OUT-OF-HOME MOBILITY: A MEASURE OF DAILY COGNITION IN YOUNG ADULTS

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Melanie Anne Butt

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Examining Committee:

Todd C. Handy, Professor, Psychology, UBC
Supervisor

Jiaying Zhao, Associate Professor, Psychology, UBC
Supervisory Committee Member

Nancy Sin, Associate Professor, Psychology, UBC
Supervisory Committee Member

Abstract

Work in gerontology has established an important relationship between cognition and mobility, in that maintaining mobility is reliant on maintaining the integrity of executive cognitive functions. While young adults do not exhibit cognitive decline as do older adults, they can experience momentary fluctuations in cognitive abilities via daily cognitive failures or errors, compounded by variations in mood states. Studying cognition, mood and mobility in an integrated fashion would be beneficial for broadening our understanding of daily cognition, yet these relationships are rarely studied in young adults. The aim of this work is to examine how fluctuations in daily cognition as well as mood impact out-of-home mobility in young adults, to see whether such relationships extend across the life span. We passively collected global positioning system (GPS) data from undergraduate and graduate student participants ($N = 173$) for two weeks; they filled out baseline measures of cognition and mood in-lab, as well as daily questionnaires on their phones, assessing cognition, mood, and daily activity patterns (place visits, transportation use, environments visited). Spearman correlations showed that at the two-week aggregate level, greater daily cognition and baseline executive functioning were associated with less time spent at home, but these measures did not provide predictive value in regression models. Greater daily positive mood was predictive of greater distances travelled, but we did not find support for cognition impacting distances travelled. Taken together, these mixed findings suggest that mobility is not as readily impacted by fluctuations in cognitive and mood states in young, healthy adults, as is seen in older adults or clinical populations. Future work should focus on extending existing theoretical frameworks to young adults and assessing what other factors may be of relevance.

Lay Summary

Researchers have found that maintaining cognitive capacities is important for maintaining mobility in old age. While young adults do not face cognitive decline, they do make errors in thinking and planning, which can be exacerbated by experiencing lower mood. So, it may be that their mobility outside the home is impacted by their variations in cognitive states, as is the case in older adults, which might help us better understand fluctuations in thinking abilities. Analysis shows that having better cognitive abilities was associated with spending less time at home, and that better mood was related to travelling farther from home, but no other expected relationships between cognition, mood and mobility were found. In sum, it appears that mobility is not impacted as much by cognition and mood in young adults, as is the case in older adults. However, more research is needed to determine what other factors influence this relationship.

Preface

This thesis is original, unpublished work by the author M. A. Butt. All research described in this report was conducted through the Department of Psychology at the University of British Columbia (UBC), under the supervision of Dr. Todd Handy.

The rationale and study design for this work was presented at APS's International Convention of Psychological Science (ICPS) 2023 and at UBC's Psychological Undergraduate Research Conference 2023.

The study was approved by UBC's Behavioural Research Ethics Board.
Certificate No. H22-00495.

Table of Contents

List of Tables

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1 Introduction

Physical mobility, defined here as whole-body movement through environmental space over time, is fundamental to life (Nathan et al., 2008). Our ability to effectively move through space over time is dependent in part on our ability to adapt to the changing demands of our environment (Patla & Shumway-Cook, 1999), made possible by our brain's ability to coalesce information we receive from our bodies, our nervous systems, and the world around us (Chiel & Beer, 1999). While there is widespread recognition within cognitive science (specifically, neuroscience) that brains evolved to adaptively coordinate between an animal's sensation of the world and its movement through it (Llinas, 1998), these evolutionary facts remain largely unincorporated into our neurocognitive understanding of the human brain. Namely, while our experience of the world is so heavily tied to how we move through it, we rarely factor *mobility* into our understanding of how our brains function. And yet, our internal states greatly influence how we choose to trade space for time (Shoval et al., 2011), impacting the experiences we have in the spaces we inhabit. In this study, we seek to explore how measures of mobility can be leveraged to broaden our understanding of daily fluctuations in well-being, particularly our cognitive states.

While connections between mobility and cognition are not widespread in the field of psychology, studies in gerontology have made important discoveries in this domain. In particular, researchers have shown that maintaining physical mobility in old age is not merely reliant on maintaining biomechanical abilities, but critically, it depends as well on maintaining the integrity of global cognition, and particularly executive function. Not only does cognitive decline correlate with increased gait perturbations, risk of falling, and destabilized gait dynamics in older adults (Muir-Hunter & Wittwer, 2016; Yogev-Seligmann et al., 2008) but also with a shrunken life space (Crowe et al., 2008; Poranen-Clark et al., 2018), decreased variability in out-of-home mobility patterns (Wettstein et al., 2015), and less activity at greater distances from home (Shoval et al., 2011). Maintaining mobility in old age is integral to maintaining a larger life space, leading to greater independence and thus quality of life, which are critical for healthy aging (Webber et al., 2010).

Similar relationships between mobility and well-being have been studied in psychopathology, showing that distance and time spent away from home vary with mood and clinical symptoms in adults with bipolar disorder (Faurholt-Jepsen et al., 2021), as well as with negative symptom severity in patients with schizophrenia (Depp et al., 2019). While such relationships have been shown to exist in young, healthy adults (Müller et al., 2020), these studies rarely integrate cognition, mood and mobility under a comprehensive framework that would bolster our understanding of its component parts (Patla & Shumway-Cook, 1999). Given the findings from gerontology and psychopathology, it is pertinent to assess whether these correlations generalize across the lifespan, and how reductions in life space may lead to reductions in quality of life (Webber et al., 2010).

The purpose of this work is twofold. First, to investigate whether connections between cognition and mobility that have long been established in gerontological populations do extend to young, healthy adults, and whether we can see impacts on mobility patterns as a result of fluctuations in self-reports of cognitive states. Second, to establish whether mood acts as a key moderator in the relationship between cognition and mobility in young, healthy populations. Our goal is to highlight how measures of physical mobility, particularly the movement path, provide a novel approach for objectively and unobtrusively studying human cognition in the natural flow of our everyday lives.

1.1 Gait dynamics

Work in gerontology has laid the groundwork in establishing the relationship between cognition and mobility. In the late 1970s, the Scottish geriatrician Bernard Isaacs first identified that older individuals diagnosed with dementia had elevated rates of falling, relative to their more cognitively healthy age-matched peers (Isaacs, 1979). On the idea that maintaining independent mobility is vital to healthy aging, this finding spurred a growing interest among health researchers in understanding the links between cognitive decline and physical mobility in seniors.

Long thought to be a rote motor task with little mental input, evidence has emerged in the literature on aging showing that maintaining stable gait dynamics requires significant use of higher-level cognitive resources (Woollacott & Shumway-Cook, 2002; Montero-Odasso et al., 2012). As biomechanical-based measures of physical mobility, the dynamics of human gait provide a rich array of parameters that can be quantified to assess the relationship between physical mobility and cognition. At the most superordinate level is gait speed itself, or how fast an individual can walk a specified distance on a flat, even surface. A common health measure employed in geriatric clinics by timing individuals as they walk down a hall, it has been proposed that gait speed qualifies as a sixth vital sign, alongside heart and respiratory rates, blood pressure and oxygen level, and body temperature (Fritz & Lusardi, 2009). Other commonly used gait assessments of relevance to cognitive research include step width, used to assess the need for lateral stability (Dean et al., 2007) and stride variability, measuring variation in stride length and swing time (Hausdorff et al., 2001).

Importantly, research in the domain of aging and cognitive health has established that a variety of gait parameters show a systematic relationship with cognitive status. For example, when older individuals are placed under a cognitive dual-task load when walking, gait speed (Montero-Odasso et al., 2005; van Kan et al., 2009), stride time (Muir et al., 2012), postural stability (Shumway-Cook et al., 1997) and step-to-step variability (Yogev-Seligmann et al., 2008) all show slowing and/or destabilization, relative to when walking without the cognitive load. Likewise, when one compares gait dynamics between groups of older individuals varying in their clinically assessed cognitive status, those diagnosed with dementia and mild cognitive impairment show systematic slowing and destabilization in gait parameters relative to their cognitively healthy, age-matched peers, and these effects on gait tend to scale with the degree of their cognitive impairment (e.g., Nagamatsu et al., 2013; Crockett et al., 2017). Taken together, such findings underscore how gait can be a highly sensitive indicator of cognitive status in older adults, including an ability to signal real-time changes in one's ongoing cognitive load.

1.2 Movement paths

A second core measure of mobility related to cognition is the movement path, or the objective trajectory an individual takes through environmental space over time. Long established in time geography and transportation planning (Hägerstrand, 1970), the movement path can be broken down into component parts to capture key measures of both in-home and out-of-home mobility. At its most basic level, one can measure the total distance travelled over a day. Other components of the movement path commonly measured are maximum distance travelled from home (Wettstein et al., 2014), time spent out of home (Shoval et al., 2011), and number of locations visited (Wahl et al., 2013).

Research in aging has identified that movement patterns are related to cognitive status, and can help inform on several health risk factors. Premised on the idea that older adults experiencing cognitive decline are at greater risk for falls relative to their more cognitively healthy age-matched peers (Tinetti, 1986), clinicians employ “smart home” technologies to sense and monitor in-home mobility patterns that are critical for aging in place (Kim et al., 2022). Such work has demonstrated that remote assessments of movement paths can validly dissociate individuals with mild cognitive impairment from age-matched healthy controls (Jekel et al., 2016), as well as identify patterns of wandering locomotion in-home that may extend beyond the home (Lin et al., 2018).

Outside the home, individuals experiencing cognitive decline exhibit movement patterns with severity of impacts that scale to their degree of cognitive impairment. Broadly, greater cognitive decline in older adults has been shown to correlate with shorter movement paths within the community, measured both in terms of distance travelled from home and time spent out of home (Shoval et al., 2011), as well as decreased variability in out-of-home mobility patterns (Wettstein et al., 2015). More specifically, greater episodic memory abilities have been predictive of more time spent out of the home and greater distances travelled from home, with greater executive functioning being predictive of greater distances travelled as well (Wettstein et al., 2014). In longitudinal studies, a more constricted life space has been shown to be significantly predictive of increased risk for developing Alzheimer's disease (James et al., 2011); inversely, greater life space has significantly predicted slower rates of cognitive decline (Silberschmidt et al., 2017). Such evidence converges on the importance of preserving cognitive abilities in old age in order to maintain mobility.

Research on mobility in aging has not just identified two informative measures of mobility that can be used in studies of naturally occurring cognitive states. In parallel, the field has also been developing a theoretical understanding of the environmental factors impacting physical mobility, including aspects of the physical environment such as weather, ambient conditions, and infrastructure design (Patla & Shumway-Cook, 1999), as well as sociocultural and economic influences (Franke et al., 2019; Webber et al., 2010). Still, few studies employ such frameworks in their designs, which could aid in bridging the gap between lab-based and community-based measures (Tung et al., 2014). Recent evidence supports the idea that cognitive ability in older adults is more predictive of "real-world mobility" (as measured via global position system (GPS) and accelerometry) than lab-based measures (Giannouli et al., 2018), while others found no associations between community mobility and global cognition (Crane et al., 2022), instead seeing significant relationships between time spent out of home and lab-based measures of cognitive ability. These discrepant findings underscore the necessity of employing unified frameworks and emphasize the need for future work to more aptly leverage measures of mobility in studying fluctuations in cognition.

1.3 Application to young adults

While it is evident that young adults do not typically experience cognitive decline in similar fashion as do older adults, they do experience fluctuations in cognitive ability, seen most prominently through daily cognitive failures (Carrigan & Barkus, 2016). These self-reported errors in thinking can inform on momentary influences of mental capacity on a variety of out-of-lab behaviours. However, the field has been slow to include such measures into our understanding of cognitive well-being, due in part to mixed evidence for their association with objective assessments of cognitive ability (Carrigan & Barkus, 2016). A variety of mental and environmental factors have been shown to influence our propensity for cognitive failures, such as negative mood (McVay et al., 2009) and exposure to distracting environments (Kane et al., 2007). However, these interactions remain understudied amongst young adults, yet could inform on how mood may act as a key moderator in the connection between cognition and mobility in young adults. As such, understanding existing relationships between mood and mobility is critical to this endeavour.

1.4 Mood as a key moderator

With the increased accessibility of smartphone technology in the past two decades, researchers in several clinical settings have been leveraging these advances to develop real-time measures for clinical monitoring. Indeed, passively collected smartphone data such as GPS coordinates have been used to assess several mobility measures that inform on the severity of clinical symptoms for a variety of disorders. For instance, negative symptom severity in patients with schizophrenia has been associated with an overall decrease in out-of-home mobility (Wang et al., 2016), more time spent at home and shorter travelled distances (Depp et al., 2019), as well as higher levels of anxiety at greater distances from home (Parrish et al., 2020). Patients with bipolar disorder have been found to have lower location entropy and be less mobile during depressive episodes (Faurholt-Jepsen et al., 2021), as well as spend more time outside of the home and clinic when in a more positive psychological state (Sabatelli et al., 2014). Individuals with depression have been shown to travel smaller distances between locations and have a more stable routine index of mobility (Canzian & Musolesi, 2015), while socially anxious college students have been found to avoid public areas and engage in fewer social activities, as well as spend more time at home (Boukhechba et al., 2018) than their less anxious peers. More generally, maintaining a greater life space has been linked with more community participation (Brusilovskiy et al., 2020) and better mental health (Townley et al., 2022). In all, smartphone-based tracking of GPS coordinates and mood states have shown promise in detecting real-life impacts of symptom severity in clinical populations, which may inform on protocols that could be applied to subclinical, young adult populations.

1.5 Hypotheses

Primarily, this exploratory study investigates the role of daily self-reported cognitive and mood states on altering daily mobility patterns in young adults. As part of these analyses, we will control for levels of four baseline self-report measures of cognition (metacognition, executive function, propensity for cognitive failures, and frequency of memory failures) as well as four baseline self-report measures of mood (depression, state and trait anxiety, and loneliness). In addition, three daily activity pattern measures will be evaluated, namely types of places visited, modes of transportation used, and types of environments frequented. It is anticipated that at the two-week aggregate level, lower levels of daily cognition and mood will correlate with less distance travelled over the day, fewer social places visited, and more time spent at home. As well, we predict that greater levels of cognitive and mood states will correlate with greater distances travelled, greater number of locations visited, and less time spent at home. Finally, we predict that supporting variables, namely age and gender, as well as tendencies of places visited, transportation used, and environments frequented will be associated with differential outcomes on the mobility measures.

2 Method

2.1 Participants

A total of 301 undergraduate and graduate student participants were recruited from The University of British Columbia (UBC). Participants from UBC's Psychology Human Subject Pool (HSP) ($N = 285$) received two course credits for their participation, while those ($N = 16$) recruited through UBC's Psychology Graduate Student Council Paid Participants Study List received a $20 (CAD) Amazon gift card.

Data from 128 participants were excluded from analyses for reasons such as technological issues with their smartphones, not completing the study, and failing attention checks while completing the in-lab questionnaires (see *Exclusion criteria*). Of the remaining 173 participants ($M_{\text{age}} = 20.67$, $SD_{\text{age}} = 3.95$, 137 women, 36 men), all were at least 18 years old and capable of leaving their home daily. Research was performed in accordance with ethics board guidelines set by UBC's Behavioural Research Ethics Board, and written informed consent was received from each participant at the outset of the study (Ethics #H22-00495).

2.1.1 Exclusion criteria

Several exclusion criteria were used to ensure quality of data analyzed. Due to the method of creating anonymized participant identification numbers (described in more detail in *Procedure*), 42 participants had identical IDs as another participant. Of these, four participants' data were removed due to overlapping participation dates, making it impossible to distinguish between their data entries. Thirteen participants did not proceed past the first in-lab session due to technological issues with their smartphones, 36 participants did not return for the second in-lab session (meaning we could not download their GPS data), and 27 participants had missing Google Location History data at the time of export.

Of the remaining 221 participants, we excluded 27 people for having fewer than 10 days of recorded survey data or fewer than seven evening surveys completed, which included questions pertaining to behaviours over the whole day. As well, 21 participants were excluded for scoring less than 75% accuracy on the eight attention check questions on either of the in-lab session questionnaires.

2.2 Materials

In-lab questionnaires were administered at UBC's Attentional Neuroscience Lab on Apple iPads (6th generation, year: 2018, model number: A1893) via Qualtrics Survey Software ("Qualtrics", 2023). GPS tracking and administration of daily mobile questionnaires were conducted on participants' personal smartphones, via Google Maps and Qualtrics, respectively. These procedures are described in more detail below.

2.3 Procedure

2.3.1 Pilot

Participants (N = 8, M_{age} = 20.50, SD_{age} = 2.78, 5 women, 3 men) were recruited from UBC's HSP system for a pilot study. The procedure consisted of two 30-minute in-lab sessions occurring eight days apart, where participants first filled out a series of questionnaires, and then had a researcher guide them through setting up the GPS tracking and mobile questionnaire delivery on their personal smartphones. The participants completed a daily questionnaire every evening for seven days before returning to the lab for the conclusion of the study. Participants received two course credits for two hours of participation over the nine-day study.

Upon entering the lab, participants were screened for symptoms of COVID-19, and after confirming their lack of symptoms, were seated at a table with an Apple iPad to complete a series of cognitive and mood questionnaires. The order of presentation of questionnaires, as well as item blocks and individual items within a questionnaire, was randomized for each participant. Safety protocols concerning COVID-19 were followed as per ethical and provincial guidelines. After providing signed, informed consent, participants were instructed to create their unique participant ID, to be used for the duration of the study. It was formed using their mother's birth month, father's birth date, and last two digits of their birth year. The formula for recreating this ID was provided at the start of every questionnaire, both for those administered in-lab and daily, to reduce error rates and memory load for the participants.

Daily mobile questionnaires were sent to participants' emails via the Qualtrics mailing list function, once every day at 8:00PM. Participants were instructed to complete the questionnaire before going to sleep that night. Questionnaire and item order was randomized.

Eight days later, participants returned for the second in-lab session, where they completed the same baseline measures of cognition and mood as in the first session, with an additional demographics' questionnaire. Following debriefing, the researcher guided the participant through reverting the location tracking settings on their phone. Data from the pilot study were not analyzed.

2.3.2 Full procedure

As in the pilot study, the procedure consisted of two 30-minute in-lab sessions, where participants were screened for symptoms of COVID-19, provided informed and written consent, created a unique participant ID, completed a series of questionnaires, and were guided through their mobile phone set up. These sessions occurred fifteen days apart, as the daily component of data collection was increased to fourteen days. Participants received two course credits (or $20) for two hours of participation over the sixteen-day study.

Daily mobile questionnaires were administered using experience sampling three times a day (at 12:00PM, 5:00PM and 9:00PM) via a calendar notification on the participants' phone. The day questionnaires (administered at 12:00PM and 5:00PM) consisted of a cognition and mood measure, while the evening questionnaire (sent at 9:00PM) included these measures plus additional self-report questions, described in more detail in *Additional evening questionnaire items*. The cognition and mood questionnaires and item presentation were randomized, while the evening self-report questions were not, to reduce response time for participants over the two-week study period.

Participants were instructed to fill out the daily questionnaires as soon as possible after receiving the beep, unless the next one was to be delivered sooner, which resulted in some missing data. After exclusions, on average participants completed 34.32 daily questionnaires over the two-week period *(SD = 6.29)*, or 2.45 per day *(SD = 0.45)*.

Fifteen days later, participants returned for the second in-lab session, and completed the same baseline measures of cognition and mood as in the first session, with an additional measure of personality and a demographics' questionnaire. Following debriefing, the researcher guided the participant through reverting the location tracking settings on their phone. Changes were made to the full study procedure based on procedural difficulties encountered during the pilot study. Different baseline measures of cognition and mood were also used during the in-lab sessions, to capture a broader array of constructs. The full procedure set up is shown in Table 1.

Table 1. Timing of sessions and measures included in the sixteen-day full study procedure

		Part 1: In Lab (Day 0)	Daily Component (Days 1-14)	Part 2: In Lab (Day 15)
Procedure and set-up		• Questionnaires • Set up Google location tracking • Set up mobile questionnaire	• Passive GPS tracking • Mobile questionnaires	• Questionnaires • Reverse Google location tracking • Download GPS data
Measures	Cognitive	• Metacognition (MAI) • Executive Function (AEFI) • Cognitive Failures (CFQ) • Memory Failures (PRMQ)	• Self-reported cognition (PROMIS® Cognitive Function Scale Short Form 8a)	• Metacognition (MAI) • Executive Function (AEFI) • Cognitive Failures (CFQ) • Memory Failures (PRMQ)
	Mood	• Depression (CES-D) • Anxiety (STAI) • Loneliness (UCLA-LS)	• Self-reported mood (Mood Zoom Questionnaire) • Stress item • Loneliness item	• Depression (CES-D) • Anxiety (STAI) • Loneliness (UCLA-LS)
	Additional		• Places visited • Transportation used • Environments visited • Work/school from home	• Personality (HEXACO-60) • Demographics

2.3.3 Smartphone set up

As part of the set up for the daily procedure, participants were guided through turning on Google Location History through the Google Maps application. This allows for passive collection of GPS data to be stored in the associated Google account.

In the pilot study, unique, anonymized Google accounts were created for each participant using their participant IDs, to maintain privacy. Given the Google accounts were created by the researcher, they had continued access to these data via their encrypted laptop computers. Due to an unforeseen issue in creating many Google accounts, participants used their personal Google accounts in the full procedure; ethics clearance was obtained for this change. Thus, during the second lab session, participants logged into their Google accounts on the researcher's encrypted laptop computer, from where the researcher could download their location tracking data.

Participants were eligible to participate regardless of the model of smartphone they had. They were not required to actively use Google Maps nor cellular data for GPS coordinates to be tracked; thus, access to cellular data did not pose a barrier to participation. However, they were required to be capable of leaving their home daily (e.g., not currently be under quarantine or isolation due to COVID-19), given the principal metric of this study was mobility patterns.

Daily mobile questionnaires hosted on Qualtrics were administered to participants' phones via email (in the pilot study) or a timed calendar invite (in the full procedure) set up by the researcher. Calendar invites were set up on the participants' preferred calendar application (e.g., iCal, Outlook); if they were not in the habit of using a mobile calendar, the default calendar on their phone was used. Given that the daily questionnaires were administered through a timed notification, familiarity with using mobile calendars was not deemed a confound in our study.

2.4 Pilot Study Measures

In the pilot study, participants completed the PROMIS® Item Bank v2.0 Cognitive Function (Cella et al., 2007) and the Brief Symptom Inventory (Derogatis, 1975) as baseline measures of cognition and mood, respectively, as well as a demographics' questionnaire in the second in-lab session. As part of the daily component, they completed the Mood Zoom Questionnaire (Tsanas et al., 2016) and the PROMIS® Cognitive Function Short Form 6a (Cella et al., 2007).

2.5 Cognitive Measures

In the full study procedure, to assess a more robust array of constructs, participants completed four baseline measures of cognition: metacognition, executive function, cognitive failures, and memory failures.

2.5.1 Metacognitive Awareness Inventory

The MAI (Schraw & Dennison, 1994) is a 52-item "true or false" self-report assessment of metacognitive awareness. It is subdivided into two broader categories, "knowledge of cognition" and "regulation of cognition". There is some evidence to show that increased levels of metacognitive awareness correlate with performing more physical activity in the future (Loprinzi et al., 2020), which we deemed relevant to our study, given the physical component of mobility and connections that this may have to maintaining a larger life space.

2.5.2 Amsterdam Executive Function Inventory

The AEFI (Van der Elst et al., 2012), designed specifically for young adults, is a brief, 13-item self-reported measure of three components of executive functioning: “Attention”, “Self-Control and Self-Monitoring”, and “Planning and Initiative”. Items were scored on a scale of 1 = “not true”, 2 = “partly true”, and 3 = “true”. Given the propensity of executive function influencing mobility patterns in older adults, it was critical to evaluate such a measure in young adults as well, to see whether similar effects could be replicated in this younger population.

2.5.3 Cognitive Failures Questionnaire

The 25-item CFQ (Broadbent et al., 1982) measures self-reported deficits in memory, as well as absent-mindedness and clumsiness in the past six months, on a scale of “0 (Never)” to “4 (Very Often)”. While young adults are not as prone to cognitive failures as are older adults, subjective reports of failures have been shown to reflect fluctuations in cognitive capacity, which may provide a more realistic assessment of daily cognitive performance (Carrigan & Barkus, 2016).

2.5.4 Prospective and Retrospective Memory Questionnaire

The 16-item PRMQ (Smith et al., 2000) evaluates self-reported prospective and retrospective memory slips on a scale of “5 (Very Often)” to “1 (Never)”. While young adults do not experience memory and executive control deficits nearly as often as do older adults (e.g., West et al., 2003), these are important to investigate given the prevalence of such issues in older adults and their impact on mobility.

2.6 Mood Measures

In the full study procedure, participants completed four baseline measures of mood: depression, state anxiety, trait anxiety, and loneliness.

2.6.1 Center for Epidemiologic Studies Depression Scale

The CES-D (Radloff, 1977) is a 20-item self-report measure of depressive symptomology. Participants rate how often they have felt or behaved a certain way in the past week, rating from “0 (Rarely)” to “3 (Most days)”. Levels of depression have been shown to influence a vast array of measures of out-of-home mobility in non-clinical populations (Saeb et al., 2016; Müller et al., 2020), hence its inclusion in this study.

2.6.2 State-Trait Anxiety Inventory

The 40-item STAI (Spielberger, 1977) evaluates anxiety at the state level (“at this moment”) and trait level (“in general”). Participants rate how often they feel a certain way, on a scale of “1 (Almost Never)” to “4 (Almost Always)”. People with higher levels of social anxiety have been shown to spend more time at home (Chow et al., 2017), making this a relevant measure to our study.

2.6.3 Revised UCLA Loneliness Scale

The UCLA Loneliness Scale (Russell, 1996) is a 20-item self-report measure of loneliness, where participants indicate how often a given statement is descriptive of them, on a scale of “1 (Never)” to “4 (Often)”. Based on Müller and colleagues’ work (2020), loneliness was included to assess its relation to time spent at home and in social places.

2.7 Personality Measure

2.7.1 HEXACO Model of Personality Structure

The HEXACO model (Ashton & Lee, 2007) is a robust alternative to the more popular Big Five measure of personality. While the HEXACO evaluates most of the same constructs as the five-factor model (Extraversion (X), Agreeableness (A), Conscientiousness (C), and Openness to Experience (O)), it adds the dimension of Honesty-Humility (H), and expands on the traditional measure of Neuroticism, replacing it with Emotionality (E). Personality types have been shown to explain the types of places people choose to spend their time in (Matz & Harari, 2021), and has a lot of relevance for understanding the relationship between people and their environments. In this study, the 60-item version (HEXACO-60) was used; however, to maintain a focused scope, these data were not analyzed here.

2.8 Daily Measures

2.8.1 Mood Zoom Questionnaire

The Mood Zoom Questionnaire (Tsanas et al., 2016) assesses four items of negative mood (*anxious, sad, angry, irritable*) and two items of positive mood (*energetic, elated*) on a 7-point Likert scale, with anchors of “1 (not at all)” and “7 (very much)”. It was developed as a compact, mobile measure to be used for simple, real-time monitoring of mood states, making it a desirable choice for this study.

2.8.2 Additional measures of mood

As part of the full procedure, the day questionnaires (administered at 12:00PM and 5:00PM) consisted of the Mood Zoom Questionnaire plus two additional 7-point Likert items assessing stress and loneliness. The items for stress and loneliness were added based on Müller and colleagues' work (2020), which identified that stress was related to evenness of time distribution spent in locations, while levels of loneliness correlated with amount of time spent in social places. However, due to time constraints these items were not included in analyses, as they could not be validly collapsed with the other established mood measures at the aggregate level.

2.8.3 PROMIS® Cognitive Function 8a

The PROMIS® Cognitive Function 8a (Cella et al., 2007) is a short-form derived from the PROMIS® Item Bank v2.0 Cognitive Function, assessing momentary subjective experience of cognitive functioning on a 5-point Likert scale, its anchors being "1 (very often)" and "5 (never)", with greater scores indicating greater cognitive function (e.g., *"I have had trouble forming thoughts", "It has seemed like my brain was not working as well as usual"*). The 8-item short form replaced the 6-item version used in the pilot, to match the length of the full study's mood measure.

The original PROMIS® Cognitive Function short forms are written to be used on a weekly time scale; the question lead asks to respond to the items based on the past seven days, and the last two response options include mentions of days (i.e., "often (about once a day)" and "very often (several times a day)"). For this study, the lead was changed to "in the past few hours", and the response options to "often (once an hour)" and "very often (several times an hour)".

2.8.4 Additional evening questionnaire items

The evening questionnaire (administered at 9:00PM) included four additional self-report questions, pertaining to types of places visited (e.g., work, a social engagement), mode of transportation used (e.g., walking, transit), types of environments visited (e.g., urban, natural), and what portion of the day was spent working or doing school from home (i.e., all, some, or none of the day) (see Appendix A for full list of items and their groupings for use in analyses). These questions were included to help qualify the GPS mobility data, to understand motivations behind an array of movement patterns and help drive future hypotheses. These questions were only included in the evening, as they captured tendencies over the entire day.

Places visited. Based on Müller and colleague's (2020) findings, place visit tendencies were an important measure of mobility that correlated with levels of depression, stress, and loneliness, to name a few. Per their procedure, place types were grouped into three categories: *home, work*, and *leisure* places. A few changes were made for this study, including removing "vehicle" due to the inclusion of a separate transportation question, removing "other" due to its ambiguity (per Müller et al., 2020), adding a category for activities of *maintenance,* and subdividing "store" based on purpose of visit (for necessity or for leisure). We also included friend's/partner's house and parent's/family's house, to help account for a participant's home base changing over the course of the two-week study.

Mode of transportation. To aid in qualifying distances travelled over the day, participants were asked to indicate the types of transportation they had used. We avoided using a catch-all "other" option to avoid ambiguity when analyzing these data. Three categories of transportation were determined: *human-powered* (including walking, biking, using a scooter/skateboard or a motorized scooter/skateboard), *transit* (bus, train/subway), and *car*. These categorizations allowed for segmentation of potential distances one could travel. Future studies will separate the car category into "driver" and "passenger", to aid in parsing the amount of agency used for each mode.

Type of environments. It has been found that urban environments are more taxing on our attentional capacities than natural ones (e.g., Kaplan, 1995, Burtan et al., 2021). Thus, assessing whether participants tend to spend more time in urban versus natural environments may inform on their well-being. We categorized urban (e.g., downtown) and residential (e.g., Kitsilano, Richmond) as *urban* environments, while urban nature (e.g., beach, park), natural (e.g., Pacific Spirit, mountains), and rural/farmland (e.g., Chilliwack) environments were categorized as *natural*. While it would be more fruitful to treat each of these as distinct points on the urban to natural continuum, this was not a primary measure in the current work, thus broader categories were created.

Work/school from home. To help capture which trips out-of-home were for necessity versus leisure, participants were asked to indicate how much of their day had been spent working or doing school from home. An individual who must leave their house daily may have a more expansive life space than they would have chosen to have had they been able to complete some of their obligations from home. These data were not included in the current work, as they pertain to daily level tendencies, which were not analyzed here.

2.9 Mobility measures

Movement patterns were assessed based on mobility measures computed from the GPS data collected on participants' smartphones through Google Maps. Table 2 provides descriptions of each of these measures; the method for calculating them is described below.

Table 2. List and descriptions of mobility measures

Measure	Description	References
Total distance travelled	Sum of distances travelled between place visits.	Shoval et al., 2011; Canzian & Musolesi, 2015; Müller et al., 2020
Number of locations visited	Number of unique locations visited.	Faurholt-Jepsen et al., 2021, Wettstein et al., 2014; Müller et al., 2020
Time spent at home	Sum of time spent at location identified as home.	Depp et al., 2019; Boukhechba et al., 2018; Müller et al., 2020

2.9.1 Mobility measure calculations

Mobility measures were calculated based on aggregate GPS data exported from participants' Google Location History data. In Google's "Semantic Location History" files, raw GPS data (i.e., time-stamped latitude-longitude pairs) are parsed into two categories: place visits (i.e., stationary events) and activity segments (i.e., time spent in travel), along with calculated values such as distance travelled between places and time spent at a location, as well as alphanumeric place IDs assigned to each unique location. Due to time constraints, these data were used to compute the desired measures, as opposed to the raw GPS records that were also made available from the participants' Google Maps export.

Total distance travelled was computed as the sum of distances between place visits per day, averaged over the two-week study period. The number of locations visited was calculated using the alphanumeric place ID as the number of unique locations visited per day, averaged over the two-week study period. We characterized a participant's home location as the location where they spent most of their time per day. While researchers recommend using a mode location during nighttime hours instead (Müller et al., 2022), the Semantic data file did not easily allow for these calculations. Given its aggregation of place visits and activity segments, multiple data points were not shown while someone was stationary at a given location. Future work will use the raw GPS data to supplement these data and calculate a more accurate home location per participant.

3 Results

3.1 Measures and analyses

The goal of data analyses was to investigate the impact of daily cognitive and mood states on out-of-home mobility while controlling for relevant covariates. The three mobility measures of interest were total distance travelled, number of unique locations visited, and time spent at home, calculated as mean daily level over the two-week study period, resulting in a two-week aggregate score for each measure. Our predictor variables of interest were daily cognition, positive mood, and negative mood scores, assessed via self-report survey three times a day over the study period, collapsed into a daily mean score for the purpose of these analyses. Nineteen covariate measures were included as well: four baseline measures of cognition (metacognition, executive function, cognitive failures, memory failures), four baseline measures of mood (depression, state and trait anxiety, loneliness), four place visit types (home, work/school, maintenance, leisure), three transportation types (human-powered, transit, car), two environment types (urban, natural), and age and gender. Baseline measures and demographics were collected in-lab, while self-reported daily activity pattern measures were collected once daily via surveys.

Before running the relevant statistical analyses, we first handled removal of outlier data based on central tendency distributions for the GPS mobility data, justifications of which are presented below, as well as handled missing data for participants' age. The final sample's descriptive statistics are presented in Table 3. Next, given the exploratory nature of this work, we computed a correlation matrix to examine the relationship between our mobility and cognition and mood measures, as well as the daily activity pattern measures. These data helped inform on which measures to include in our regression analyses, based on the strength of correlations between measures, as well as evaluate the validity of our mobility measures. Finally, we wrote regression models to test the predictive value of our variables in detecting changes in our outcome mobility measures. Each of the three regression models was computed for each mobility measure, resulting in nine models overall, the results of which are presented in *Regression models*. All correlations and regression models were assessed at an alpha of .05.

3.2 Removal of outliers and handling missing data

Due to complexities associated with collecting GPS data, some participants' data were excluded from individual analyses using Tukey's fences. Although a Shapiro-Wilk test determined violations in normality across most of our measures, we opted to use Tukey's fences to remove only extreme outliers, as opposed to a robust method such as median absolute deviation. Preserving statistical power was crucial in our exploratory work, especially given that over 25% of participants' data ($N = 80$) were lost due to procedural issues. Future analyses will use a more robust method of removing outliers.

After establishing upper and lower bounds based on interquartile range, 10 participants were removed from the distance analyses for having recorded travelling more than an average of 90 kilometers a day over the two-week study period ($M = 336.17$, $SD = 365.79$). No outliers were identified for number of unique locations visited per day, and no meaningful criterion could be set to determine theoretical outliers. No outliers were identified for time spent at home using Tukey's fences, but we chose to remove 11 participants whose data fell two standard deviations below the median level, indicating they spent less than 1.5 hours at home a day over the two-week period ($M = 0.67$, $SD = 0.57$). No meaningful cut-off could be determined for the upper limit of time spent at home, and no values fell above 24 hours. Descriptive statistics for measures of cognition and mood in the final sample are presented in Table 3, while those for mobility and daily activity pattern measures are presented alongside their correlation matrices.

Five participants did not report their age in the demographics survey. To preserve the rest of their data for the correlation and regression analyses, we imputed these missing values as the mean age of the sample. While more robust methods of imputation exist, we deemed this a suitable method given the low variance in age in this student sample.

Table 3. Descriptive statistics for well-being measures of cognition and mood

		N participants	*N* observations	Mean	SD	Med.	Min.	Max.
Daily	Mood (negative)	173	5922	1.90	0.66	1.81	1.00	4.36
	Mood (positive)	173	5922	2.76	0.91	2.65	1.20	5.22
	Cognition	173	5922	32.56	4.84	32.84	13.18	40.00
Baseline cognition	Metacognition	173	346	38.53	6.14	39.00	21.00	51.00
	Executive function	173	346	26.12	2.33	26.00	20.50	33.50
	Cognitive failures	173	346	45.22	13.09	45.50	5.00	85.00
	Memory failures	173	346	42.26	9.79	42.00	18.00	74.00
Baseline mood	Depression	173	346	18.96	6.73	18.00	6.50	41.00
	State anxiety	173	346	44.29	4.85	44.50	31.50	56.00
	Trait anxiety	173	346	45.24	5.36	44.50	31.50	59.50
	Loneliness	173	346	43.32	8.54	43.50	26.50	65.00

3.3 Correlation matrix

Spearman correlations were computed across all variables; non-parametric methods were chosen due to violations of normality. The full matrix of significant correlations is provided in Appendix B, including relationships between cognition and mood measures, as well as between computed measures of mobility and self-report daily activity pattern measures. Here we briefly present a few key findings from correlations between cognition and mood measures. Then, we expand on significant correlations pertaining to the three criterion mobility measures (distance travelled, number of locations visited, and time spent at home) and self-reported daily activity pattern measures (places visited, transportation used, environments visited) and their associations with cognitive and mood measures. These are presented alongside their associated descriptive statistics to aid in interpretation of results.

As expected, the daily cognition and mood scores were strongly and significantly correlated with their associated baseline measures. Furthermore, significant correlations were observed between daily mood and baseline cognition, as well as between daily cognition and baseline mood. Positive daily mood was linked with higher levels of metacognition ($r(173) = .24$, $p = .002$) and lower memory failures ($r(173) = -.16$, $p = .039$), but not with executive function ($r(173) = -.14$, $p = .071$) nor propensity for cognitive failures ($r(173) = -.13$, $p = .081$). Negative daily mood was related to lower levels of metacognition ($r(173) = -.15$, $p = .049$), higher propensity for cognitive failures ($r(173) = .28$, $p<.001$) and memory slips ($r(173) = .18$, $p = .017$), but not executive function ($r(173) = .10$, $p = .197$). Daily cognition was linked with low levels for all measures of baseline mood, namely depression ($r(173) = -.51$, $p<.001$), state anxiety ($r(173) = -.26$, $p<.001$), trait anxiety ($r(173) = -.32$, $p<.001$), and loneliness ($r(173) = -.24$, $p = .001$). At the daily level, participants with greater cognition exhibited low levels of negative mood ($r(173) = -.63$, $p<.001$), but a similar relationship was not found for positive mood ($r(173) = -.04$, $p = .594$). While further analyses are required to understand these relationships more readily, there appears to be an interaction between cognition and mood in our sample, which likely is contributing to multicollinearity in the regression models presented below. Future work will assess fewer constructs and be driven by more directed hypotheses to combat these issues.

The data collected via GPS signals correlated strongly and significantly with self-report measures of daily mobility pattern tendencies, particularly with the transportation measure (see full correlation matrix in Appendix B). Time spent at home was only significantly correlated with total distance travelled ($r(162) = -.24$, $p = .004$), reasoning for which is presented in the *Discussion*. Taken together, these findings help validate the GPS data and their use for computing mobility scores.

3.3.1 Mobility measures

In our data, those who report greater daily cognitive ability tended to spend less time at home, as did those with higher executive functioning. And, participants with higher levels of trait anxiety tended to visit more unique locations in a day than those with lower levels. Age was positively associated with number of locations visited.

Table 4. Significant correlations for the mobility measures

	Distance	Locations	Time at home
Daily cognition			$r(162) = -.16$ ($p = .049$)
Executive function			$r(162) = -.17$ ($p = .030$)
Trait anxiety		$r(173) = .22$ ($p = .002$)	
Age		$r(173) = .23$ ($p = .003$)	

Table 5. Descriptive statistics for the mobility measures

	N participants	*N* observations	Mean	SD	Med.	Min.	Max.
Distance	163	6740	24.12	16.45	19.26	0.73	75.40
Locations	173	6819	3.01	1.07	2.90	1.00	6.07
Time at home	162	2191	13.35	5.38	13.99	1.86	23.42

3.3.2 Place visits

Participants with a greater propensity for memory slips tended to spend fewer days at home. As well, a few baseline measures of cognition and mood correlated with the number of days on which an activity of maintenance was completed. These activities included shopping for necessities, going to the gym or playing sports, and visiting a religious establishment. Participants with greater state anxiety levels tended to spend more days performing activities of maintenance, as did those who are older. Those with greater memory, executive function ability, lower levels of depression, and who experience fewer cognitive failures tended to spend fewer days performing maintenance activities.

Table 6. Significant correlations for the place visits

	Days - home	Days - work/school	Days - leisure	Days - maintenance
Executive function				$r(152) = -.24$ ($p = .001$)
Cognitive failures				$r(152) = -.21$ ($p = .006$)
Memory failures	$r(172) = -.16$ ($p = .040$)			$r(152) = -.22$ ($p = .003$)
Depression				$r(152) = -.24$ ($p = .001$)
State anxiety				$r(152) = .18$ ($p = .019$)
Age				$r(152) = .17$ ($p = .025$)

Table 7. Descriptive statistics for place visits

	N participants	*N* observations	Mean	SD	Med.	Min.	Max.*
Home	172	2393	11.36	2.43	12	0	15
Work/social	171	1949	6.55	2.79	7	0	14
Maintenance	152	759	3.46	2.92	3	0	13
Leisure	169	1911	6.54	3.58	6	0	16

*Note: some participants filled out the evening questionnaire multiple times a day by mistake, resulting in additional evening records, hence maximum values exceeding 14.

3.3.3 Mode of transportation

A few baseline measures of cognition and mood were correlated with mode of transportation used. Participants with lower negative mood, fewer cognitive failures, lower memory abilities, and lower levels of depression tended to use human-powered modes of transportation more often (being walking, biking, using a scooter/skateboard, or using a motorized scooter/skateboard). Those with higher daily cognitive ability tended to use human-powered modes of transit on more days than those who had lower ability. And, participants with more frequent cognitive failures and higher levels of trait anxiety tended to use public transit more often than those with lower levels, as did participants who are older.

Table 8. Significant correlations for mode of transportation

	Days - human powered	Days - transit	Days - car
Daily mood (negative)	$r(171) = -.18$ ($p = .019$)		
Daily cognition	$r(171) = .27$ ($p<.001$)		
Cognitive failures	$r(171) = -.21$ ($p = .006$)	$r(150) = .24$ ($p = .001$)	
Memory failures	$r(171) = -.22$ ($p = .004$)		
Depression	$r(171) = -.25$ ($p<.001$)		
Trait anxiety		$r(150) = .18$ ($p = .017$)	
Age		$r(150) = .19$ ($p = .014$)	

Table 9. Descriptive statistics for mode of transportation

	N participants	*N* observations	Mean	SD	Med.	Min.	Max.*
Human-powered	171	2394	10.87	2.92	12	0	16
Transit	150	1317	5.03	3.77	4	0	13
Car	120	723	3.59	3.88	2	0	14

*Note: some participants filled out the evening questionnaire multiple times a day by mistake, resulting in additional evening records, hence maximum values exceeding 14.

3.3.4 *Type of environment*

The number of days spent in urban environments was correlated with greater daily cognitive ability, fewer cognitive failures, and greater memory ability. The number of days spent in natural environments was correlated with greater daily positive mood, metacognitive awareness, state anxiety, age, as well as fewer cognitive failures and lower levels of loneliness.

Table 10. Significant correlations for environments visited

	Days - urban	Days - natural
Daily mood (positive)		$r(107) = .22$ ($p = .003$)
Daily cognition	$r(172) = .19$ ($p = .012$)	
Metacognition		$r(107) = .16$ ($p = .033$)
Cognitive failures	$r(172) = -.16$ ($p = .034$)	$r(107) = -.16$ ($p = .037$)
Memory failures	$r(172) = -.16$ ($p = .035$)	
Depression		$r(107) = -.16$ ($p = .034$)
State anxiety		$r(107) = .17$ ($p = .024$)
Loneliness		$r(107) = -.20$ ($p = .010$)
Age		$r(107) = .19$ ($p = .012$)

Table 11. Descriptive statistics for environments visited

	N participants	*N* observations	Mean	SD	Med.	Min.	Max.*
Urban	172	3241	11.66	2.33	12	0	16
Natural	107	421	1.76	2.45	1	0	13

*Note: some participants filled out the evening questionnaire multiple times a day by mistake, resulting in additional evening records, hence maximum values exceeding 14.

3.4 Regression models

Three robust regression models were tested on each of the three mobility variables, resulting in a total of nine individual models. Model 1, the full model, examined mean daily scores of cognition, positive mood and negative mood, and included all nineteen covariates. Model 2, the daily model, consisted of the three daily well-being measures and the three daily activity pattern measures (place visits, transportation, environments). Model 3, the baseline model, looked at baseline measures of cognition and mood alongside the daily activity pattern measures, and did not consider the daily measures of cognition and mood. Since the daily well-being measures were strongly and significantly correlated with many of the baseline measures, these measures were observed separately in Models 2 and 3 to dissociate between their presumed overlap in explaining variance amongst the criterion variables in Model 1. Wild Robust Regression was used due to violations of normality and multicollinearity, since it allows for down-weighing of outlier values (Biesanz, 2020; Biesanz, 2022). 95% confidence intervals were calculated as Biased Corrected and Accelerated (*BCa*) using casewise resampling. All data were standardized to standard deviation units to aid in interpretation of results. For brevity, significant results are presented below, categorized by mobility measure. Full regression tables are presented at the end of *Results*.

3.4.1 Total distance travelled

The full model was significantly predictive of mean daily distance travelled over the two-week period, $R^2_{adj} = .31$, $F(22,140) = 4.35$, $p<.001$. Neither the daily nor baseline measures of cognition had a significant impact on distance travelled. However, larger distances were associated with higher daily positive mood, $\beta = .12$, $t(140) = 2.00$, $p = .048$, 95% CI [.02, .32]).

Unsurprisingly, the number of days on which public transportation ($ß$ = .30, $t(140) = 4.71$, p<.001, 95% CI [.17, .48]) or a car ($ß$ = .61, $t(140) = 9.90$, p<.001, 95% CI [.42, .74]) was used were reliable indicators of greater distance travelled. These results help validate the mobility data collected, as we would expect to see greater potential distances travelled in vehicles as compared to human-powered modes of transit.

The daily model was significantly predictive of distance travelled, $R^2_{adj} = .29$, $F(14,148) = 5.74$, p<.001, whereas none of the daily measures of well-being exhibited significant predictive power for distance travelled. As in the full model, the number of days on which public transportation ($ß$ = .30, $t(148) = 5.13$, p<.001, 95% CI [.19, .46]) or a car ($ß$ = .62, $t(148) = 9.40$, p<.001, 95% CI [.45, .76]) was used was significantly predictive. Similarly, the baseline model predicted daily distance travelled ($R^2_{adj} = .33$, $F(19,143) = 6.65$, p<.001), but none of the measures of well-being did. As in the other distance models, use of public transportation ($ß$ = .33, $t(143) = 5.22$, p<.001, 95% CI [.22, .52]) or a car ($ß$ = .62, $t(143) = 9.70$, p<.001, 95 CI% [.45, .75]) were strong predictors of distance travelled.

3.4.2 Number of unique locations visited

The full model was significantly predictive of mean daily number of unique locations visited over the two-week period ($R^2_{adj} = .44$, $F(22,150) = 7.26$, p<.001), however none of the daily measures of well-being were. Greater metacognitive awareness was associated with fewer locations visited, $ß$ = -.15, $t(150) = -2.11$, $p = .037$, 95% CI [-.27, .02]. Unsurprisingly, the number of days spent at work or school was significantly predictive of number of locations visited, $ß$ = -.19, $t(150) = -3.19$, $p = .002$, 95% CI [-.36, -.08]. This likely indicates that the more time one spends at work or school, the less time is available to visit other locations. As in the models for distance travelled, the number of days on which public transportation (β = .48, t(150) = 8.04, p<.001, 95% CI [.39, .67]) or a car (β = .40, t(150) = 6.99, p<.001, 95% CI [.27, .55]) was used was significantly predictive of greater number of locations visited. Age was also associated with more locations visited, β = .12, t(150) = 2.11, p = .037, 95% CI [-.02, .26].

The daily model was significantly predictive of number of locations visited over the two-week period (R^2_{adj} = .41, F(14,158) = 6.35, p<.001), whereas none of the measures of well-being were. As in the full model, the number of days spent at work or school was significantly associated with fewer locations visited, β = -.22, t(158) = -3.27, p = .001, 95% CI [-.38, -.10]. And, the number of days on which public transportation (β = .52, t(158) = 8.30, p<.001, 95% CI [.43, .69]) or a car (β = .40, t(158) = 6.84, p<.001, 95% CI [.28, .56]) was used were strong predictors of visiting more unique places. Age was also associated with more locations visited, β = .10, t(158) = 2.23, p = .027, 95% CI [-.02, .20].

The baseline model was significantly predictive of number of locations visited over the two-week period, R^2_{adj} = .44, F(19,153) = 7.18, p<.001. As in the full model, greater levels of metacognitive awareness were associated with fewer locations visited, β = -.15, t(153) = -2.06, p = .041, 95% CI [-.27, .02]. As in the daily model, the number of days spent at work or school was significantly associated with fewer locations visited, β = -.20, t(153) = -3.23, p<.001, 95% CI [-.37, -.10]. And, the number of days on which public transportation (β = .49, t(153) = 7.94, p<.001, 95% CI [.40, .68]) or a car (β = .40, t(153) = 6.88, p<.001, 95% CI [.27, .56]) was used was significantly predictive. Age was also associated with more locations visited, *ß* = .12, *t*(153) = 2.27, *p* = .025, 95% CI [-.01, .26].

3.4.3 Time spent at home

While the full model did not predict a significant proportion of variance in time spent at home (R^2_{adj} = .06, *F*(22,139) = 1.48, *p* = .144), several individual variables were predictive. Namely, greater levels of daily cognition were associated with less time spent at home (*ß* = -.26, *t*(139) = -2.50, *p* = .013, 95% CI [-.49, -.04]), as were levels of loneliness (*ß* = -.20, *t*(139) = -2.05, *p* = .042, 95% CI [-.41, -.01]) and use of public transportation (*ß* = -.20, *t*(139) = -1.99, *p* = .049, 95% CI [-.42, -.02]). Both age (*ß* = .16, *t*(139) = 2.65, *p* = .009, 95% CI [-.03, .31]) and gender (*ß* = -.19, *t*(139) = -2.30, *p* = .023, 95% CI [-.35, -.01]; man=0) were determinants of time spent at home as well.

In the daily model, which lacked predictive ability (R^2_{adj} = .003, *F*(14,139) = 1.02, *p* = .504), greater daily cognition was a reliable indicator of less time spent at home, *ß* = -.29, *t*(139) = -3.12, *p* = .002, 95% CI [-.14, .14]. Self-reports of the number of days spent at home were associated with more time spent at home (*ß* = .25, *t*(139) = 2.09, *p* = .038, 95% CI [-.32, .11]), and greater number of days using public transportation was predictive of spending less time at home, *ß* = -.23, *t*(139) = -2.58, *p* = .011, 95% CI [.43, .69]. Age predicted more time spent at home, *ß* = .14, *t*(139) = 2.34, *p* = .020, 95% CI [-.02, .20]. It is important to note, however, that most of these effect sizes lay outside their confidence intervals, meaning we cannot make strong claims about these results.

In the baseline model, which was not significantly predictive of time spent at home (R^2_{adj} = .03, $F(19,142) = 1.20$, $p = .318$), greater levels of depression were associated with more time spent at home, β =.34, $t(142) = 2.76$, $p = .007$, 95% CI [.03, .54]. As in the full and daily models, more days spent using public transportation was a reliable determinant of less time spent at home (β = -.21, $t(142) = -2.08$, $p = .040$, 95% CI [-.42, -.03]), and age was predictive of more time spent at home (β = .15, $t(142) = 2.38$, $p = .019$, 95% CI [-.05, .30]).

3.5 Control analyses

One concern regarding interpretation of these results was to what extent these relationships may be influenced by lack of power. To address this issue, post-hoc power analyses were run to determine the level of achieved power for each of the nine models. All models predicting variability in total distance travelled achieved power ranging from 56-65%. While including all participants removed due to our exclusion criteria would garner a large enough sample to achieve 80% power for the baseline model (N = 221), we chose not to rerun these analyses due to supposed lack of quality in these participants' data. All models predicting number of unique locations visited achieved power of 94-95%, suggesting that the null results exhibited across many cognition and mood measures cannot confidently be dismissed due to lack of power. Further analyses and data are needed to make strong interpretations of these results. All models predicting time spent at home achieved power of 5-6% with negligible effect sizes, suggesting noteworthy concerns with these values, further reasoning for which is detailed in the *Discussion*.

Table 12. Achieved power and effect sizes and required sample size for each regression model

		N participants	Effect size (f^2)	Achieved power (*B*)	*N* for *B* = .80
Model 1: Full	Distance	163	0.10	0.56	239
(25 predictors)	Locations	173	0.20	0.94	127
	Time at home	162	0.004	0.06	5814
Model 2: Daily	Distance	163	0.08	0.60	228
(17 predictors)	Locations	173	0.19	0.94	122
	Time at home	162	0.000009	0.05	1 966 918
Model 3: Baseline	Distance	163	0.11	0.65	206
(22 predictors)	Locations	173	0.20	0.95	120
	Time at home	162	0.0007	0.05	28540

3.6 Full regression tables

Table 13. Total distance travelled - Model 1 (Full)

						BCa 95% CI	
		β	*SE*	*t*(140)	*p*	*LL*	*UL*
Daily	Cognition	-.07	.07	-0.99	.325	-.25	.12
	Mood (negative)	-.06	.05	-1.12	.265	-.22	.08
	Mood (positive)	**.12**	**.06**	**2.00**	**.048**	.02	.32
Baseline cognition	Metacognition	-.14	.08	-1.78	.077	-.35	.01
	Executive function	.00	.06	0.00	.996	-.15	.17
	Cognitive failures	-.13	.11	-1.18	.239	-.41	.16
	Memory failures	.04	.11	0.42	.678	-.24	.27
Baseline mood	Depression	.02	.09	0.19	.848	-.20	.23
	State anxiety	-.17	.09	-1.95	.053	-.43	.04
	Trait anxiety	.06	.06	1.01	.313	-.14	.20
	Loneliness	-.10	.07	-1.40	.163	-.27	.06
Place visits	Days - home	-.21	.12	-1.74	.084	-.56	.09
	Days - work/school	-.07	.06	-1.14	.257	-.25	.05
	Days - maintenance	-.03	.05	-0.63	.530	-.21	.08
	Days - leisure	-.09	.06	-1.42	.157	-.31	.01
Transportation	Days - human-powered	.05	.07	0.66	.509	-.15	.24
	Days - transit	**.30**	**.06**	**4.71**	**<.001**	.17	.48
	Days - car	**.61**	**.06**	**9.90**	**<.001**	.42	.74
Environments	Days - urban	-.07	.10	-0.75	.454	-.45	.18
	Days - natural	.00	.05	-0.04	.967	-.11	.17
Demographics	Age	.03	.05	0.51	.609	-.16	.20
	Gender	-.03	.06	-0.52	.601	-.18	.13

$R^2_{adj} = .31$
$F(22,140) = 4.35, p<.001$

Table 14. Total distance travelled - Model 2 (Daily)

		β	*SE*	$t(148)$	*p*	BCa 95% CI *LL*	BCa 95% CI *UL*
Daily	Cognition	-.02	.06	-0.41	.681	-.13	.15
	Mood (negative)	-.08	.05	-1.48	.140	-.23	.05
	Mood (positive)	.05	.05	1.16	.250	-.04	.24
Place visits	Days - home	-.18	.10	-1.83	.069	-.56	.03
	Days - work/school	-.08	.06	-1.40	.162	-.26	.04
	Days - maintenance	-.06	.05	-1.22	.224	-.24	.04
	Days - leisure	-.03	.06	-0.56	.574	-.25	.05
Transportation	Days - human-powered	.03	.07	0.40	.690	-.14	.22
	Days - transit	**.30**	**.06**	**5.13**	**<.001**	.19	.46
	Days - car	**.62**	**.07**	**9.40**	**<.001**	.45	.76
Environments	Days - urban	-.08	.09	-0.81	.420	-.39	.20
	Days - natural	-.01	.05	-0.20	.842	-.11	.16
Demographics	Age	.00	.04	0.00	.999	-.17	.14
	Gender	-.02	.06	-0.37	.712	-.19	.11

$R^2_{adj} = .29$
$F(14,148) = 5.74$, $p<.001$

Table 15. Total distance travelled - Model 3 (Baseline)

						BCa 95% CI	
		β	*SE*	*t*(143)	*p*	*LL*	*UL*
Baseline cognition	Metacognition	-.13	.08	-1.63	.106	-.32	.02
	Executive function	.00	.06	-0.06	.952	-.17	.16
	Cognitive failures	-.12	.11	-1.07	.288	-.40	.17
	Memory failures	.04	.10	0.43	.670	-.24	.27
Baseline mood	Depression	.02	.08	0.20	.843	-.19	.18
	State anxiety	-.10	.07	-1.48	.141	-.30	.06
	Trait anxiety	.05	.06	0.79	.430	-.15	.17
	Loneliness	-.12	.07	-1.81	.073	-.30	.03
Place visits	Days - home	-.20	.12	-1.64	.103	-.52	.10
	Days - work/school	-.08	.06	-1.32	.189	-.28	.01
	Days - maintenance	-.04	.06	-0.76	.449	-.22	.06
	Days - leisure	-.06	.06	-0.95	.346	-.29	.01
Transportation	Days - human-powered	.04	.07	0.63	.532	-.13	.23
	Days - transit	**.33**	**.06**	**5.22**	**<.001**	.22	.52
	Days - car	**.62**	**.06**	**9.70**	**<.001**	.45	.75
Environments	Days - urban	-.09	.10	-0.92	.361	-.48	.15
	Days - natural	-.02	.05	-0.37	.716	-.12	.15
Demographics	Age	.02	.05	0.48	.632	-.15	.18
	Gender	-.03	.06	-0.48	.629	-.18	.13

$R^2_{adj} = .33$
$F(22,143) = 6.65$, $p<.001$

Table 16. Number of unique locations visited - Model 1 (Full)

						BCa 95% CI	
		β	*SE*	*t*(150)	*p*	*LL*	*UL*
Daily	Cognition	-.01	.08	-0.08	.936	-.21	.16
	Mood (negative)	-.01	.07	-0.12	.901	-.16	.16
	Mood (positive)	.05	.06	0.89	.376	-.08	.20
Baseline cognition	**Metacognition**	**-.15**	**.07**	**-2.11**	**.037**	-.27	.02
	Executive function	.04	.07	0.60	.550	-.06	.22
	Cognitive failures	-.01	.11	-0.05	.958	-.24	.26
	Memory failures	-.04	.11	-0.39	.698	-.29	.19
Baseline mood	Depression	-.01	.10	-0.07	.942	-.25	.19
	State anxiety	-.08	.08	-1.04	.301	-.27	.09
	Trait anxiety	.15	.08	1.75	.082	-.07	.31
	Loneliness	-.01	.08	-0.19	.850	-.20	.14
Place visits	Days - home	-.14	.09	-1.52	.132	-.32	.16
	Days - work/school	**-.19**	**.06**	**-3.19**	**.002**	-.36	-.08
	Days - maintenance	-.01	.07	-0.08	.939	-.14	.15
	Days - leisure	.03	.05	0.50	.615	-.08	.16
Transportation	Days - human-powered	-.17	.09	-1.82	.071	-.44	-.01
	Days - transit	**.48**	**.06**	**8.04**	**<.001**	.39	.67
	Days - car	**.40**	**.06**	**6.99**	**<.001**	.27	.55
Environments	Days - urban	.10	.09	1.10	.273	-.27	.25
	Days - natural	.08	.06	1.40	.162	-.08	.20
Demographics	**Age**	**.12**	**.06**	**2.11**	**.037**	-.02	.26
	Gender	.00	.06	0.05	.962	-.13	.15

$R^2_{adj} = .44$
$F(22,150) = 7.26, p<.001$

Table 17. Number of unique locations visited - Model 2 (Daily)

						BCa 95% CI	
		β	*SE*	*t*(158)	*p*	*LL*	*UL*
Daily	Cognition	-.01	.07	-0.17	.865	-.14	.14
	Mood (negative)	.03	.07	0.47	.643	-.11	.21
	Mood (positive)	.00	.05	0.05	.959	-.09	.11
Place visits	Days - home	-.14	.09	-1.50	.136	-.32	.11
	Days - work/school	**-.22**	**.07**	**-3.27**	**.001**	-.38	-.10
	Days - maintenance	-.01	.07	-0.17	.865	-.14	.13
	Days - leisure	.06	.06	1.13	.259	-.04	.19
Transportation	Days - human-powered	-.18	.09	-1.90	.059	-.42	-.02
	Days - transit	**.52**	**.06**	**8.30**	**<.001**	.43	.69
	Days - car	**.40**	**.06**	**6.84**	**<.001**	.28	.56
Environments	Days - urban	.11	.09	1.22	.224	-.22	.26
	Days - natural	.07	.06	1.21	.226	-.08	.19
Demographics	**Age**	**.10**	**.05**	**2.23**	**.027**	-.02	.20
	Gender	.01	.06	0.25	.805	-.12	.14

$R^2_{adj} = .41$
$F(14,148) = 6.35$, $p<.001$

Table 18. Number of unique locations visited - Model 3 (Baseline)

						BCa 95% CI	
		β	*SE*	*t*(153)	*p*	*LL*	*UL*
Baseline cognition	**Metacognition**	**-.15**	**.07**	**-2.06**	**.041**	-.27	.02
	Executive function	.03	.07	0.52	.604	-.07	.21
	Cognitive failures	-.01	.11	-0.05	.957	-.22	.27
	Memory failures	-.05	.11	-0.42	.675	-.28	.18
Baseline mood	Depression	-.01	.09	-0.16	.877	-.23	.17
	State anxiety	-.06	.07	-0.89	.375	-.20	.10
	Trait anxiety	.15	.08	1.89	.061	-.07	.30
	Loneliness	-.03	.07	-0.38	.703	-.20	.12
Place visits	Days - home	-.14	.09	-1.52	.130	-.31	.16
	Days - work/school	**-.20**	**.06**	**-3.23**	**.002**	-.37	-.10
	Days - maintenance	-.01	.07	-0.19	.847	-.14	.14
	Days - leisure	.03	.05	0.60	.549	-.06	.17
Transportation	Days - human-powered	-.17	.10	-1.78	.078	-.42	-.01
	Days - transit	**.49**	**.06**	**7.94**	**<.001**	.40	.68
	Days - car	**.40**	**.06**	**6.88**	**<.001**	.27	.56
Environments	Days - urban	.10	.08	1.20	.233	-.29	.23
	Days - natural	.09	.06	1.49	.139	-.06	.20
Demographics	**Age**	**.12**	**.05**	**2.27**	**.025**	-.01	.26
	Gender	.00	.06	0.04	.965	-.11	.15

$R^2_{adj} = .44$

$F(19,153) = 7.18, p<.001$

Table 19. Time spent at home - Model 1 (Full)

						BCa 95% CI	
		β	*SE*	*t*(139)	*p*	*LL*	*UL*
Daily	**Cognition**	**-.26**	**.10**	**-2.50**	**.013**	-.49	-.04
	Mood (negative)	-.06	.11	-0.55	.583	-.29	.16
	Mood (positive)	-.09	.10	-0.92	.359	-.28	.12
Baseline cognition	Metacognition	-.06	.09	-0.66	.508	-.26	.12
	Executive function	-.15	.10	-1.49	.138	-.35	.07
	Cognitive failures	-.06	.18	-0.34	.735	-.40	.32
	Memory failures	-.02	.16	-0.15	.880	-.36	.30
Baseline mood	Depression	.24	.14	1.79	.076	-.09	.48
	State anxiety	.15	.11	1.35	.180	-.12	.37
	Trait anxiety	-.10	.11	-0.88	.383	-.31	.17
	Loneliness	**-.20**	**.10**	**-2.05**	**.042**	-.41	-.01
Place visits	Days - home	.25	.13	1.96	.052	-.06	.55
	Days - work/school	.06	.09	0.68	.499	-.09	.29
	Days - maintenance	.07	.07	0.97	.334	-.09	.22
	Days - leisure	.06	.10	0.61	.545	-.15	.24
Transportation	Days - human-powered	-.13	.08	-1.57	.118	-.32	.07
	Days - transit	**-.20**	**.10**	**-1.99**	**.049**	-.42	-.02
	Days - car	-.17	.09	-1.75	.083	-.38	.02
Environments	Days - urban	-.01	.13	-0.10	.919	-.39	.29
	Days - natural	-.05	.07	-0.81	.419	-.21	.10
Demographics	**Age**	**.16**	**.06**	**2.65**	**.009**	-.03	.31
	Gender	**-.19**	**.08**	**-2.30**	**.023**	-.35	-.01

$R^2_{adj} = .06$
$F(22,139) = 1.48$, $p=.144$

Table 20. Time spent at home - Model 2 (Daily)

						BCa 95% CI	
		β	*SE*	*t*(147)	*p*	*LL*	*UL*
Daily	**Cognition**	**-.29**	**.09**	**-3.12**	**.002**	-.14	.14
	Mood (negative)	-.07	.10	-0.67	.503	-.11	.21
	Mood (positive)	-.01	.08	-0.13	.900	-.09	.11
Place visits	**Days - home**	**.25**	**.12**	**2.09**	**.038**	-.32	.11
	Days - work/school	.05	.09	0.58	.563	-.38	-.10
	Days - maintenance	.10	.07	1.43	.155	-.14	.13
	Days - leisure	.05	.10	0.48	.631	-.04	.19
Transportation	Days - human-powered	-.14	.08	-1.71	.090	-.42	-.02
	Days - transit	**-.23**	**.09**	**-2.58**	**.011**	.43	.69
	Days - car	-.17	.09	-1.90	.059	.28	.56
Environments	Days - urban	-.01	.12	-0.08	.937	-.22	.26
	Days - natural	-.04	.07	-0.53	.595	-.08	.19
Demographics	**Age**	**.14**	**.06**	**2.34**	**.020**	-.02	.20
	Gender	-.14	.08	-1.69	.093	-.12	.14

$R^2_{adj} = .003$
$F(14,147) = 1.02$, p=.504

Table 21. Time spent at home - Model 3 (Baseline)

						BCa 95% CI	
		β	*SE*	*t*(142)	*p*	*LL*	*UL*
Baseline cognition	Metacognition	-.06	.09	-0.60	.552	-.26	.12
	Executive function	-.16	.11	-1.46	.145	-.35	.08
	Cognitive failures	-.04	.17	-0.21	.832	-.38	.34
	Memory failures	.04	.15	0.23	.817	-.29	.34
Baseline mood	**Depression**	**.34**	**.12**	**2.76**	**.007**	.03	.54
	State anxiety	.18	.11	1.60	.111	-.05	.39
	Trait anxiety	-.13	.12	-1.09	.279	-.33	.14
	Loneliness	-.19	.10	-1.83	.070	-.39	.02
Place visits	Days - home	.25	.13	1.92	.057	-.09	.52
	Days - work/school	.09	.09	0.99	.323	-.06	.31
	Days - maintenance	.07	.07	1.04	.300	-.08	.23
	Days - leisure	.07	.10	0.74	.461	-.14	.24
Transportation	Days - human-powered	-.13	.08	-1.60	.113	-.34	.04
	Days - transit	**-.21**	**.10**	**-2.08**	**.040**	-.42	-.03
	Days - car	-.16	.10	-1.66	.098	-.39	.02
Environments	Days - urban	-.04	.13	-0.34	.736	-.40	.29
	Days - natural	-.06	.07	-0.92	.360	-.21	.10
Demographics	**Age**	**.15**	**.06**	**2.38**	**.019**	-.05	.30
	Gender	-.15	.08	-1.92	.057	-.32	.01

$R^2_{adj} = .03$
$F(19,142) = 1.20$, $p=.318$

4 Discussion

In this exploratory study, we examined the role of daily cognitive and mood states on daily mobility patterns in young adults over a fourteen-day period. We examined three measures of mobility (total distance travelled, number of locations visited, and time spent at home) and their relation to four baseline measures of cognition (metacognitive awareness, executive function, propensity for cognitive failures, and memory failures), four baseline measures of mood (depression, state and trait anxiety, and loneliness), three activity pattern measures (places visited, transportation used, environments visited), and age and gender. Statistical analyses showed that, in line with our hypotheses, greater daily positive mood was predictive of greater distances travelled, but we did not find support for cognition impacting distances travelled. As well, greater levels of daily cognition and baseline executive functioning were significantly correlated with less time spent at home, lower levels of loneliness and depression were predictive of less time spent at home, while greater memory was significantly correlated with fewer days spent at home. However, these interpretations should be tempered, as these models did not predict a significant proportion of variance in the outcome variable. Contrary to our hypotheses, greater trait anxiety as well as lower metacognitive awareness were significantly correlated with more locations visited. Taken together, these mixed findings suggest that mobility is not as readily impacted by fluctuations in cognitive and mood states in young, healthy adults, as is seen in older adults or clinical populations.

4.1 Weak links between cognition and mobility

While research in gerontology provides clear evidence for impacts of cognition on mobility (at both biomechanical and community levels), perhaps such a strong relationship does not exist in young adults. This is not to say that cognitive ability does not relate to mobility across the lifespan, but perhaps that the impacts of fluctuations in cognition do not lead to detectable changes in mobility patterns. Such claims are in line with the literature on effects of physical activity (PA) on cognition in young adults. Given that young adulthood is characterized by peak cognitive performance, the few studies examining PA's impacts on cognitive ability show mixed support for aerobic fitness impacting cognition in young adults over prolonged periods (Voss et al., 2011). It appears that the beneficial impacts of PA on cognition exist earlier and later in life, but more nuanced studies are needed to determine whether these effects exist for young adults (Prakash et al., 2015), particularly in terms of differentiating mode of exercise as well as cognitive domains (Loprinzi & Kane, 2015). Studies that do find beneficial impacts show that increased cardiovascular exercise in teenage years can predict cognitive ability in early adulthood and beyond (Åberg et al., 2009). And, at the acute level, quick bouts of exercise show improvements in scoring on cognitive tests directly following exercise (Hogan et al., 2013). Based on these findings, it may be that young adults' typically stable cognitive abilities do not lead to differential effects in amount of out-of-home mobility.

4.2 Different cognitive constructs at play

Although effects of mobility on cognition may not exist in young adults, they may also be difficult to parse due to the impacts of PA influencing cognitive constructs at different mechanistic levels (e.g., cellular, structural, behavioural) (Stillman et al., 2020). Presumably, it is equally as important to parse these levels when investigating the relationship between cognition and movement in young adults, as has been done in work with older adults. At the behavioural level, physical functioning has been suggested as a moderator in the relationship between executive function and distance travelled from home (Wettstein et al., 2014), in that executive function resources may be necessary for deploying physical abilities in order to successfully adapt to changes in the environment. Along these lines, cognitive resources have been found to be particularly important for execution of more physically demanding out-of-home activities (e.g., shopping, sports), as they may be required for behaviours such as postural control (Wahl et al., 2013). If the effect of executive function on out-of-home mobility is moderated by physical ability in older adults, then it is unlikely that young adults would face congruent impacts, due to their greater physical and cognitive abilities, as compared to older adults. If these relationships do extend more broadly across the lifespan, then other mechanisms are surely at play to moderate these effects, and more constructs need to be evaluated in order to successfully explain this potential relationship.

Beyond cognition, other critical factors relating to experiencing the environment may be at play when studying mobility in young adults. While important models in the field surrounding mobility in older adults outline the importance of considering aspects of the physical environment such as weather, ambient conditions, and infrastructure design (Patla & Shumway-Cook, 1999) when assessing these relationships, these same factors may not readily apply to young adults. Thus, specific work exploring how the built and natural environments impact mobility are vital to evaluate whether these models can be extended to younger populations. The presence of urban greenness beyond classically characterized green spaces has been found to increase walking levels in city environments (Vich et al., 2019), supporting greater levels of outdoor physical activity and possibly greater well-being. As well, increased cognitive load imposed by the density of urban environments has been shown to impact gait dynamics in young adults (Burtan et al., 2021), pointing to ways in which studying the environment can help inform on our understanding of momentary fluctuations in cognitive capacity. Other models propose looking more globally at sociocultural and economic influences as critical factors that might impact mobility across the lifespan (Franke et al., 2020; Webber et al., 2010). In any case, future work is needed to extend our existing theoretical models to include other age populations, and look at what might cause parallel fluctuations in mobility in young adults.

4.3 Impacts of mood did not replicate

While it is not entirely surprising that our study could not replicate findings from the literature in gerontology, we expected to replicate some of the relationships between mood and mobility seen in both clinical and subclinical populations. Some of our results are in line with the literature, particularly that daily positive mood was predictive of distance travelled (Sabatelli et al., 2014) and that depressive symptomology was predictive of spending more time at home (Faurholt-Jepsen et al., 2021). However, we expected to see meaningful relationships between place visit tendencies and mood, particularly in regards to time spent in social places, as this has been found to correlate with levels of anxiety (Boukhechba et al., 2018) and loneliness (Müller et al., 2020). Additionally, we expected to see significant results in relation to time spent at home (Müller et al., 2020), but those models achieved low power and had negligible effect sizes. We attribute these null results to imprecisions in our measures of mobility, and discuss these limitations below.

4.4 Additional factors of importance

Apart from challenges faced with the mobility measures, it could be that other factors are at play in the connections between well-being and mobility amongst young adults, and that cognitive ability and mood alone are not enough to explain presumed fluctuations in movement patterns. Notably, there may be an important interaction between cognition and mood driving changes in mobility, evidenced in the many significant correlations between daily and baseline measures of cognition and mood (see correlation matrix in Appendix B). However, more work is needed to correctly interpret these findings. A number of other measures might be relevant in this relationship as well. For instance, personality types have been shown to explain certain mobility tendencies, particularly wayfinding preferences (Meneghetti et al., 2016) and types of places people choose to spend their time in (Matz & Harari, 2021). Such relationships may help explain some of the motivational factors underlying mobility tendencies amongst young adults, and future work will analyze this sample's personality data to investigate this empirical question.

4.5 Limitations and conclusions

In this study, we examined the effect of daily and baseline cognition and mood on three measures of out-of-home mobility in young adults over a two-week period. Our mixed results suggest that while greater daily cognitive ability and mood influence distances travelled and time spent at home, more work assessing tendencies at the daily level are needed to further parse these relationships. Despite assessing a multitude of cognitive and mood constructs, our differential findings suggest that there may be other nuanced factors at play, and that well-being may not influence daily mobility patterns as readily as it does in geriatric and clinical populations. Given that few studies have assessed these relationships in young, healthy populations (Müller et al.,

2020) and few guidelines exist for analyzing GPS data in psychological contexts (Müller et al., 2022), it is critical that we develop more apt methodologies to assess these frameworks in young adults, as a novel way of bringing long-needed objective, empirical traction to our understanding of daily cognition.

Three specific limitations from this study should be noted to guide future work in this domain. First, due to feasibility challenges in cleaning GPS data, the mobility measures were not always reflective of participants' true movement patterns. For instance, large outliers existed for daily distance travelled that were inconceivable within the study parameters (i.e., participants travelling an average of at least 90 kilometers per day over the two-week period). Google Location History GPS data have been validated as functionally equivalent to more robust GPS tracker data (Ruktanonchai et al., 2019), so this was not deemed to be an issue with data collection. Instead, it is assumed that the inaccurate distance values, including GPS coordinate values bouncing to other countries within a single day, were due to location spoofing via the use of virtual private networks (VPNs) (Zhao & Sui, 2017). Future work should pay careful attention to smartphone compliance to ensure participant data can be analyzed.

Additionally, values for the time spent at home variable appear to be inaccurate for some participants, most significantly evident in the achieved power of 5-6% for these regression models. Due to time constraints in analyzing these data, Google's aggregate GPS file, the "Semantic Location History" file, was used in lieu of raw GPS records. In this aggregation, intermediate GPS records were not available, in that multiple data points were not shown when someone was stationary at a given location. Given this, it was not possible to use the recommended method of determining home location, which is to extract the most visited location between the hours of 12AM and 6AM (Müller et al., 2022), which may have led to inaccurate representations of home in our sample.

Another notable issue arose due to aggregation of GPS data in relation to UBC's campus. Upon inspecting the data more closely, we inferred that UBC is treated as one distinct location. As such, for any individual who lives on campus, it was not possible to parse how much time was spent at home versus in the vicinity, e.g. at the library or a café. Given our sample consisted of undergraduate students, some of whom reside at UBC, we anticipate this significantly impacted the accuracy of our home measure. Future analyses will leverage other data analysis methods, such as clustering raw GPS records (Müller et al., 2022) to calculate more accurate home locations. And, other collected measures such as days spent at a partner or family member's house will be used to distinguish between multiple mode locations.

A second limitation of our findings is that the regression models predicting mobility from well-being were conducted using two-week aggregate level scores of all included variables. As outlined earlier, many of our measures showed significant correlations beyond our main hypotheses that would be meaningful to investigate further, such as the interaction between cognition and mood, as well as the relation amongst mobility and daily activity pattern measures. However, generally our measures did not show much predictive ability at the aggregate level. Collapsing these values into two-week aggregates reduces the impact of any daily variability that might exist, which is of greater interest in this population, given young adults' lack of decline in trait cognitive abilities, and their propensity for experiencing daily fluctuations via cognitive failures (Carrigan & Barkus, 2016). Predictive models in the literature have reported findings at the daily level (Müller et al., 2020, Chow et al., 2017), thus future work will use multilevel modeling to analyze changes at the within-subject, daily level.

A third limitation of this study is that the daily activity measures included to help qualify the mobility measure values could have been more specific. For instance, place visits should have included more activities of maintenance, such as seeing a doctor or going to the bank, to capture a broader array of daily experiences. While significant correlations appeared between performing activities of maintenance and levels of cognition and mood, we temper our interpretation of these mixed results, as this place visit category had the fewest number of observations. While our measures of transportation mode correlated significantly with our measures of mobility, validating both sets of measures, a few improvements could be made. The *car* category should be subdivided into "driver" versus "passenger" to capture agency involved in the trip purpose. As well, correlations for human-powered modes of transit are difficult to interpret, as anecdotally, participants often chose "walking" even when they had not left their house, due to forced-choice responses in the mobile survey. Further, while correlations exist in our data regarding days spent in natural environments and greater levels of cognition and mood, it is important to note that participants frequented urban environments more than seven times as much as they did natural ones. And, some participants completed the evening questionnaire multiple times a day in error, leading to over-reporting of certain values of daily activity patterns.

In sum, future work should focus on improving measures of daily activity patterns, as they can be helpful in qualifying and interpreting quantitative mobility measures and their connections to well-being. While only recently has the field of transportation planning begun measuring subjective well-being in regards to travel (Singleton & Clifton, 2021), employing this field's well-established methods in capturing characteristics of the built environment is vital to uncovering connections that exist between mobility and well-being (Zhu & Fan, 2018), and informing on how our daily movements through space may in turn impact our quality of life.

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Appendices

Appendix A. Categorization of additional evening questionnaire items

Question	Category	Items
Place visits	Home	Home
	Work/school	Work, classroom, library
	Maintenance	Shopping for necessities, religious establishment, gym/sports
	Leisure	Bar/party, café/restaurant, friend/partner house (if distinct from your home), parent/family house (if distinct from your home), shopping for leisure, recreational activity (e.g., movie theatre)
Mode of transportation	Human-powered	Walk, bike, scooter/skateboard, motorized scooter/skateboard
	Transit	Bus, train/subway
	Car	Car
Environments	Urban	Urban (e.g., downtown, Commercial Broadway), urban residential (e.g., Kitsilano, Richmond)
	Natural	Urban nature (e.g., park, beach), nature (e.g., Pacific Spirit, mountains), rural/farmland (e.g., Chilliwack)

Appendix B. Full correlation matrix.

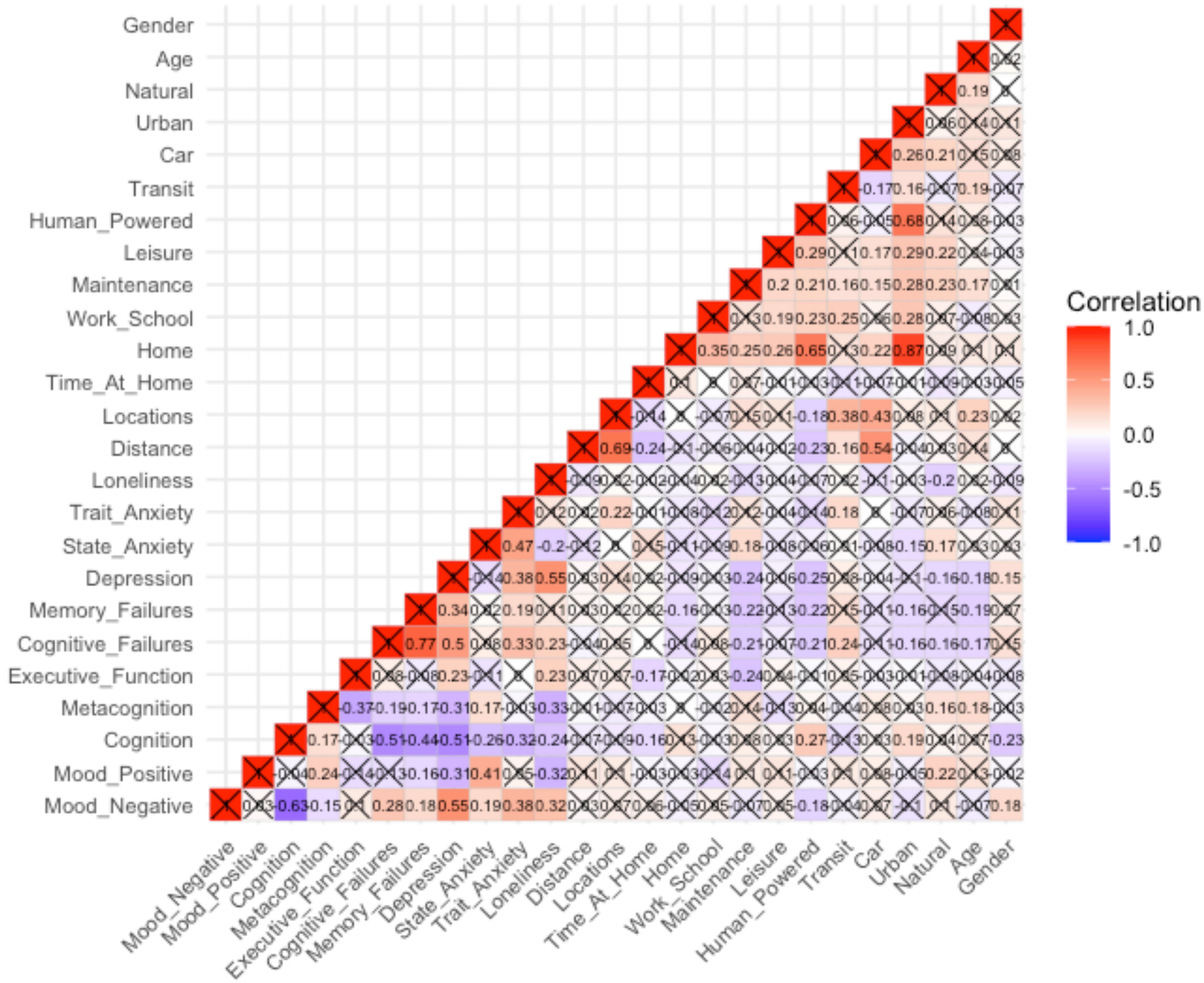

Figure 1. Full correlation matrix. Spearman correlation values for all 25 variables are presented inside the cells. Colour indicates the direction of correlation, while saturation indicates its strength (see legend). "X" marks cells with non-significant correlations, alpha = .05.