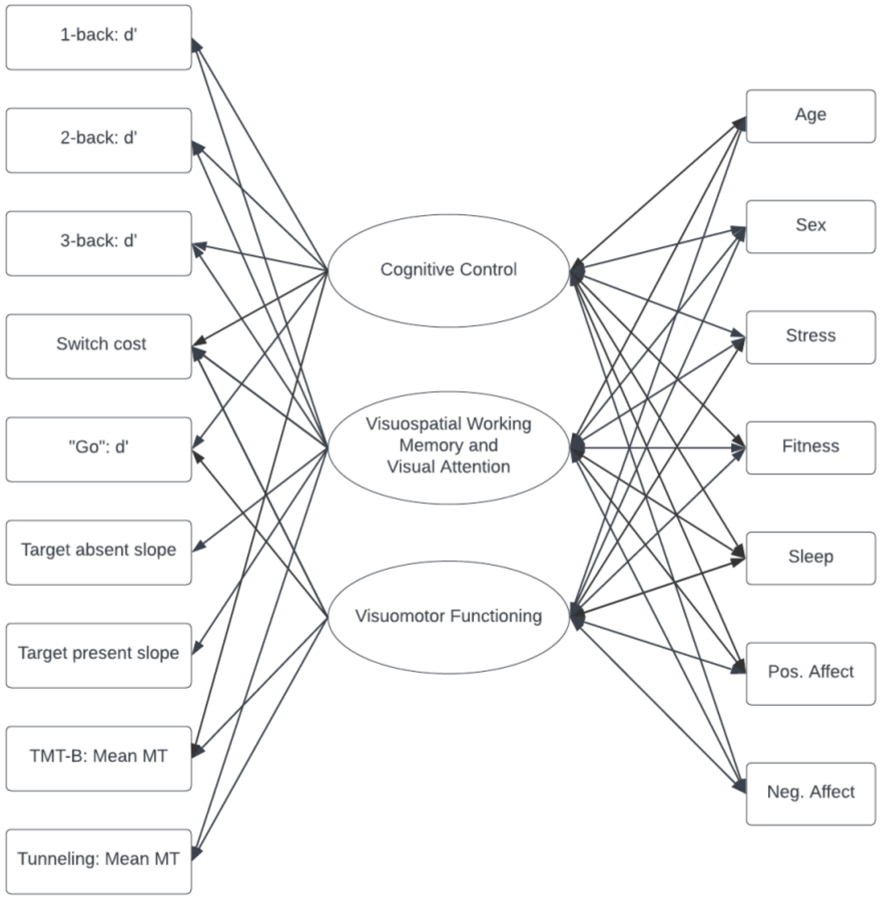

Figure 7. Initial Hypothesized Cognitive Latent Variable Model

included. For (2) visuospatial working memory and visual attention, three of the six hypothesized indicators were not loaded. None of the three N-Back d' measures loaded significantly onto the LV, whereas visual search (target absent and target present) and tunneling did load. For both of (1) cognitive control and (3) visuomotor functioning, all hypothesized loadings were significant. Within the LVs, each of the three LVs were positively correlated with each other. Covariances between LVs are not pictured but can be found in Table 4.

Reduced switch cost and lower meant MT for TMT-B and increased d' across N-Back and Go/No-go result in increased (1) cognitive control. These findings are cohesive as reduced switch cost, faster TMT-B completion time and increased sensitivity are all indicative of greater

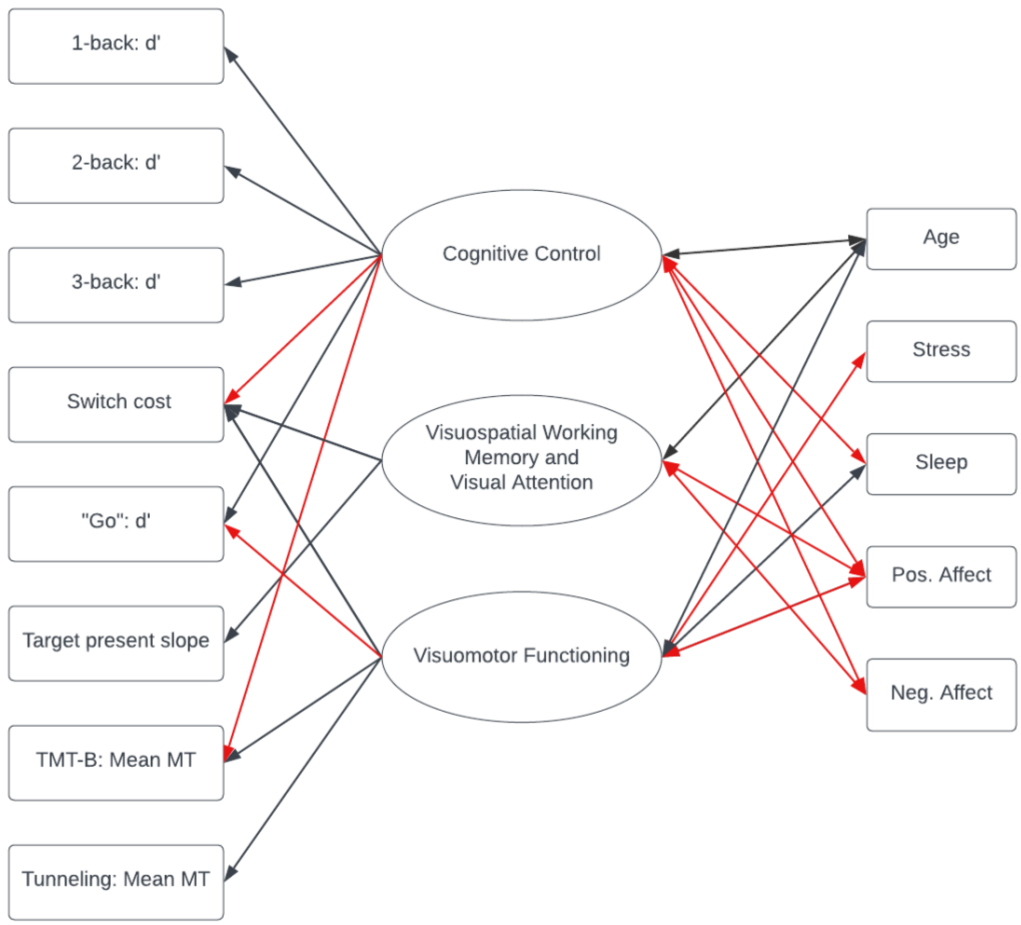

Figure 8. Final Cognitive Latent Variable Model. Only significant paths are included, and red paths represent negative estimates.

cognitive control. Each of the visual search (target absent and targe present) and switch cost load positively onto (2) visuospatial working memory and visual attention. This is interpreted as a greater increase in RT with increases in array size are in visual search and increases slowing of RT between instruction sets in task switching were related to increases in working and memory and attention. Longer TMT-B and tunneling MTs, increased switch cost, and reduced sensitivity were correlated with increased (3) visuomotor functioning.

Table 4

Final Model Loadings

Latent Variable		Loaded/Covaried Variable	Estimate
Cognitive Control	=~	Gng. go d’	0.29***
		TMT-B mean MT	-0.33***
		Tsw. switch cost	-0.23***
		Nbk. 1-back d’	0.32***
		Nbk. 2-back d’	1.30***
		Nbk. 3-back d’	0.63***
	~~	Age	0.51***
		Sleep	-0.09***
		Pos. affect	-0.10***
		Neg. affect	-0.17***
		Visuospatial Working Memory and Attention	0.62***
		Visuomotor	0.42***
Visuospatial Working Memory and Visual Attention	=~	Vis. absent slope	0.80***
		Vis. present slope	0.86***
		Tsw. switch cost	0.25***
	~~	Age	0.21***
		Pos. affect	-0.10***
		Neg. affect	-0.14***
		Visuomotor	0.49***
Visuomotor Functioning	=~	TMT-B Mean MT	0.70***
		Tsw. switch cost	0.33***
		Gng. go d’	-0.11***
		Tun. mean MT	0.55***
	~~	Age	0.51***
		Stress	-0.15***
		Sleep	0.13***
		Pos. affect	-0.19***

Note. =~ specifies a variable loading, ~~ specifies a covariance. * = $p < .05$, ** = $p < .01$. *** = $p < .001$

Demographic and Lifestyle

Age and affect (PA, NA, or both) was related to each cognitive LV. Lower sleep quality,

Table 5

Final Model Fit Indices

$\chi^2(79)$	RMSEA	SRMR
1152.34, $p < .001$	0.109, 90% CI [0.104, 0.115]	0.104

GFI	CLI	TLI	BIC
0.850	0.611	0.409	39 933.53

reduced levels of PA and NA, and increased ages was related to increased (1) cognitive control. Similarly, reduced levels of PA and NA, and increased ages was related to increased (2) visuospatial working memory and visual attention. Increased (3) visuomotor functioning was related to reduced stress, lower PA, increased sleep quality, and increased age.

Hierarchical Multiple Regression on Cognitive Measures

As mentioned above, the limiting factor for directional relationships is the missing data in the lifestyle and demographic measures. For directional insights, a follow-up series of hierarchical multiple regressions was conducted. Hierarchical multiple regressions allow for the evaluation of the relative strength of predictors when accounting for the shared variable among predictors. Recall, that the model fit is not optimal. It is possible that the specified cognitive LV structure is not well suited. Therefore, the following series of hierarchical multiple regressions will use the measured combined cognitive task measures and not the LVs. For the N-Back task, the 2-back condition was selected, all other combined cognitive task measures are included.

The first model step in each is a demographic model that regresses each combined measured on age and sex. The second model step is the full lifestyle model that adds stress, fitness, sleep (PSQI), and affect (PANAS – PA & NA). For each of the models, the second lifestyle model accounted for more variance in the combined measure outcome variable. For a full summary and all parameters, see Appendix C. Of note is that the condition for regression is complete cases, the regression models for each criterion variable uses a different subset of participants. A condensed summary of regression equations with significant predictors ($p < .05$) is presented below. These seven regression equations show that while controlling for demographics, lifestyle measures account for a statistically significant proportion of the variance in the combined task measures. This insight serves as reassurance that lifestyle measures have predictive properties on the cognitive performance and lays foundation that a different modelling approach.

(1) $Nbk.\widehat{2-back}\ d' = (-0.22) * \text{sex} + (-0.02) * \text{neg. affect} + 2.95$

(2) $V\imath s.\widehat{absent}\ slope = (0.002) * \text{age} + (-0.002) * \text{neg. affect} + 0.26$

(3) $V\imath s.\widehat{present}\ slope = (0.002) * \text{age} + (-0.002) * \text{neg. affect} + (-0.002) * \text{pos. affect} + 0.16$

(4) $\widehat{Gng\ go}\ d' = (-0.020) * \text{age} + (-0.035) * \text{neg. affect} + 4.93$

(5) $Tsw.\widehat{Sw\imath tch}\ cost = (0.013) * \text{age} + (-0.040) * \text{fitness} + (0.018) * \text{sleep} + 0.25$

(6) $Trl.Mean\ \widehat{Movement}\ T\imath me = (0.664) * \text{age} + (-1.086) * \text{stress} + (1.044) * \text{fitness} + (-0.448) * \text{pos. affect} + 23.53$

(7) $Tun.Mean\ \widehat{Movement}\ T\imath me = (0.082) * \text{age} + (0.344) * \text{sex} + (-0.056) * \text{neg. affect} + (-0.060) * \text{pos. affect} + 4.27$

In sum, the combined measures method provides insight into the latent constructs underlying cognitive performance and how these are related to lifestyle and demographic attributes. However, the model specified could not account for directionality and the structure itself may have not been optimal as evidenced by the poor model fit. To acknowledge these limitations, a data-driven approach and directionality are tested in an exploratory PCA-SEM approach.

PCA on Response Time and Accuracy Data

Given the limitations of the combined measures model, an additional series of exploratory analyses were tested. These models retained response time (RT) and performance accuracy (Ac) as predictors of cognitive performance. Recall, movement time (TMT-B and tunneling) and proportion in-track (tunneling) are considered equivalent to RT and Ac, respectively. Unlike the combined measures, this method for dimensionality reduction is purely data-driven. For descriptive statistics of all 45 measures of cognitive performance, see Appendix B. A Principal Components Analysis (PCA) was conducted on the RT and Ac data from each task, as there are several RTs and ACs for each. The dimensionality reduction will reduce the total number of measures from 40.

Data was assuming to be Missing Completely at Random (MCAR) (Rubin, 1976). Missing values in the behavioural cognitive performance data were imputed using a regularized method, which is recommended as it reduces the probability of overfitting (Husson & Josse, 2020). A PCA on 40 variables would create 40 principal components (PCs) along those 40 dimensions. First, the optimal number of PCs was estimated to be 5. Then, data was imputed along these 5 PCs. The properties of these PCs are presented in Table 6. Regularized imputation methods involve estimating missing data based on the similarity across participants and the between variables. These five PCs are used as a representation of the behavioural data. The correlations between the RT and Ac measures and the PCs above |.50| are presented in Table 7. For full correlation table, see Appendix D.

Table 6

First 5 Principal Components of RT and AC Performance Measures

Principal Component	Eigenvalues	% of Variance	Cumulative % of Variance
1	9.60	21.33	21.33
2	7.52	16.70	38.03
3	4.83	10.73	48.77
4	3.90	8.68	57.44
5	2.80	6.21	63.65

Table 7

Correlations Between PCs and Cognitive Task Measures

Principal Component (PC)	Cognitive Task Measures	
PC1 - Response Time	Task-switching	Switch RT (0.62), Non-switch RT (0.52), Congruent RT (0.59), Non-congruent RT (0.58)
	Go/No-go	"Go" RT (0.53)
	Visual Search	target absent slope [6 (0.72), 12 (0.73), 18 (0.71)], target present slope [6 (0.61), 12 (0.71), 18 (0.73)]
	Tunneling	MT [40% (0.68), 60% (0.67), 80% (0.69), 100% (0.69)]
PC2 - Speed-accuracy trade-off	Task-switching	Switch RT (0.51), Non-switch RT (0.62), Congruent RT (0.56), Non-congruent RT (0.58), Switch Ac (-0.59), Non-switch Ac (-0.68), Congruent Ac (-0.64), Non-congruent Ac (-0.63)
	N-Back:	2-back absent Ac (-0.65), 3-back absent Ac (-0.57),
PC3 - Tunneling	Tunneling:	MT [40% (0.56), 60% (0.58), 80% (0.58), 100% (0.58)], Ac [40% (0.54), 60% (0.51), 80% (0.57), 100% (0.52)]
PC4 - Sensitivity	N-Back:	1-back false alarm RT (0.55), 2-back hits RT (0.58), 3-back hits RT (0.64), 3-back false alarm RT (0.67)
	TMT-B	MT 2 (-0.52)
PC 5 - Detection Error	N-Back:	2-back present Ac (-0.56), 3-back present Ac (-0.50)

Based on the correlated cognitive task measures, the PCs are interpreted to represent the psychophysical properties in the behavioural data. The first PC is exclusive RT and MT across the tasks and "Go" signals, where increases in these measures correlated with increases along the Response Time PC. Speed-accuracy trade-off is the second PC as increases in RT and decreases in Ac are correlated to the PC. The tunneling task Ac and MT loads exclusively onto its own PC for each of the 4 scales. Hit rates and false alarms from the N-Back task, along with a single trail making measure, load onto a shared PC. This PC likely represents these distributions which from signal detection theory determines sensitivity, the TMT-B negative correlation may be an artefact as none of the other TMT-B measures reach threshold. The last PC is correlated with participant's accuracy on the N-Back task, in that lower accuracy was correlated with the fifth PC. Thus, detection error could be captured in this PC.

SEM on Principal Components

With the PC structure, the addition of the lifestyle and demographic measures can be done simultaneously using a structural SEM. This effectively creates a simultaneous series of regressions that regresses each PC on each of the lifestyle and demographic measures. All data from the PC and lifestyle and demographics are standardized. Since the cognitive data was imputed, any missing data is due to missingness in the lifestyle and demographic measures. The significant paths are presented Figure 9. Given the standardization of the PCs and lifestyle and demographic data, the magnitudes of estimated coefficents, as shown in Table 8, can be interpreted as relative importance of each demographic and lifestyle measure to the PC.

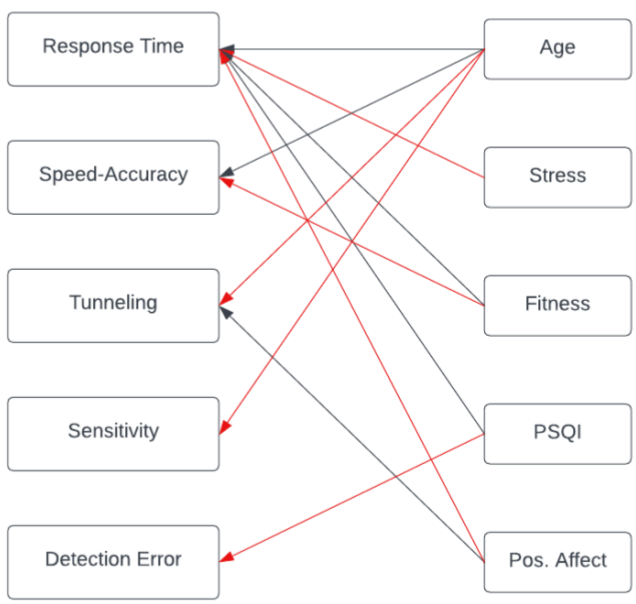

Figure 9. SEM of Cognitive PC and Demographic and Lifestyle Measures. Red lines indicate negative estimates.

From the estimated loadings in Table 8, Response Time is increased with older ages and greater fitness and decreased with increased positive affect and self-reported stress. Age is the most important factor, contributing to the largest changes in Response Time.

Table 8

Coefficents for SEM of Cognitive PCs, Demographic, and Lifestyle Measures

Principal Component		Demographic/ Lifestyle	Estimate
Response Time	~	Age	0.33***
		Stress	-0.10***
		Fitness	0.12***
		Positive affect	-0.14***
Speed-accuracy Trade-off	~	Age	0.10***
		Fitness	-0.10***
Tunneling	~	Age	-0.17***
		Positive affect	-0.08***
Sensitivity	~	Age	-0.21***
Detection Error	~	Sleep quality	-0.11***

* = $p < .05$, ** = $p < .01$, *** = $p < .001$

Increased Speed-accuracy Trade-off is seen in older participants with lower self-reported fitness. Reduced levels of positive affect and younger age account for increases on the Tunneling PC. Increased Sensitivity is seen in younger participants, and increased Detection Error in those with poorer sleep quality.

Chapter 4: Discussion

Summary of Findings

I aimed to examine how both demographics and lifestyle affect cognitive performance simultaneously using the SEM framework. I expected that lifestyle factors in addition, and perhaps above, demographics would account for the variability in cognitive performance. The hypothesized LV model for the combined measures of cognitive performance showed generally poor fit. Additionally, issues with missing data impeded the testing of directional relationships with the demographic and lifestyle measures. It should be noted that while this approach was entirely theory-driven, a regularized SEM was specified as a data-driven method to identify weak or uninformative loadings in the cognitive LV model. Removing indicators from the model did not result in improved model fit and as a result, the initially specified model was retained. While not all combined measures loaded where hypothesized, each of the three LVs: (1) cognitive control, (2) visuospatial working memory and visual attention, and (3) visuomotor functioning were positively correlated with each other. This is important as increases in one latent construct should be correlated increases with the other.

Post-hoc hierarchical multiple regression analyses were performed with the demographic indicators, age and sex, serving as the base model and the simultaneous addition of the lifestyle measures serving as the second, lifestyle model. Since the LV structure had poor model fit, the combined indicators themselves were used. These analyses revealed that the addition of lifestyle measures did not fully reduce the variance accounted for by the demographic measures as in each model, with significant lifestyle predictors, either sex or age remained a significant predictor of the combined cognitive measure.

Together, my findings from the LV model and hierarchical multiple regression support the general hypothesis that lifestyle factors in addition to demographic measures would account for variability in cognitive performance. However, due to data constraints, these analyses were not directional and only represent covariances (equivalent to correlations since all measures were scaled). To further probe these relationships and acknowledge some limitations in this approach, a follow-up data-driven model was tested.

Follow-up PCA and SEM

An additional series of analyses was conducted using PCA as a means for dimensionality reduction in the cognitive performance data. Missing data issues in the cognitive data were handled through imputation to preserve more data. The five PCs used represented the psychophysical properties in behavioural response patterns. Sex and negative affect (NA) were the only two lifestyle measures not predictive of any PC. Only Detection Error was not predicted by age and was the only PC to be predicted by sleep quality. In sum, evidence from both the theory-driven LV and data-driven PCA approach provide evidence that variability and predictor of cognitive performance is improved, and perhaps contingent on, not only demographic but lifestyle as well.

Findings in Context

Across the LV and PC approaches, each of the four lifestyle indicators were found to be related to either LV or PC. Fitness was only included as a predictor of the Response Time PC. However, increased self-reported fitness predicted increased Response Time, where Response Time was also increased by lower stress. Increased fitness cooccurring with decreased stress is congruent with the literature, but in a PC representing Response Time remains an unexpected finding. In the SEM analyses by Padulo et al. (2019), fitness was a hypothesized LV, but the revised model did not include fitness, but rather it was found it be a moderator. It may be that a simultaneous linear relationship is not appropriate for modelling the effect of fitness on cognitive performance. Additionally, fitness was self-reported and a single-item measure and much of the literature employs performance or biometric measures for fitness (Lemes et al., 2017).

Interestingly, sex only appeared as a significant predictor in the hierarchical regression analyses. Mean MT across tunneling trials and 2-back d’ had a significant proportion of variance accounted for by sex, where females had longer MT and lower sensitivity (d'). However, the failure of sex to correlate with a LV or predict a PC suggests that sex is not a strong predictor. This is endorsed by the literature, and the competing results surround sex difference in cognition. The present findings are aligned with the Gender similarity Hypothesis (GSH), as sex difference fail to account for a consistent and significant proportion of variance in cognitive performance (Hyde, 2005).

Affect, both positive and negative was negatively related to the LVs and PCs. Cognitive control and visuospatial working memory and visual attention both were increased with reduction in both valences for affect. If affect is shifted into an arousal contest, greater magnitude of PA and NA represent greater arousal. In this case, it could be argued that greater, or too much, arousal is associated with decreased cognitive control and visuospatial working memory and visual attention. This would be mirrored, on the visuospatial working memory and visual attention LV where increases in stress was correlated with a reduction in the LV.

Age was the only consistent and robust measure across every analysis, corelating with each LV and predicting all PCs with the exception of Detection Error. This result is somewhat unexpected as the sample of participants was very homogeneous in age. However, the cognitive tasks selected are incredibly well-validated, many having clinical applications. Therefore, it may serve as a testament to ability of these tasks to detect fine-grained signal from noise or variance in age.

Visuomotor Functioning as a Latent Variable

Stress was correlated with the visuomotor LV exclusively, where lower levels of stress occurred at increased level of visuomotor function. This was in turn representing a higher switch cost, lower Go/No-go sensitivity, and longer MT in TMT-B and tunneling. It would be expected that a higher degree of visuomotor functioning would be indexed by better performance on these tasks (i.e., lower switch cost, increased sensitivity, faster MT). Taking into consideration the relatively expected relationships with the other LVs, the visuomotor LV may be primarily responsible for the poor model fit.

The hypothesized LV structure reflected the frameworks and dominating theories in cognition and each of the tasks were contingent on visuomotor functioning as all tasks were visual in nature and required responses through keyboard and cursor. Thus, a visuomotor LV was specified. However, it could be that this behaviour is not significant contributor to cognitive task performance. Or, that visuomotor functioning is not an equal contributor in the same sense as processes such as working memory, attention, and cognitive control. The contingency of the visuomotor processes may better indicate a mediation or moderation relationship over one with equal weighting, or level, to be accounted for.

In an investigation into the construct validity of the TMT, Sanchez-Cubillo and colleagues (2009), explore the contribution of several cognitive processes on TMT performance. The contribution of visuomotor ability and performance was a main investigation, as the authors highlight the research and notion that the TMT measures and draws on visuomotor processes in participants. A cognitive battery of several tasks aimed to measure working memory, response inhibition (inhibitory control), task-switching, and visuomotor abilities was conducted. Specifically, for TMT-B, Sanchez-Cubillo et al. found that task-switching and working memory to account for the greatest variability in performance. The lack of significant visuomotor contribution suggests that visuomotor ability may not underlie TMT-B performance. In a similar vein, the tunneling task is visuomotor in nature but the primary processes are hypothesized to be proprioception. While noting behavioural learning, such as improvement in speed-accuracy trade-off (Mirdamadi & Block, 2020), it is possible that the tunneling task is does not represent the same nature of cognitive performance as the remainder of the battery; in particular, those hypothesized to represent the visuomotor functioning LV.

Another consideration is the operational definition of visuomotor contribution. The above study with the TMT-B and tunneling describes visuomotor functioning as a key cognitive process. In contrast, “visuomotor” in other tasks (visual search, Go/No-go, task switching) is conceptualized more as the mapping between visual perception and outputted motor movement. TMT-B and tunneling also require proprioception on the part of participants to navigate between targets (i.e., connecting circles and drawing trails) (Mirdamadi & Block, 2020; Sanchez-Cubillo et al., 2009). The constant coordination in the navigation of the tunneling and TMT-B may be functionally distinct the visual perception and motor response required from tasks such as a visual search. Consequently, more specificity in what is encompassed in “visuomotor” may improve model fit, both with respect to metrics and the framework.

Theory-driven versus Data-driven Insights

At a higher level, comparing the two dimensionality techniques on the cognitive data yielded very different results. The theory-driven LV structure reduced the measures on each task using known measures of performance, combined measures, such as d’ from signal detection theory. The measurement model was then created using frameworks from the literature. Given each of the two steps drew from pre-existing and adopted frameworks in the literature, the following hypothesis was that the tasks would represent these frameworks. The use of LV structure for cognition is well explored. A common line of inquiry asks “do there exist some latent ability that affects cognitive processing?”, which informs model of the subsequent observed behaviour (Vandekerckhove et al., 2014). The functioning and structure of many cognitive domains, such as working memory or executive function, are inferred though the use of several tasks and measures (Vandekerckhove et al., 2014). Given the method and application are sound, the structure derived from data reduction, or the data itself may have lent to the poor model fit.

The data-driven PCA approach to data reduction used each of the measures across all six cognitive tasks. The discriminant validity of each of the 6 tasks were selected to represent distinct, yet related, measures of cognitive performance. It follows that the theory-driven model aimed to represent this; however, the PCs did not mirror the LVs. The correlation from each of those measures to the PCs matched well with the type of indicator across tasks in addition to the types of indicators within tasks. The PCs were dominated by psychophysical response patterns over cognitive concepts and theory. In a neuropsychological study, Levin et al. (2013), found that their PCs on a battery of tasks was best represented by 4 PCs: cognitive processing speed, visual memory, verbal memory, and post-concussion and post-traumatic symptoms. While the latter clinical component is not of interest, the first 3 represent both theoretical components and one on speeded response. Thus, representing a middle point between the theory and psychophysical.

PCA has been credited for reducing the interpretation of spurious relationships. Identifying fundamental and underlying cognitive processes is of great interest to cognitive scientists. however, some investigations show that PCA for cognitive data may not be as robust as previously thought. An investigation by Sperber (2022) on simulated data revealed that PCA can produce the proposed underlying variables, even with high simulated noise (i.e., variance). In the case that no measures in the data measured the specific proposed PCs, the PC did not well-represent these constructs, which Sperber attributes to issues with factor rotation. This highlights that while statistical tools, especially data dimensionality reduction techniques, are powerful and can perform at high and useful levels, they are entirely dependent on the quality of data used.

Aside from the approach of the dimensionality reduction method, another distinction between the LV model is that at its core, it is a factor analysis. Each latent factor represents a series of regression equations, where each measured variable is a function of the LV. PCA, however, has each PC represented a single equation. In that, the PC is the linear combination of the measured variables. While often discussed together due to the similar aims of reducing data, the computations and following interpretations of the results are very distinct. Consequently, comparisons across PC and LV models should not ignore the fundamental building blocks of both the underlying statistics and the potential weaknesses of either method.

Online Data Collection during the COVID-19 Pandemic

Online implementations of computerized cognitive studies have been shown to produce similar results to laboratory-based studies. Crump et al. (2013) recruited participants through Amazon's Mechanical Turk platform, a crowdsourcing platform for research participants, to test the validity of several ubiquitous cognitive psychology paradigms through online data collection. The results of analyzing RT across four cognitive study protocols (e.g., Stroop task, flanker task, task switching task, Simon task) were all replicated. To further probe the reliability of online data collection, Semmelmann and Weigelt (2017), divided participants to complete the study into three conditions: (1) remotely on the web, (2) in the lab but on the web, and (3) in the lab using local software. This procedure allowed for comparisons to isolate software and environment contributions across two tasks (e.g., Stroop task, flanker task). Additional to RT, Semmelmann and Weigelt collected Ac data. Participants in each of the three conditions replicated literature findings in both the RT and Ac analyses. Taken together, the process of online data collection alone is a reliable instantiation and means of testing cognitive performance.

However, these studies remained highly controlled and were conducted on motivated participants. Other consideration in the current study is that collection of data was concurrent to, and a result of, the COVID-19 Pandemic. Unfortunately, the myriad of effects on both immediate cognitive functioning secondary to societal shifts are incredibly difficult to quantify. However, what is known is that the environments and lifestyles of participants changed drastically. A study on university students in the United States revealed that most of the participants, 71%, experienced an increase in self-reported stress and anxiety due to the pandemic (Wang et al., 2020). Furthermore, only 43% of students reported being able to cope with the added stress from academic, health, and their personal lifestyles. In a systematic review conducted by Vindegaard and Benros (2020), the authors found that studies reported increased depressive and anxious symptoms in the general public during COVID-19 Pandemic than before. It is well understood that clinical symptoms such as heightened levels of anxiety, stress, and depression are correlated with changes in memory and attention tasks. Depression is correlated with impairment on cognitive tasks spanning the domains of attention, executive function, visuospatial memory (Porter et al., 2003). Accordingly, the results presented here may be limited in generalizability.

Limitation and Future Directions

Missing Data

The issue of missing data is a field of research in and of itself. Missing data, and the methods for handling it, can have undue and artificial influence on the data and subsequent results and inferences drawn. In the LV approach and subsequent regressions, missing data by case-wise deletion. The loss of data impeded testing the directional effects of demographic and lifestyle measures on the cognitive LVs. In the exploratory PCA, all cognitive task data was assumed to be MCAR, meaning that missing data was not due to systematic issues with participants, study confounds, etc. (Rubin, 1976). Thus, the only issue to be considered is the loss of data itself. Therefore, missing data could be imputed using a regularization algorithm. However, this was only done for the cognitive task data and not for the demographic and lifestyle data.

Imputing data in the demographic and lifestyle measures was not done in the PCA, as the rationale for estimating variables such as age or sex based on the similarities within and across variables was not justified. This is corroborated by the imputation of the cognitive task data, as imputing the predictor variables would be influenced by the imputation of the outcome variables. Further, the assumption that demographic and lifestyle data is MCAR, is more difficult to conceptualize than a missed RT. While future studies may be concerned with recovering the missing data in the demographic and lifestyle measures., this study used a more conservative method by opting remove missing cases.

Analysis Design

Beyond handling missingness in data sets, analysis methods are subject to limitations, often as a consequence to the nature of data. In the context of SEM models and dimensionality reduction, the methods selected offer restrictions. Thus, follow-up analyses of entirely different approaches may be better suited for the data, or the inferences intended to be drawn.

For example, statistical tools such as machine learning offer a novel set of insights. Machine learning methods, namely neural network models, are being heavily used to draw mechanistic insights into human cognition. Approaches such as deep neural networks and the following convolutional neural networks allow for hidden layers of variables to drive the relationship between input and output. Efforts to create machine learning-based models have employed human constraints to simulate cognitive processes such as attention (Pulvermüller et al., 2021). These “brain-constrained models” may be improved by understanding and accounting for the influences demographic and lifestyle have on cognitive processes such as attention, memory, visuomotor functioning.

Many statistical and analytical approaches are built upon fairly simple foundations. Many of the commonly used univariate methods (t-tests, ANOVA, regression) are specific or limited cases of the SEM framework. Additionally, these methods are linear, as they assume linear relationships between variables of interest. However, many aspects of human performance are non-linear. A foremost example being the curvilinear inverted-U shape (where stress or arousal in along the X-axis and performance along the Y-axis), whereby there is an optimal level of stress and arousal that results in peak performance (highest point in the inverted-U) (Sandi, 2013). This phenomenon is commonly referred to as the Yerkes-Dodson Law. With this insight, allowing for non-linear relationships between certain lifestyle measures may better represent the drivers of human cognitive performance.

Conclusions

I sought to disentangle how lifestyle in addition to demographic factors can account for and predict performance on cognitive tasks. Through two methods, I reduced the cognitive task measures to summarize cognitive performance and examine how demographic and lifestyle measures are related to these latent, or unmeasured, variables (LVs) and principal components (PCs). Lifestyle measures did significantly account for and predict cognitive performance above and beyond the influence of demographics. The dimensionality reduction techniques of cognitive performance data differ in their basis, challenges, relationship with demographic and lifestyle measures, and subsequent inferences drawn. These differences could be due to artefact from missing data, the conceptual difference that are captured by each approach, or other components in the study process. Overall, cognition and cognitive performance is subject to the complex, and challenging to measure, influences of our lifestyle.

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Appendix A

Complete List of Data Collected

Cognitive Tasks	Demographic Measures	Lifestyle Measures
N-Back*	Age*	Fitness*
Task Switching*	Sex*	Stress*
Visual Search*	Height (in cm)	(multi)Lingualism
Go/No-go*	Year of study	Video game use
Trail Making Test B*	Handedness	Mediation
Tunneling*	Neurological disorder	Recreational drugs use (excl. marijuana and alcohol)
Interesting Points	Method of birth	
Mirror Reversal	Born preterm	Marijuana use
Mirror	Family history of dementia	Sleep quality (PSQI)*
Generalization		Affect (I-PANAS-SF)*
Frame Dots		History of concussion
Iowa Gambling Task		ADHD diagnosis
		ASD diagnosis
		Musical ability

COVID-19	Device/Experiment
History of COVID-19	Device being used
Hospitalization due to COVID-19	Cursor control
Symptom onset	Hand being used
Symptom length	Browser
Symptoms following negative test	Computer adeptness
Peri-COVID-19 Functional Status Scale	Visual corrective aids (vision)
Post-COVID-19 Functional Status Scale	Use of visual corrective aid

Note. Items indicated with * are those included in the present study.

Appendix B

Descriptive Statistics for all Cognitive Response Time and Accuracy Measures

Measure	Mean(*SD*)	Skew	Kurtosis
N-Back (12)			
1-back hit RT	0.598(*0.462*)	2.75	14.27
1-back false alarm RT	0.658(*0.314*)	1.05	1.96
2-back hit RT	0.617(*0.165*)	1.81	7.53
2-back false alarm RT	0.762(*0.234*)	1.45	3.01
3-back hit RT	0.585(*0.190*)	1.82	6.44
3-back false alarm RT	0.644(*0.244*)	1.15	2.04
1-back target abs. Ac	0.950(*0.135*)	-5.02	27.71
1-back target pres. Ac	0.845(*0.122*)	-0.71	-0.19
2-back target abs. Ac	0.910(*0.133*)	-3.44	15.04
2-back target pres. Ac	0.725(*0.211*)	-0.522	-1.00
3-back target abs. Ac	0.885(*0.149*)	-3.08	10.96
3-back target pres. Ac	0.505(*0.225*)	0.33	-0.60
Task Switching (8)			
Congruent RT	1.196(*0.417*)	1.60	5.64
Non-congruent RT	1.249(*0.408*)	1.39	4.57
Switch RT	1.424(*0.488*)	1.28	3.30
Non-switch RT	0.996(*0.359*)	1.75	5.97
Congruent Ac	0.951(*0.060*)	-1.99	5.81
Non-congruent Ac	0.901(*0.010*)	-1.59	2.75
Switch Ac	0.898(*0.103*)	-1.08	0.21
Non-switch Ac	0.940(*0.065*)	-2.11	6.05
Go/No-go (1)			
"Go" RT	0.366(*0.058*)	0.916	2.34
Visual Search (6)			
6-absent RT	2.131(*0.694*)	0.93	2.58
12-absent RT	3.458(1.*210*)	0.53	1.36
18-absent RT	4.616(1.*740*)	0.38	0.62
6-present RT	1.614(*0.491*)	2.50	15.29
12-present RT	2.484(*0.734*)	0.51	1.36
18-present RT	3.240(1.*036*)	0.43	1.74

Measure	Mean(*SD*)	Skew	Kurtosis
TMT-B (5)			
Trail 1 MT	53.570(*33.094*)	7.28	105.08
Trail 2 MT	37.570(*17.269*)	2.68	11.41
Trail 3 MT	33.907(*19.436*)	8.91	119.75
Trail 4 MT	33.097(*14.448*)	5.40	61.27
Trail 5 MT	31.284(*12.526*)	3.06	20.56
Tunneling (8)			
40% MT	4.730(*2.086*)	0.90	1.87
60% MT	4.681(*2.154*)	1.09	2.21
80% MT	4.693(*2.179*)	1.34	4.51
100% MT	4.768(*2.160*)	1.27	3.72
40% Ac	0.872(*0.162*)	-1.57	1.80
60% Ac	0.896(*0.135*)	-1.70	2.63
80% Ac	0.897(*0.156*)	-1.95	2.83
100% Ac	0.921(*0.115*)	-1.96	3.90

Appendix C

Full Results of Hierarchical Regressions

For all tables, Model 1 is the base demographics model including only age and sex. Model 2 is the lifestyle model which adds stress, fitness, sleep (PSQI), and affect (PANAS - negative affect and positive affect). An ANOVA was run between the two models to determine which model is retained. A non-significant F-test would retain base demographic model as the addition of the lifestyle measures did not improve the variance accounted for in the outcome variable, a combined measure of cognitive performance, whereas the lifestyle model retained for a significant F-test. The retained model is bolded.

Table 1

N-Back N2 d'

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.018***	-0.300**					
Lifestyle Model	0.003	-0.221*	-0.050	0.066	-0.022	-0.029*	-0.017

Note. Lifestyle model retained (R^2 = 0.096), $F(5) = 6.92$, $p < .001$.

Table 2

Task-switching switch cost

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.012***	0.068					
Lifestyle Model	0.013***	0.080	-0.016	-0.040*	0.018*	-0.003	0.009

Note. Lifestyle model retained (R^2 = 0.068), $F(5) = 2.82$, $p = .016$.

Table 3

Go/no-go d'

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	-0.010*	-0.134					
Lifestyle Model	-0.020***	-0.076	-0.041	-0.009	-0.009	-0.035**	0.000

Note. Lifestyle model retained (R^2 = 0.042), F(5) = 4.41, p < .001.

Table 4

Visual Search Target-absent Slope

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.003***	-0.003					
Lifestyle Model	0.002***	-0.003	-0.001	-0.004	-0.002	-0.002*	-0.002

Note. Lifestyle model retained (R^2 = 0.090), F(5) = 3.52, p = .004.

Table 5

Visual Search Target-present Slope

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.002***	0.001					
Lifestyle Model	0.002***	0.002	0.000	0.001	-0.000	-0.002**	-0.002***

Note. Lifestyle model retained (R^2 = 0.103), F(5) = 4.16, p < .001.

Table 6

Trail making Mean Movement Time

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.724***	2.030					
Lifestyle Model	0.664***	2.199	-1.086**	1.043*	0.323	0.213	-0.448***

Note. Lifestyle model retained (R^2 = 0.215), F(5) = 7.29, p < .001.

Table 7

Tunneling Mean Movement Time

	Age	Sex	Stress	Fitness	Sleep	Neg. Affect	Positive Affect
Demographic Model	0.092***	0.315					
Lifestyle Model	0.082***	0.344*	-0.021	-0.085	0.046	-0.056*	-0.060***

Note. Lifestyle model retained (R^2 = 0.186), F(5) = 5.44, p < .001.

Appendix D

All Correlations Between the Principal Components and the Cognitive Performance Data

Measure	PC 1	PC 2	PC 3	PC 4	PC 5
N-Back (12)					
1-back hit RT	0.39	0.42	-0.07	0.37	0.10
1-back false alarm RT	-0.11	0.25	-0.27	0.55	0.15
2-back hit RT	0.04	0.49	-0.02	0.58	0.09
2-back false alarm RT	0.12	0.21	0.10	0.46	0.25
3-back hit RT	0.07	0.41	0.19	0.64	-0.19
3-back false alarm RT	-0.07	0.36	0.05	0.67	0.02
1-back target abs. Ac	0.35	-0.47	-0.33	0.03	-0.02
1-back target pres. Ac	0.02	-0.19	-0.06	0.03	-0.28
2-back target abs. Ac	0.32	-0.65	-0.25	-0.24	0.00
2-back target pres. Ac	-0.03	-0.20	0.29	0.11	-0.56
3-back target abs. Ac	0.24	-0.57	-0.27	-0.33	0.10
3-back target pres. Ac	-0.16	0.00	0.39	0.23	-0.50
Task Switching (8)					
Congruent RT	0.59	0.56	-0.21	0.03	0.31
Non-congruent RT	0.58	0.58	-0.23	0.00	0.31
Switch RT	0.62	0.51	-0.20	-0.02	0.29
Non-switch RT	0.52	0.62	-0.23	0.04	0.29
Congruent Ac	0.30	-0.64	-0.23	0.01	0.30
Non-congruent Ac	0.43	-0.63	-0.28	0.11	0.28
Switch Ac	0.36	-0.59	-0.24	0.17	0.34
Non-switch Ac	0.43	-0.68	-0.29	-0.01	0.25
Go/No-go (1)					
“Go” RT	0.53	0.35	-0.16	-0.10	0.22
Visual Search (6)					
6-absent RT	0.72	0.02	-0.40	0.11	-0.41
12-absent RT	0.73	-0.09	-0.39	0.14	-0.43
18-absent RT	0.71	-0.13	-0.38	0.10	-0.43
6-present RT	0.61	0.18	-0.32	0.19	-0.33
12-present RT	0.70	0.04	-0.37	0.15	-0.42
18-present RT	0.73	-0.04	-0.35	0.10	-0.44

Measure	PC 1	PC 2	PC 3	PC 4	PC 5
TMT-B (5)					
Trail 1 MT	0.34	0.34	0.12	-0.41	-0.19
Trail 2 MT	0.48	0.37	0.23	-0.52	-0.14
Trail 3 MT	0.28	0.39	0.17	-0.36	0.07
Trail 4 MT	0.33	0.37	0.24	-0.48	-0.15
Trail 5 MT	0.33	0.42	0.21	-0.48	-0.08
Tunneling (8)					
40% MT	0.68	-0.16	0.56	-0.05	0.08
60% MT	0.67	-0.14	0.58	-0.09	0.08
80% MT	0.69	-0.12	0.58	-0.07	0.07
100% MT	0.69	-0.13	0.58	-0.13	0.05
40% Ac	0.48	-0.44	0.54	0.33	0.07
60% Ac	0.47	-0.46	0.51	0.33	0.06
80% Ac	0.45	-0.37	0.57	0.34	0.07
100% Ac	0.46	-0.47	0.52	0.28	0.07

Note. PC 1 – Response Time, PC 2 – Speed-accuracy Trade-off, PC3 – Tunneling, PC 4 – Sensitivity, PC 5 – Detection Error. Correlations above |.50| are highlighted, green for positive valence and red for negative valence.