Exploring Wearable Technologies for Health Monitoring: Applications in Motion Sickness and Dehydration

by

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Dedication

To my family, and my lifelong partner.

Acknowledgements

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Abstract

Wearable devices have enhanced health monitoring in clinical settings by effectively measuring physiological signals to inform prevention strategies. With the rapid development of sensors and data-driven decision-making, wearables can be applied in non-clinical settings to monitor various health conditions. Oftentimes, the most direct, accurate measurements are inaccessible or impractical during real-life, unscripted daily activities (e.g., equipment access). In this dissertation, signal-based models were developed to evaluate common wearables for health monitoring, with specific applications on motion sickness and dehydration.

Motion sickness can range from stomach discomfort to severe nausea and affects passengers more frequently than drivers. As automated vehicles and mobility solutions become normalized, motion sickness incidence is anticipated to increase among on-road passengers. As such, there is a greater need for early detection of vehicular motion sickness. Previous studies have shown postural instability to be associated with motion sickness. Therefore, assessments of standing balance may be useful for estimating levels of motion sickness. However, there are limited studies of post-drive standing balance that have been conducted in passenger vehicles or under ecologically-relevant conditions. In this dissertation, three studies quantified motion sickness and standing balance of vehicle passengers following continuous driving exposures deployed on a closed test track and on-road environments using a wearable inertial measurement unit. In the closed test track study, trunk postural sway increased significantly during the more challenging balance exercises. Post-drive changes to postural sway metrics (e.g., sway velocity and path length) were larger for drives during which participants performed a visual-based task

on a handheld tablet-based device, as compared to drives without a task. In the on-road study, changes in post-drive postural sway were consistent with the findings from the closed test track study. However, there was no meaningful effect of performing a task on changes in postural sway metrics. In the third study, significant changes in post-drive postural sway were associated with the severest motion sickness responses, suggesting that sway metrics could characterize motion sickness. While preliminary, these findings could inform monitoring approaches of vehicular motion sickness using postural sway data from wearable sensors. Additional work would further explore wearables as a potential screening tool for motion sickness susceptibility prior to the drive.

In the fourth study of this dissertation, wearables were used to develop a noninvasive method for continuously measuring dehydration; untreated, dehydration can lead to performance detriments and in severe cases, death due to heat-related complications. Participants performed a series of orthostatic postural movements before and after a cycling session while donning common wearable that measured heart rate and trunk kinematic data. A machine learning model was trained and accurately classified a level of fluid loss equivalent to 2% of bodyweight. Using data from wearable devices, this method can support preemptive fluid replenishment and subsequently minimize potential decreases in performance; reduce the risk of serious heat injuries; and inform users to take additional hydration assessments.

These findings demonstrated the feasibility of wearable technologies for monitoring health conditions that are difficult to assess in non-clinical settings. Specifically, this dissertation developed models that could relate motion sickness and post-drive postural sway measured from wearable devices, and could reliably leverage common sensor-based signals to minimize dehydration. Future applications with wearable devices could especially support secondary prevention strategies, which are approaches aimed at minimizing the impacts of health conditions once they have occurred.

Chapter 1 Introduction and Background

1.1. Introduction

The growth and development of wearable technology has the potential to significantly enhance health monitoring, especially in non-clinical settings. Sensors embedded in wearable devices can measure various biomarkers including physiological signals (e.g., heart rate) to support data-driven models. These models can then estimate the state of a health condition, inform additional assessments, and prevent severer outcomes. However, actual applications are limited in practice, and more work is needed to evaluate the performance of such applications, especially when these approaches require extensive validation for usage in health monitoring. As such, there is a need to understand the extent to which data-driven models and sensor-based signals can support health monitoring. In this dissertation, wearable technologies are used to explore data-driven approaches for addressing nontrivial health conditions in non-clinical settings, with a focus on motion sickness and dehydration. Due to current limitations in quantifying these health conditions, this dissertation conducts preliminary analyses using wearables to leverage known relationships and estimate different levels of motion sickness and dehydration.

1.2. Prevention Strategies

Preventive measures at the patient level are classified depending on when the intervention occurs during the history of a health condition. Primary prevention describes strategies that aim to prevent the onset of a health condition and limit the risk of its occurrence. Secondary prevention strategies seek to detect and treat symptoms early and limit the progression of a disease. Tertiary prevention strategies reduce the severity of long-term effects after a health condition is detected [1]. This hierarchical model of prevention strategies can be applied in multiple domains of health (e.g., stroke, cancer, behavioral disorders, mental health) [2]–[6]. For example, primary and secondary prevention strategies for cardiovascular disease can consist of a combination of regular physical activity, tobacco cessation, blood pressure screenings, and prescribed β-blockers [7].

Recent advances in technology have enhanced secondary prevention strategies [8]–[10]. Specifically, wearable devices can support health monitoring by remotely collecting pertinent data about patient behavior that supports and informs clinical assessments for early detection and treatment of serious health conditions [8]. Additionally, smartphones and other wireless applications allow clinicians to directly and frequently communicate their recommendations to patients to reduce the risk of serious health conditions [11], [12]. In synthesizing and interpreting the literature, a high-level, conceptual map of the relationship between prevention strategies, health conditions, and wearables was created. Figure 1.1 illustrates the general progression of a health condition, starting from a stimulus, leading to the onset of symptoms, and ending with potential outcomes. Different types of prevention strategies can be taken at different stages to reduce the severity and treat the health condition. Wearable technologies can be leveraged at the stage of secondary prevention to increase the likelihood of success.

Wearable devices are especially useful for health monitoring in non-clinical settings because direct, accurate clinical measurements can be impractical or inaccessible. Wearables can support data-driven models to make indirect estimations and infer the progression of a health condition. However, the actual applications of wearables for health monitoring in non-clinical settings are limited in part due to the physical limitations of the sensors, the lack of computational power to support large models and signal processing, environmental conditions, and validated studies [13]. Moreover, assessments of health conditions using wearables is limited by what signals are available from the devices. This dissertation seeks to leverage data from wearable technology to explore data-driven approaches for monitoring nontrivial health conditions in non-clinical settings. In particular, this dissertation explores two areas of application: motion sickness and dehydration.

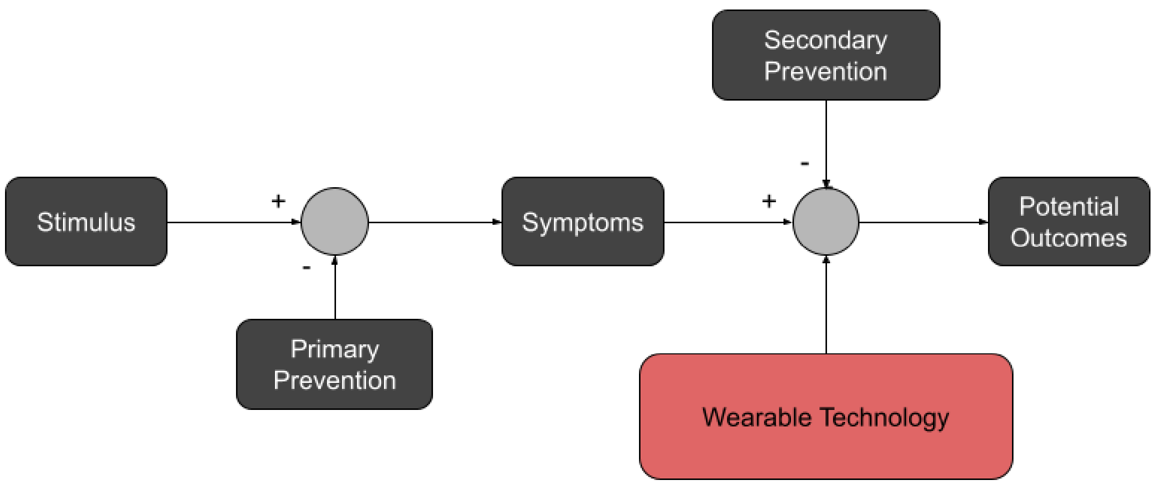

Figure 1.1: Diagram of the general progression of health conditions, relating stimulus, prevention strategies, symptoms, wearable technologies, and potential outcomes. Primary prevention strategies can reduce the effects of a stimulus. Secondary prevention strategies should be taken once symptoms have occurred to reduce the likelihood of potential outcomes. Wearable devices can further support secondary prevention strategies.

1.3. Wearable Technology

Wearable technology—or more commonly, “wearables”—describes a broad spectrum of devices designed to be affixed on the body during use of the sensor. Due to their compact size and unobtrusive nature, wearables enable a wide range of designs and portable applications [14]. Typical embodiments of wearable devices include: 1) accessories (e.g., smart watches [15],

[16]), 2) e-textiles (e.g., smart clothing [17]), and 3) e-patches (e.g., smart patches [18]) [19]. As wearables grow in popularity, their flexibility has encouraged researchers to innovate, develop, and validate new approaches to traditional health monitoring, which is one of the most common applications of wearable technology [19]–[23]. Wearables in health monitoring combine physiological and kinematic data captured in real-time to offer insights into the user's health and condition [24], creating health applications that range from cardiovascular diseases [25] to gait and falls [22], [26]–[28]. As such, there is potential for clinicians to adopt wearable technology for in-patient care [29], [30], home-based assessments [31], [32] and tele-health [33]. In the consumer space, wearables have become prevalent among the sports science and athletics communities as a tool for measuring, analyzing, and maintaining physical performance, or even detecting the risk of injuries [20], [34]–[38]. The extent to which wearables are integrated in an application depends on the system design. In some cases, wearable devices act simply as sensors that wirelessly communicate with larger, integrated networks to perform complex functions; for example, local transmitters from wearables allow tracking of players' field positions in an athletics setting [39], [40]. In contrast, some wearables devices fully operate as a singular, offline package. A common paradigm that utilizes these two concepts comprises a wearable device that transmits data to a smartphone (e.g., Polar heart rate monitor).

1.3.1. Inertial Sensors

Many wearable devices (including mobile devices and smartphones) use inertial measurement units (IMUs) to measure the motion and orientation of the device to perform various features [41]. Embodiments of IMUs typically consist of a combination of a triaxial accelerometer, gyroscope, and magnetometer to capture linear acceleration, angular velocity, and magnetic fields, respectively. By fusing these signals (e.g., using a Kalman filter), users can obtain reliable measurements of the IMU's orientation and position with respect to an origin [42], [43]. When attached to a rigid body, IMUs can provide valuable information regarding the orientation of the body with respect to a reference frame (typically gravity) [42]. Furthermore, a system of IMUs can provide the orientation of each device relative to other devices within the system [44], [45]. As such, they are a useful tool in human motion measurement and application. For instance, multiple IMUs attached to particular body segments (e.g., forearms, trunk, shank) comprise a system for analyzing gait patterns and other motion artifacts [45]–[47]. Balance can similarly be measured using a single IMU placed on the lower back [48]–[51]. Kinematic data from the IMU at the lower back are used to estimate the small deviations in the angle of the trunk relative to the gravity vector, which can then be decomposed into different metrics of postural sway [52]. In this dissertation, IMUs embedded in wearable devices were used to analyze standing balance performance.

1.4. Standing Balance

Balance control is a complex activity governed by multiple physical and sensory systems. Standing balance specifically refers to the dynamic control of the body's center of mass (COM) over the base of support to maintain upright stability and prevent falling [53]. Three sensory systems play a critical role in maintaining balance [54], [55]. The visual sensory system consists of receptors within the retinas of the eyes that process visual stimuli. The somatosensory system consists of the different receptors in the body (i.e., skin, joints, muscles, fascia) that sense information about position, movement, and touch. Lastly, the vestibular system consists of the otoliths and semicircular canals located within the inner ear. Two otolith organs in each ear detect linear accelerations of the head. The utricle is sensitive to horizontal accelerations, while the saccule is sensitive to vertical accelerations. Three semicircular canals within each inner ear sense rotational velocities of the head. Each of these semicircular canals are roughly orthogonal to each other, which allows the body to sense three-dimensional angular velocity and sense the orientation of the head relative to gravity. The signals from these sensory systems are integrated to assist with postural control [56].

1.4.1. Measuring and Assessing Balance

During standing balance, an IMU secured around the lower back measures acceleration and angular rate to capture the kinematics of the body's approximate center of mass (COM) [57]. Alternatively, force plates are frequently used to record the movements of the center of pressure (COP), which is defined to be the point where the resultant ground reaction force acts under the base of support [58]. Furthermore, laboratory-based optical systems use reflective markers (placed on anatomical landmarks) and multiple cameras for measuring the position of said markers for passive motion tracking [59]. However, IMUs offer the advantage of inexpensive and portable data collections [60], [61]. As such, many studies opt to use IMUs as the primary instrument for studying balance [57], [62].

It is common to decompose the time series into anteroposterior (A/P) and mediolateral (M/L) components, which reflect body motion in the sagittal and frontal planes, respectively. From the individual signals, various metrics in the time and frequency domain have been derived and validated for quantifying standing balance [52]. Some metrics have been shown to discriminate between different populations (e.g., fallers and non-fallers) with greater accuracy than others [51], [63], [64]. Other commonly used metrics include the root mean square (RMS) of the sway position and velocity, the area of the ellipse that encompasses the sway trajectory, and the total length of that trajectory [48]. Using these metrics, researchers have shown that changes in standing balance ability are indicative and associated with various pathologies and health conditions, including motion sickness. In addition, comprehensive balance tests have been developed for clinical assessments, such as the Berg Balance Scale, Mini Balance Evaluation Systems Test, and the Romberg Test [65].

1.5. Motion Sickness

Motion sickness describes a general state of unwellness caused by incompatible motion. Surveys have shown that a significant percentage of the population has experienced some form of motion sickness across various forms of transportation, with the most common type being carsickness [66], [67]. Symptoms can range from physiological sensations such as nausea and emesis, to symptoms indicative of sopite syndrome (e.g., fatigue and drowsiness) [68], [69]. The multidimensional symptom profile of motion sickness can detract from daily activities and severely affect comfort during routine travel. With respect to sex and age, females have been shown to report motion sickness more often than males, and older adults tend to be less susceptible to motion sickness due to habituation [70]. The most popular theory for describing the onset of motion sickness is the sensory conflict theory. First described by Reason and Brand (1975) [71], the sensory conflict theory proposes that motion sickness arises from a mismatch between afferent signals to the sensory systems. The integration of the visual and vestibular sensory signals contributes to maintaining postural control and gait stability. However, when the summative motion is incompatible with the existing model developed by previous experiences, sensory conflict occurs and leads to the onset of motion sickness [72].

1.5.1. Vehicular Motion Sickness

Carsickness is one of the most common examples of motion sickness. In a survey of coach passengers, over 30% of people have reported feeling carsick [66]. Age affects the likelihood of motion sickness, with older adults experiencing fewer symptoms at a lower rate [66], [73], [74]. One reason is that an age-related decline (or total loss) of vestibular function significantly reduces the rate of motion sickness and could even render a person immune [73], [75]. Increased travel experience seems to reduce the likelihood of motion sickness as well, which points to habituation to vehicle motion as a potential countermeasure to motion sickness. In the context of sensory conflict theory, the visual information of the vehicle interior can be mismatched with the dynamic vehicle motion sensed by the vestibular system. This mismatch is evident in the differences in reports of motion sickness between drivers and passengers [76], [77]. When passengers' views of the oncoming road are obscured (e.g., sitting in the rear seat), motion sickness is more likely to occur [77]. For drivers, their view of the road aligns with the motion of the vehicle, so it has been hypothesized that active control of the vehicle contributes to reducing likelihood of vehicle motion sickness [76].

In-vehicles tasks are another aggravator of increased motion sickness for vehicular passengers. Passengers must stabilize their view of the task, which involves suppressing the reflexes of the vestibular system. Activities such as reading a book or watching a movie on a mobile device contributes to the sensory mismatch between the visual field and vehicle motion [78]–[80]. Passengers who complete in-vehicle tasks report more severe symptoms and frequency of motion sickness compared to those that do not perform a task [77], [81]–[83]. Depending on the type of task, motion sickness and incompatible motion may negatively affect the performance of the in-vehicle task [78].

1.5.2. Effects of Motion Sickness on Balance

Increased postural sway has been associated with motion sickness. An ecological theory of motion sickness posits that being in a state of postural instability leads to motion sickness [84]. More specifically, novel types of motion demand different postural control strategies to maintain stability. Consequently, a person's inability to adapt their posture in these circumstances leads to motion sickness. Therefore, the theory implies that increased postural sway should be observed prior to the onset of motion sickness. Although there are limitations to this theory [85], studies have observed these effects by measuring postural sway during a sickness-inducing exposure (e.g., virtual moving rooms or optokinetic drums). Postural sway increased especially among those that later reported motion sickness after the exposure [86]–[89], or those that were highly susceptible to motion sickness [90], [91].

In contrast, some studies have focused on the relationship between balance following an exposure and motion sickness, but there has not been firm evidence of a relationship between the severity of motion sickness and increased postural sway [92]–[96]. Moreover, prior work on balance and vehicle motion sickness have only taken place in virtual and motion-based driving simulators. Given the ecological differences between simulators and on-road driving, there is a need to understand how balance may be affected by vehicle motion sickness.

1.5.3. Quantifying Motion Sickness

Subjective reports of motion sickness are typically used to quantify motion sickness within individuals. To capture the full spectrum of symptoms, sensations, and severity, previous studies have used a combination of history questionnaires, surveys, and rating scales. Motion sickness rating scales usually consist of an enumerated, ordinal scale on a predetermined range and anchor points throughout. One of the more common rating scales is the “Fast Motion Sickness” rating scale [97], which prompts users to rate their overall motion sickness on a scale between 0 (no sickness at all) and 20 (frank sickness). The rating scale captures the development of motion sickness over time by being quick to administer throughout a protocol.

In comparison, questionnaires capture a more in-depth profile of motion sickness. Given the diverse profile of motion sickness symptoms, questionnaires such as the “Simulator Sickness Questionnaire” probe for scores on multiple symptoms [98]. The “Motion Sickness Assessment Questionnaire” similarly measures motion sickness as a multidimensional phenomenon, categorizing the symptoms as either gastrointestinal, central-, peripheral-, or sopite-related [99]. A subset of questionnaires pertains to motion sickness susceptibility and history as opposed to measuring symptoms. The “Motion Sickness Susceptibility Questionnaire”, one of the more commonly used tools, asks about a participant’s frequency of motion sickness in various motion modalities (e.g., cars, boats, planes, swings) before and after the age of 12 [100]. Participants respond to each questionnaire item with “never”, “rarely”, “sometimes”, “frequently”, or “always”. The overall score is then computed by weighing each item response, adjusted for the participant’s travel experience. Variants of the motion sickness susceptibility questionnaire have modified the scoring method, the relevant history, and the types of motion modalities included [101].

Ultimately, the lack of objective, quantitative assessments of motion sickness make it difficult to determine whether the severity of symptoms may lead to a potential injury. Wearables are capable of leveraging the relationship between standing balance performance and motion sickness to develop an inexpensive measurement method. Such an approach may be implemented as a preventative screening tool or integrated into existing wearable devices as a complementary feature.

1.6. Dehydration

Dehydration is defined as the process of losing total body water, which is all the water content distributed between the extracellular fluid (ECF) and intracellular fluid (ICF) compartments [102]. If unaddressed, dehydration beyond the daily variability in mass leads to dehydration, a state of low total body water. Depending on the ratio of water and sodium excreted during dehydration, different types of dehydration occur. In one case, a greater loss of body water compared to sodium leads to an increased sodium concentration in the ECF. Osmotic shifts in body water between the ICF compartments and ECF compartments lead to hypertonic dehydration. Some of most common causes of hypertonic dehydration are excessive sweating and a lack of fluid replenishment, usually during extended, intensive exercise [103], [104]. In another case, if sodium loss is equivalent to fluid loss, isotonic dehydration occurs. Cases of isotonic dehydration are usually attributed to diuretics [105]. This dissertation focuses on hypertonic dehydration, where exercise plays the primary role in dehydration.

1.6.1. Exercise-induced Dehydration

During intensive, extended exercise, the core temperature of the body increases [106], [107]. The human body excretes sweat and increases subcutaneous blood flow as a thermoregulatory response [108]–[110]. However, a deficit in total body water occurs when the volume of sweat output is greater than the amount of fluid replenished. The rate of sweat is highly dependent on body composition, participant demographic, and fitness level [111], [112]. Additionally, sweat rates vary substantially across different sports and physically demanding activities (e.g., military training) [113], [114]. Athletes are often in a state of dehydration even before the start of training or competition, with up to 44% of athletes finishing their activities dehydrated [115]. Fluid losses beyond 2% of bodyweight have been associated with increased perception of exertion, decreased aerobic capacity, decreased cognitive performance, and decreased physical performance [114]. This threshold has been considered controversial though, as recent bodies of work have called for improved, controlled study designs to validate the effect of dehydration on athletic performance [116], [117]. Nevertheless, severe levels of dehydration decrease the body's ability to thermoregulate, which can lead to various heat-related injuries [118], [119]. Among high school athletes, heat stroke is one of the three leading causes of death [120]. Therefore, it is important to monitor hydration status before, during, and after exercise to maintain performance and reduce the risk of injury to heat exhaustion.

1.6.2. Estimations of Hydration Status

Many approaches exist for estimating the amount of total body water lost during exercise. Due to the complicated, dynamic, physiological processes of dehydration, a "gold standard" has been difficult to define [121], [122]. Laboratory-based methods typically involve invasive samples of bodily fluids to compute correlated measures of dehydration. Biochemical indices of blood/plasma, saliva, and urine have all been shown to be acceptable measures of dehydration [123]–[125]. Although highly accurate, stable isotope dilution is a costly, time-consuming process that is unadaptable to field settings [122], [126].

Most field applications use quick, gross measurements of bodyweight and urinalysis tests that provide decent short-term estimates of fluid loss. However, other sources of fluid exchange (e.g., substrate oxidation) are not completely captured by bodyweight measurements, and long-term changes in body composition invalidate previous baseline measurements [127]. Indices of urine samples can be limited due to a lack of research on their validity in different populations [128], [129]. Nevertheless, using a combination of bodyweight and urinalysis measurements provides inexpensive, quick assessments with sufficient accuracy for most field applications [122], [130].

Clinics can diagnose dehydration by monitoring changes in orthostatic vital signs after a postural movement. Patients are typically asked to stand up after lying supine for several minutes, after which the cardiovascular response is measured. Upon standing, there is an expected decline in blood pressure due to venous blood pooling in the lower body, leading to an overall decreased venous return to the heart [131]. Baroreceptors in the body detect this drop in blood pressure, and heart rate increases as part of a compensatory response to these orthostatic changes [132]. However, large increases in heart rate of over 30 bpm after standing may be indicative of hypovolemia, which is partly symptomatic of low total body water [105]. In this dissertation, a combination of bodyweight measurements and simple urinalysis tests are used to adapt clinical methods for hydration assessments.

1.7. Dissertation Aims

This dissertation seeks to evaluate wearable technology for health monitoring to support secondary prevention approaches for nontrivial health conditions—specifically, motion sickness and dehydration. Figure 1.2 expands on the conceptual map shown in Figure 1.1, and further adds specific examples of stimuli, symptoms, potential outcomes, and prevention strategies associated with motion sickness. Moreover, wearable devices can potentially support secondary prevention through balance measurements for health monitoring. Figure 1.3 similarly uses the conceptual map to illustrate the progression of dehydration, and indicates when wearable devices can contribute to health monitoring needs to inform secondary prevention strategies. Using wearable devices, the goals are to: 1) quantify how motion sickness, vehicle motion, and task performance on a closed test track affect standing balance; 2) assess how these effects of motion sickness on standing balance translate to an on-road driving environment; and 3) develop a potential noninvasive approach to monitoring hydration status that could be more easily integrated in a field setting.

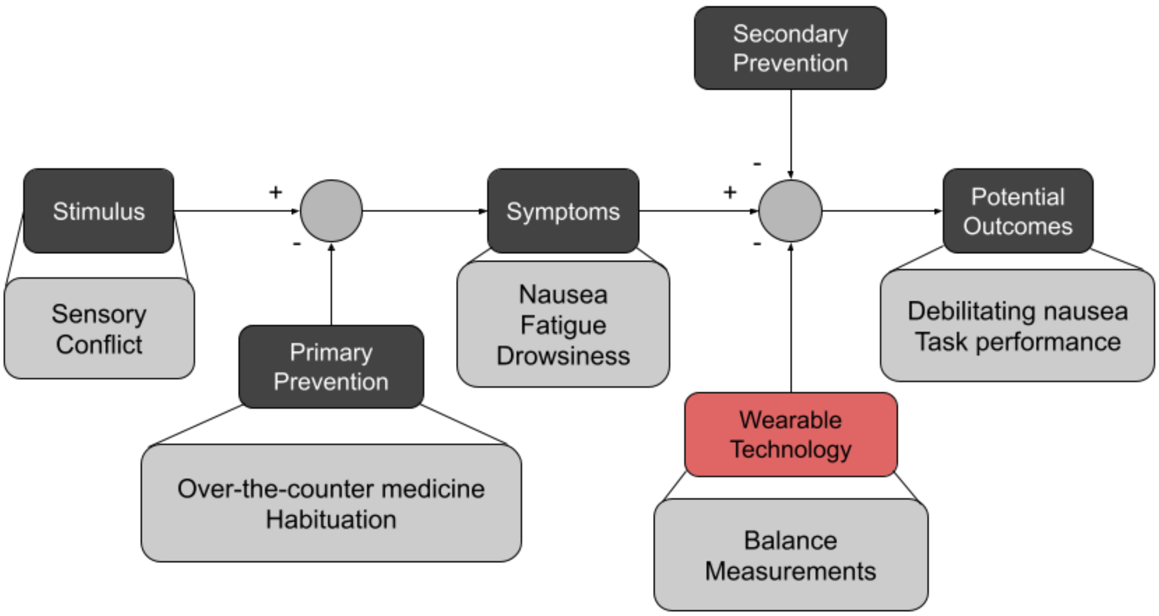

Figure 1.2: Progression of motion sickness using the conceptual map shown in Figure 1.1, with examples of stimuli, symptoms, and potential outcomes. Examples of primary prevention strategies are included as well. In the case of motion sickness, wearable technologies can measure balance and monitor the development of motion sickness to support secondary prevention approaches.

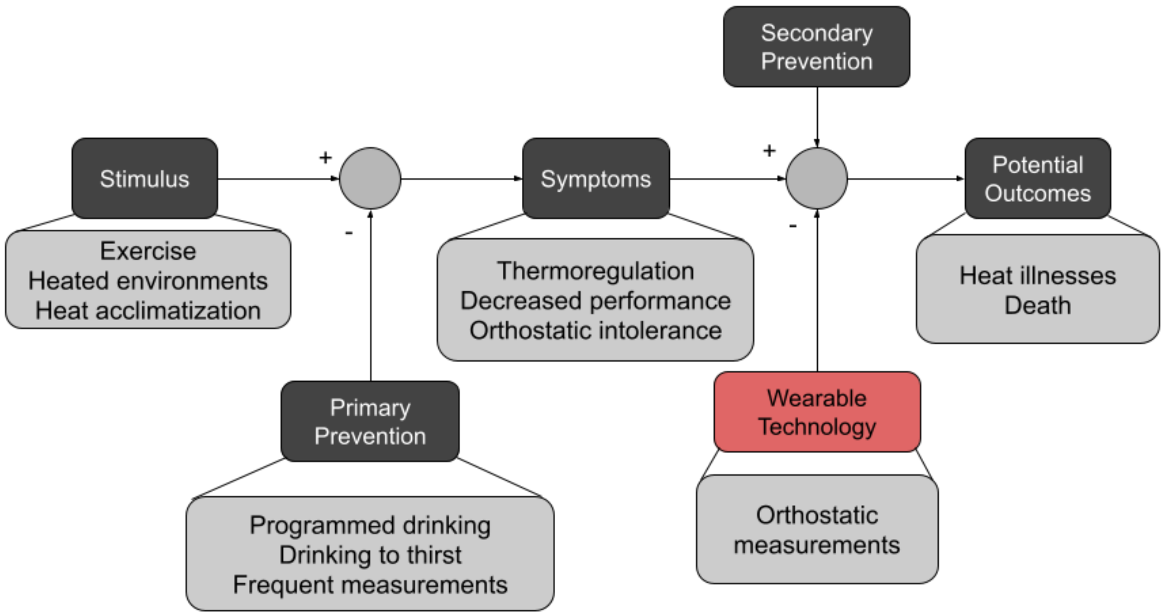

Figure 1.3: Progression of dehydration using the conceptual map shown in Figure 1.1, with examples of stimuli, symptoms, and potential outcomes. Some examples of primary prevention are shown as well. Wearable technologies can monitor orthostatic variables to monitor dehydration and support secondary prevention approaches.

Aim 1: Standing balance has been shown to be negatively affected by motion sickness, but there is a lack of work performed in ecologically relevant driving conditions. Differences between the motion modality and the symptom profiles of virtual motion sickness and motion-induced sickness necessitate additional work in the on-road space. In this study, the goal was to characterize the effects of a drive and task performance on a closed test track on passenger's standing balance. Balance was assessed using a wearable IMU and conventional metrics of postural sway, such as the RMS of trunk tilt and velocity, elliptical area of sway, and the total path length of the sway trajectory. This study tested the following hypotheses:

> **H1.1:** Postural sway would be negatively affected as a function of motion sickness severity, and motion sickness susceptibility.
>
> **H1.2:** Larger changes in balance will be expected in exercises that are more challenging.

Aim 2: Compared to driving on a closed test track, on-road driving introduces several factors that significantly alter the experience, such as other vehicles and on-road actors. Given the need to investigate whether the effects of motion sickness on standing balance performance translate to real-time on-road traffic, two studies sought to adapt and extend the methodology from the previous study by exploring standing balance following a combination of on-road driving and task performance in real-time traffic. In particular, on-road driving consisted of a highway-based route, and an urban route that emphasized local and neighborhood driving behavior. Similar metrics of postural sway were computed, and motion sickness was measured throughout the tests to compare against changes in balance. Moreover, a preliminary analysis was performed to determine if the pre-drive balance metrics could be predictive of motion sickness incidence during the drive. These studies tested the following hypotheses:

> **H2.1:** Changes in balance would reflect the limited intensity of driving in real-time traffic. Assuming a less severe response to motion sickness, standing balance performance would still be affected negatively, but not to the extent hypothesized in the previous study. Still, the pre-drive balance metrics would show good performance in predicting motion sickness incidence.
>
> **H2.2:** Wearable devices would sufficiently measure postural sway off-site and enable portable data collections.

Aim 3: The goal was to develop and test the accuracy of a noninvasive method that used currently existing wearables to estimate exercise-induced dehydration. Current field methods for assessing hydration (i.e., changes in body weight, urinalysis tests) capture gross measurements of fluid loss, and may be limited in accuracy and reliability. As such, additional approaches are needed to complement existing methods and improve overall accuracy of hydration assessments. In a fast-paced athletic environment, methods for assessing hydration should be inexpensive, quick to administer, and noninvasive. Considering the ubiquity of wearable devices among athletic programs and individuals, there is an opportunity to extend the function of existing wearables to detect dehydration.

In this study, a noninvasive method for estimating dehydration was developed by leveraging the cardiovascular response to orthostatic postural changes. When transitioning standing from a supine position, heart rate increases as part of a compensatory response to decreased venous return and blood pooling in the lower extremities. Increased heart rate has been observed in other orthostatic movements as well (e.g., sit-to-stand). In this study, wearable devices were used to capture these dynamic changes in heart rate and posture using embedded EKG leads and IMUs. Predictive models were developed to test the following hypotheses:

H3.1: Continuous measurements from wearable devices would contribute to building a machine learning model capable of weighing different features of the heart rate to accurately estimate dehydration.

H3.2: Beyond standard supine-to-stand tests, other postural movements commonly seen in the field (e.g., toe-touches) would elicit sufficient orthostatic changes for building a reliable, predictive model.

1.8. Chapter Overview

Chapter 2, *Standing balance among vehicle passengers following a drive on a closed test track*, describes a mixed factorial design experiment to understand how various factors during a continuous driving exposure altered a passenger's standing balance. Specifically, the study explored the relationship between motion sickness, test drive conditions, and post-drive standing balance. For the drives, participants were randomly assigned one of two acceleration levels (Low, Moderate), and repeated two scripted drives. One of the drives involved a visual-based task performed on a handheld tablet device (*Task* and *No-Task* conditions). During the tests, participants were driven in the front passenger seat of a midsized sedan on a 20-min. scripted drive around a closed test track. Before and after each scripted drive, participants completed two standing balance exercises: 1) feet tandem, eyes open, on firm support, and 2) feet together, eyes closed, on foam support. A wearable IMU worn around the waist captured estimates of postural trunk sway, from which various postural sway metrics were derived. The results of this study suggested that standing balance was negatively affected following a script drive, especially when an in-vehicle task was involved. However, there were only weak relationships between the magnitude of changes in balance, participants covariates, and motion sickness severity. Changes in balance were also much larger for the more challenging exercise, during which participants stood with their feet together on a foam support with eyes closed.

Chapter 3, *Post-Drive Standing Balance of Vehicle Passengers Using Wearable Sensors: The Effect of On-Road Driving and Task Performance*, describes a study similar in design to that of Chapter 2. Standing balance was explored as a function of participant covariates and an on-road driving exposure to real-time traffic. Participants were randomly assigned to either a Highway route or an Urban route; two repeated drives under *No-Task* and *Task* conditions were consistent with the previous study as well. Participants were similarly driven in the front passenger seat of a midsized sedan for up to 60-min on the designated route. The balance exercises performed increased in difficulty: 1) feet together, eyes open, on firm support, 2) feet together, eyes closed, on firm support, and 3) feet together, eyes closed, on foam support. The wearable IMU setup was the same as described in the previous study. The results of this study suggested that standing balance was negatively affected by ecologically relevant vehicle motion (especially when a task was involved), such that a plausible increase in fall risk may have been observed.

Chapter 4, *Motion sickness affects passengers' standing balance performance*, describes the formal analysis of standing balance performance (captured using wearable IMUs) and motion sickness in on-road environments. Using the data collected from the previous studies in this dissertation, a mixed model approach was used to correlate post-drive standing balance metrics, participant covariates, and motion sickness. A predictive analysis was also performed using pre-drive balance metrics, where a random forest model was trained to predict whether or not a participant would report motion sickness during a drive. The mixed models found a significant association between postural sway velocity and different levels of motion sickness reported during the drive. The predictive model achieved fair performance when predicting motion sickness incidence during the drive, suggesting that pre-drive balance metrics could potentially predict whether or not a person is prone to vehicular motion sickness. Overall, these companion chapters illustrated the efficacy of wearables for novel applications in health monitoring—in this case, vehicular motion sickness.

Chapter 5, *Noninvasive approach to hydration assessments using a data-driven approach based on orthostatic changes*, describes a study focused on developing a potential approach by collecting participant data using wearable devices, building a predictive model, and then evaluating its accuracy and reliability. The data collection consisted of athletic individuals exercising without fluid replenishment to a loss of 2% bodyweight, and performing a varied set of postural movements before and after the exercise. Acting as their own controls, participants repeated this protocol, but replenished any lost body weight with sports drink. Throughout the data collections, participants' heart rate and postural data from wearable devices were used to train and validate a predictive model. The results of the trained model suggested that dehydration (parameterized as bodyweight loss) could be accurately estimated from orthostatic measurements. Non-standard and shorter postural movements achieved similar discriminative performance. Moreover, the overall approach leveraged data from wearable technology to make informed predictions of hydration status.

Chapter 5, *Discussion*, summarizes the major findings; the limitations and implications of the studies; and makes suggestions for future work.

1.9. References

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Chapter 2 Standing Balance Among Vehicle Passengers Following a Drive on a Closed Test Track

2.1. Introduction

Mobility solutions such as autonomous vehicles (AVs) and ride-sharing services, have the potential to increase user productivity, reduce traffic congestion, and provide a broader population with access to personal transportation [1]. Prior studies have shown that passengers experience motion sickness more frequently and severely than drivers, especially when they are focused on other visual activities (e.g., reading on a handheld device, watching movies on an in-vehicle screen) [2]–[5]. By implementing mobility solutions, the number of passengers on the road is projected to increase as drivers are transformed to passengers and transportation becomes more accessible to the population [1]. Consequently, a larger population will be at risk of experiencing motion sickness. This population may exhibit multidimensional sensations [6] that range from physiologically-related responses (e.g., nausea and fatigue) to difficulties concentrating on a task [5,7,8]. Furthermore, passengers affected by motion sickness may observe concomitant changes in their balance abilities post-drive [9]. Subsequently, this change in balance ability could affect the coordination of movements and increases the risk of injury and falls [10]. Therefore, the current study sought to investigate the effects of a drive on a closed test track and task performance on post-drive standing balance.

Currently, there are no in-vehicle studies that explore balance following on-road or closed test track conditions. Although high-fidelity driving simulations may provide visual, auditory, and motion stimuli, the summative, real-world experience of physically riding in a passenger vehicle may be substantially different [11]. Additionally, naturalistic passenger vehicle-induced motion sickness manifests itself differently than simulator-induced motion sickness [12]. The sensory conflict theory suggests that motion sickness results from conflicts or differences between visual and vestibular inputs, kinesthetic proprioception of motion, and the brain's "internal model" of what is expected [13]. In passenger vehicles, motion sickness is hypothesized to result from a sensory conflict between the static, visual perception of the vehicle interior and the global, inertial motion of the body perceived by the vestibular system [13,14]. Therefore, an in-vehicle, closed test track study is needed to quantify the effects of vehicle motion and task performance on standing balance.

Several studies have investigated the association between passengers' balance and motion sickness in simulated driving environments that include a range of physical motion and visual modalities [9], [15], [16]. Keshavarz et al. [9] used a high-fidelity, 6 degree-of-freedom (DOF) motion platform and had participants complete four simulation-based drives at constant speed over 7 km. Throughout the simulations, visual, audio, and motion cues were varied. During an eyes-open standing exercise, the pre-post change in the center of pressure (COP) path length was compared with results from the Simulator Sickness Questionnaire (SSQ) and the Fast Motion Sickness Scale (FMS) ratings. The study participants were divided into two groups: "well group" (participants who reported a score of 0-4.9 on a scale of 0-20) and the "sick group" (participants who reported a score of 5 or greater on a scale of 0-20). Path length increased following the simulation regardless of the sensory cues given. However, there was no meaningful difference between the "sick group" and the "well group"; only weak associations were found between the path length and the FMS and SSQ scores. One major difference between the study performed by

Keshavarz et al. [9] and the current study is that participants were not passengers, but instead drivers during the simulations.

In a fixed-base simulation study [17] that provided exclusively visual cues via a head-mounted display, participants completed 5-min. drives on a simulated highway (60 mph), rural (60 mph), and city (25 mph) course. Participants' maximum time in single-leg stance (eyes closed) decreased following the highway and rural courses and SSQ oculomotor discomfort scores were higher in all simulated driving environments. However, the relationship between SSQ scores and maximum time in single-leg stance was not reported [17]. Reed-Jones et al. [15] used a fixed-base driving simulator to explore post-drive balance performance of 30 participants during eyes-open and eyes-closed, single-leg stance. Path velocity during eyes-open single-leg stance decreased following two 20-min. simulated drives at a constant speed of 90 km/h. Poorer balance was also correlated with lower SSQ scores (i.e., less severe motion sickness). Lee at al. [18] used a fixed-base driving simulator to induce vection and compensatory postural responses and analyzed the immediate changes in balance during a feet-tandem exercise. The increase in M/L sway velocity (measured at the head) of 11 participants approached statistical significance following a 5-min. simulated drive at a speed of 30 mph. Overall, these fixed-base simulator studies reveal quantifiable changes in balance following exposure. However, the fixed-base simulations lacked a vestibular stimulus, and the optical, spatial, and temporal characteristics of the simulator displays may not have directly mapped to the visual stimuli experienced during on-road, closed test-track-based exposures [11].

Given (1) the lack of in-vehicle, on-road or closed test track based studies that examine the effects of passenger vehicle exposures on standing balance, (2) the inconsistent methodologies and results among prior studies, and (3) the increasing implementation of mobility solutions, there is a need to understand the naturalistic effects of vehicle motion and the concurrent performance of a task on post-drive balance. Investigating balance after exposure to vehicle motion that result during closed test track operations and visual-based task can extend the results of existing literature. Assessing the aftereffects can contextualize the risks involved with using AVs, ridesharing services, and passenger vehicles, which can potentially inform the development of countermeasures. The objective of this study was to quantify the effect of vehicle motion, based on a scripted drive on a closed test track, and task performance on post-drive balance.

2.2. Methods

2.2.1. Participants and Experimental Design

A broad overview of the experimental protocol is shown in Figure 2.1. 50 adults (23 males, 27 females; between the ages of 18 and 78 years (40.0 ± 20.6 yr.) participated in a mixed factorial design experiment: 33 were age < 60 (28.3 ± 8.5), 17 were age ≥ 60 (66.4 ± 4.8). During recruitment, participants were asked about (1) the relative frequency of their prior experience of motion sickness, and (2) their assessment of their level of susceptibility to motion sickness. Motion sickness susceptibility was categorized into four levels based upon on how often motion sickness was experienced (never, rarely, sometimes, and frequently). The scripted drive was conducted on a closed test track where participants sat in the front passenger seat of the vehicle. It was developed to include many instances of longitudinal and lateral acceleration profiles consistent with driving on public roadways. The scripted drive was a continuous, concentrated driving exposure, 20 min. in duration that consisted of a series of frequent 90-degree turns, along with braking, acceleration and lane change events [5], [19]. Participants were assigned to one of two levels of acceleration (Low or Moderate) so that there were no significant differences between the groups in age and self-reported motion sickness susceptibility [5]. Two levels of an ecologically relevant task were performed during the in-vehicle scripted drive: i) *No-Task* condition involved normative passenger behavior and unrestricted gaze; and ii) the *Task* condition instructed participants to complete a visual-based task on a handheld tablet device [5]. Participants completed the *No-Task* and *Task* test conditions on different days. The order of the *No-Task/Task* test conditions was randomized. Each participant provided written informed consent and the study was conducted in accordance with the Declaration of Helsinki. The study was reviewed and approved by the University of Michigan Institutional Review Board (HUM00128751).

2.2.2. Balance Measurements and Instrumentation

A smartphone-based (6th generation iPod touch, 2015) inertial measurement unit (IMU) [20] was used to estimate trunk postural sway in the anteroposterior (A/P) and mediolateral (M/L) directions, sampled at 50 Hz [20], [21]. The raw data were from the smartphone's accelerometer and gyroscope sensors. Tilt angles and tilt velocity were computed from the accelerometer and gyroscopes, respectively. The raw data were passed through an extended Kalman filter before computing the metrics. The data were processed in MATLAB (The MathWorks, Natick, MA) to calculate the following six balance metrics for analysis: root-mean-square (RMS) tilt in the A/P (A/P RMS) and M/L (M/L RMS) directions, RMS of sway velocity in the A/P and M/L directions, total path length of the sway trajectory, and the elliptical fit of the sway trajectory area [20], [22]. RMS was calculated by taking the square root of the average of the squared values (A/P RMS and M/L RMS are in degrees, A/P RMS and M/L RMS velocity are in degrees per second). The elliptical area was computed by fitting a 95% confidence ellipse to the raw tilt values in each trial (elliptical area (EA) is in degrees2) [21], [22]. Total path length was captured by summing the absolute distance between consecutive sampled values of the tilt trajectory (path length is in degrees) [22].

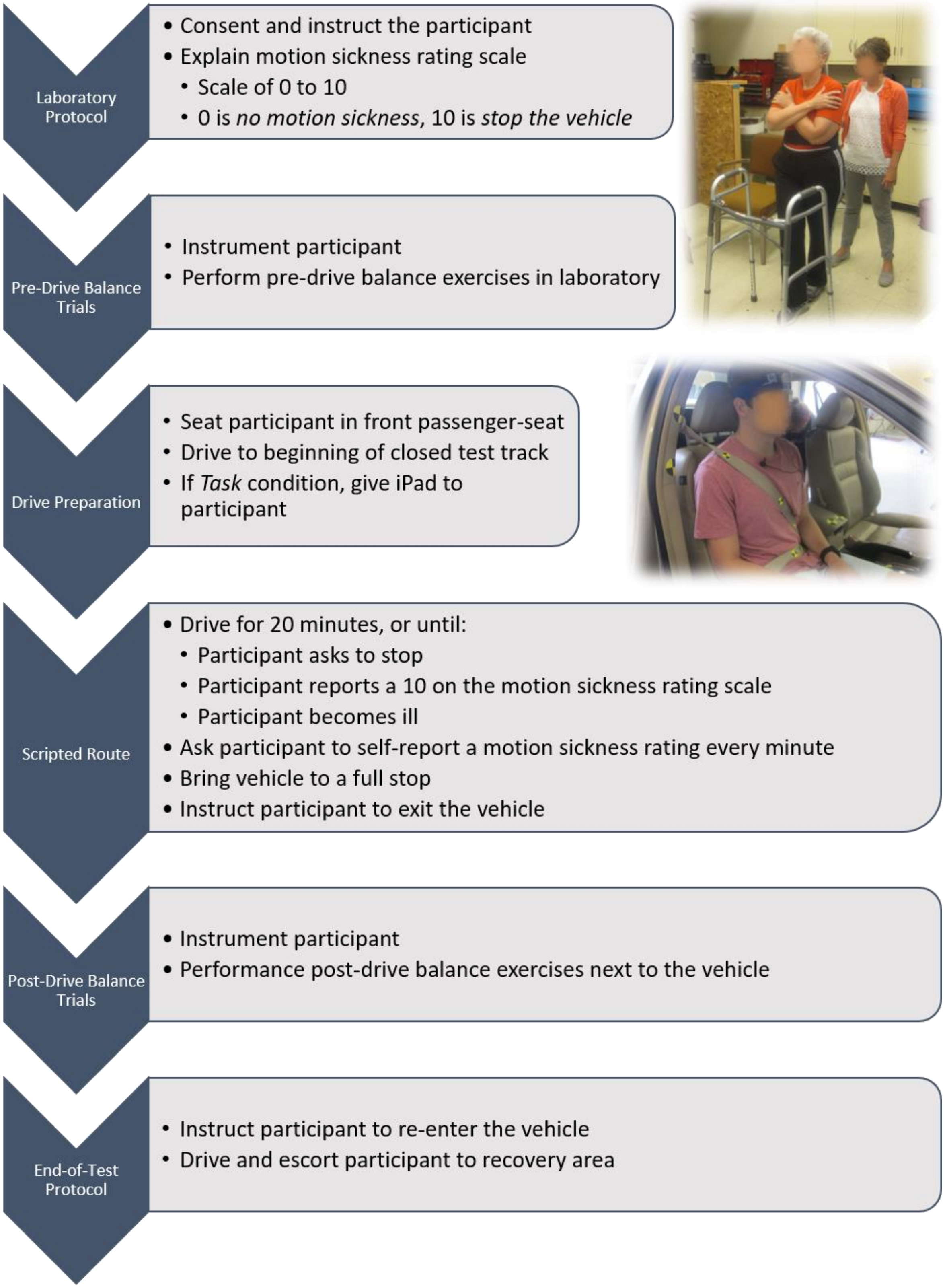


Figure 2.1: Flowchart of the experimental protocol.

2.2.3. In-Vehicle Test Conditions

Participants were asked to maintain a standardized posture in the passenger seat while being driven on the closed test track, which is further detailed in Jones et al. [19]. Each scripted drive concluded a maximum of 20 minutes or when the participant requested to stop the drive, whichever came first. Scripted drives were scheduled on two separate days, with a minimum of 24 hours between sessions, to prevent any lingering symptoms of motion sickness from influencing the second drive. Participants self-reported an overall motion sickness rating every minute using an 11-point integer scale during the scripted drives (with 0 representing "no motion sickness” and 10 representing “stop the car”) [5]. For *Task* test conditions, participants were asked to complete a questionnaire administered on a handheld device. The acceleration levels were characterized by maximum speed achieved during the scripted drive: up to 10-15 mph for Low Acceleration, and up to 20-25 mph for Moderate Acceleration [5], [19]. In total, there were four test conditions: Moderate Acceleration, *Task*; Moderate Acceleration, *No-Task*; Low Acceleration, *Task*; and Low Acceleration, *No-Task*.

2.2.4. Balance Exercises

Prior to and following a scripted drive, participants performed three trials of two standing balance exercises in the following order: feet tandem on firm support with eyes open, and feet together on foam support with eyes closed. The former was chosen because it is representative of post-drive posture and the latter was chosen to perturb the visual and somatosensory systems. Participants had no practice for either balance exercise prior to performing the three pre-drive trials. During the balance protocol, participants were instructed to stand tall, but to avoid being stiff or tense. In addition, participants crossed their arms and were given a reference target at eye-level to partially control participants' visual field. Each trial lasted 30 seconds unless the participant either stepped out of the prescribed position or lost their balance. Loss of balance was marked by (1) a participant's need to grab a walker positioned nearby or (2) a participant's failure to perform the exercise as described.

2.2.5. Data Analysis

Fourteen trials were excluded from the subsequent analysis (out of 1200 trials) due either to step-outs or to a participant's inability to safely complete the exercise, which precluded direct comparisons to trials that were completed for the full 30-s. Given that the data were non-normal, all statistical comparisons used nonparametric statistical tests with a significance level of 0.05. To assess differences among the test conditions, the intra-variability of participants' balance metrics was removed by normalizing participants' post-drive metrics. Due to a marked learning effect, the post-drive metrics were divided by the metrics of the third pre-drive trial. Furthermore, to capture the immediate effects of the drives, the analysis focused on the comparison between the first post-drive and third pre-drive trials.

Nonparametric statistics were used to analyze the data given that the data were not normally distributed. Both normalized and non-normalized balance metrics were compared across the four test conditions using Wilcoxon sign rank and rank sum tests. A Bonferroni correction factor or adjusted alpha level of 0.025 per statistical test (0.05/2) was applied. The initial comparisons between the Moderate Acceleration, *Task*; Moderate Acceleration, *No-Task*; Low Acceleration, *Task*; and Low Acceleration, *No-Task* conditions showed no significant differences between the levels of acceleration across any of the balance metrics. As a result, the data were further collapsed into *No-Task* and *Task* groups. One-sided Wilcoxon signed rank tests were then used to compare the normalized balance metrics between the *No-Task* and *Task* groups for each exercise at an alpha level of 0.05. No Bonferroni corrections were applied because the data were non-independent.

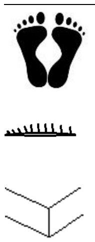
Subsequent statistical comparisons were performed for each balance exercise among the four test conditions after stratifying by the covariate descriptors. Specifically, these descriptors were age stratified as younger (age < 60) and older (age > 60), age as a continuous measure, sex, and motion sickness susceptibility. Wilcoxon rank sum tests were performed, and Spearman rank correlations were explored between balance, test conditions, and the covariate descriptors.

2.3. Results

Comparisons between the non-normalized pre-drive and post-drive metrics were made to determine the effect of the scripted drive. The non-normalized metrics were stratified by *Task* condition and balance exercise, as shown in Table 2.1. In the *Task* condition, for the feet together, foam support, eyes closed exercise, post-drive A/P RMS ($p = 0.012$), M/L RMS ($p = 0.0025$), A/P RMS sway velocity ($p < 0.001$), M/L RMS sway velocity ($p < 0.001$), elliptical area ($p < 0.001$), and path length ($p < 0.001$) were significantly greater than pre-drive values. In the *No-Task* condition, M/L RMS ($p = 0.017$), A/P RMS sway velocity ($p < 0.001$), M/L RMS sway velocity ($p < 0.001$), elliptical area ($p < 0.001$), and path length ($p < 0.001$) were greater post-drive values. For the feet tandem, firm support, eyes open exercise, post-drive A/P RMS sway velocity ($p < 0.001$), and path length ($p < 0.001$) were significantly greater in the *Task* condition compared with the *No-Task* condition. Similarly, for the *No-Task* condition, post-drive A/P RMS sway velocity ($p = 0.0024$), and path length ($p = 0.02$) increased following the drive.

Table 2.1: Pre-drive vs. post-drive tests of non-normalized balance metrics by exercise and *Task*. Data are presented as median (1st quartile, 3rd quartile). RMS = Root Mean Square, A/P = Anteroposterior, M/L = Mediolateral, EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per sec. EA and Path Length are in degrees^2 and degrees,

respectively. P-values are computed from statistical comparisons between the pre-drive and the post-drive metrics in either the *No-Task* or *Task* condition. A * indicates a significant difference between pre-drive and post-drive (p-value less than 0.05).

	Balance Metric	***No-Task***				***Task***			
		Pre-drive	Post-drive	Z	p	Pre-drive	Post-drive	Z	p
 FIRM	A/P RMS [deg]	0.99 (0.68, 1.65)	1.05 (0.70, 1.64)	0.61	0.54	0.95 (0.59, 1.44)	1.07 (0.72, 1.70)	1.23	0.22
	M/L RMS [deg]	0.43 (0.31, 0.72)	0.49 (0.33, 0.89)	0.95	0.34	0.52 (0.30, 0.73)	0.51 (0.36, 0.75)	0.88	0.38
	A/P RMS Velocity [deg/s]	0.61 (0.44, 0.83)	0.82 (0.54, 1.08)	3.04	*<0.01	0.63 (0.49, 0.75)	0.87 (0.66, 1.11)	3.33	*<0.001
	M/L RMS Velocity [deg/s]	0.40 (0.32, 0.53)	0.48 (0.38, 0.65)	1.73	0.08	0.43 (0.35, 0.55)	0.61 (0.36, 0.79)	2.92	*<0.01
	EA [deg^2]	1.87 (0.88, 3.41)	2.03 (1.19, 3.84)	1.35	0.18	1.84 (1.03, 2.34)	2.18 (1.25, 4.11)	1.73	0.08
	Path Length [deg]	32.8 (23.0, 40.2)	35.7 (26.6, 48.0)	2.32	*0.02	31.4 (24.2, 38.3)	41.7 (32.4, 53.2)	3.58	*<0.001
 FOAM	A/P RMS [deg]	1.45 (0.81, 1.87)	1.49 (1.04, 2.29)	1.44	0.15	1.30 (1.88, 2.23)	1.93 (1.06, 2.89)	2.52	*0.01
	M/L RMS [deg]	0.81 (0.59, 1.05)	0.95 (0.64, 1.23)	2.39	*0.02	0.86 (0.63, 1.20)	1.16 (0.77, 1.45)	3.02	*<0.01
	A/P RMS Velocity [deg/s]	0.99 (0.76, 1.28)	1.43 (1.18, 1.68)	4.61	*<0.001	1.07 (0.87, 1.30)	1.66 (1.13, 2.31)	5.37	*<0.001
	M/L RMS Velocity [deg/s]	1.07 (0.88, 1.36)	1.46 (1.00, 2.14)	4.13	*<0.001	1.08 (0.80, 1.39)	1.40 (1.14, 2.26)	4.52	*<0.001
	EA [deg^2]	4.72 (3.73, 7.14)	6.92 (4.52, 11.53)	3.81	*<0.001	5.04 (3.51, 7.46)	8.80 (5.49, 14.1)	4.37	*<0.001
	Path Length [deg]	55.4 (42.9, 68.2)	66.8 (57.0, 95.74)	4.86	*<0.001	54.2 (45.2, 68.1)	80.9 (56.67, 113)	5.50	*<0.001

To isolate the effect of *Task*, intra-variability in the balance metrics was removed. Analysis of these normalized metrics by *Task* condition and balance exercise are shown in Figure 2.2 and Figure 2.3. For the feet tandem, firm support, eyes open exercise, normalized M/L RMS velocity (p = 0.043) and path length (p=0.011) values were significantly larger in the *Task* condition compared to the *No-Task* condition (Figure 2.2). For the feet together, foam support, eyes closed exercise, normalized M/L RMS (p = 0.023), M/L RMS velocity (p = 0.047), and path length (p = 0.025) values were significantly larger following the drive when comparing *Task* vs. *No-Task* conditions (Figure 2.3). The individual medians and quartiles for each group are shown in Table 2.2, alongside the corresponding p-values for the *Task* and *No-Task* statistical comparisons.

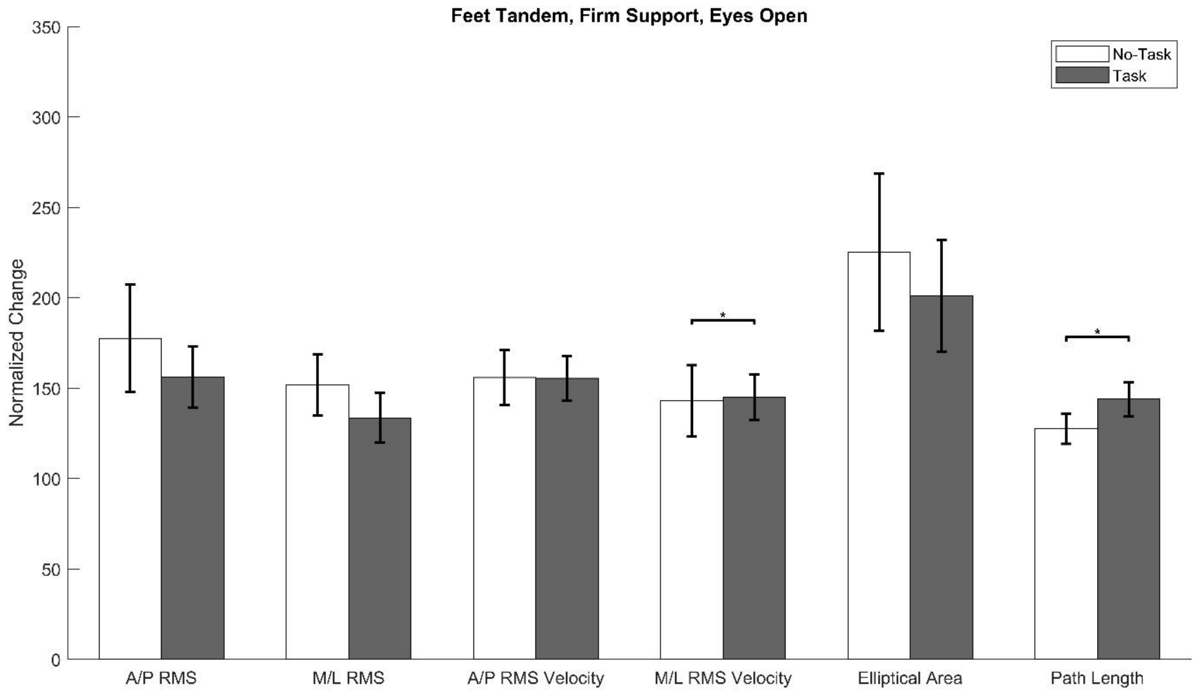
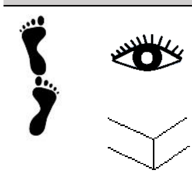
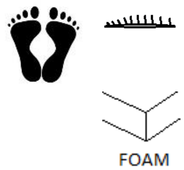


Figure 2.2: Bar plot showing the means of the six normalized balance metrics grouped by the *Task* condition for the feet tandem, firm support, eyes open exercise. The error bars represent standard error. A/P RMS and M/L RMS are in degrees. A/P RMS and M/L RMS velocity are in degrees per second. Elliptical Area (EA) and Path Length are in degrees^2 and degrees, respectively. The measurements were normalized by dividing the first post-drive balance trial by the last baseline trial preceding the drive. An asterisk denotes a significant p-value less than 0.05.

When comparing balance metrics across the levels of acceleration, no meaningful differences were found. Moreover, balance was analyzed only as a function of *Task* because no significant contrasts were found between the test conditions when the balance data were stratified by participant age, sex, and motion sickness susceptibility.

Table 2.2: *Task* vs. *No-Task* tests of normalized values of balance metrics by exercise and *Task*. Data are normalized by dividing the first post-drive metrics by the last pre-drive metric. Data are presented as median (1st quartile, 3rd quartile). RMS = Root Mean Square, A/P = Anteroposterior, M/L = Mediolateral, EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per second. EA and Path Length are in degrees^2 and degrees, respectively. A * denotes a significant difference (p-value less than 0.05) between the *No-Task* and *Task* groups for that balance metric.

	Balance Metric	***No-Task***	***Task***	**Z**	**p**
 FIRM	A/P RMS [deg]	0.98 (0.67, 1.93)	1.08 (0.62, 2.31)	0.03	0.51
	M/L RMS [deg]	1.00 (0.60, 2.11)	1.09 (0.69, 1.47)	0.47	0.68
	A/P RMS velocity [deg/s]	1.22 (0.94, 1.65)	1.28 (0.94, 2.11)	0.87	0.19
	M/L RMS velocity [deg/s]	1.10 (0.88, 1.37)	1.21 (0.92, 1.59)	1.72	*0.043
	EA [deg^2]	1.16 (0.79, 2.33)	1.49 (0.70, 2.33)	0.23	0.41
	Path Length [deg]	1.12 (0.89, 1.42)	1.24 (0.97, 1.80)	2.29	*0.011

	A/P RMS [deg]	1.33 (0.75, 1.87)	1.24 (0.86, 1.97)	0.10	0.46
	M/L RMS [deg]	1.22 (0.92, 1.76)	1.48 (0.89, 1.95)	1.99	*0.023
	A/P RMS velocity [deg/s]	1.39 (1.01, 1.69)	1.45 (1.09, 2.15)	1.61	0.053
	M/L RMS velocity [deg/s]	1.37 (1.01, 1.85)	1.45 (0.99, 2.17)	1.68	*0.047
	EA [deg^2]	1.32 (0.88, 2.11)	1.55 (1.03, 2.63)	1.38	0.084
	Path Length [deg]	1.26 (1.07, 1.58)	1.34 (1.11, 1.88)	1.96	*0.025

The current study is part of a larger effort to quantify motion sickness within vehicles on a closed test track. In an effort to explore the association between motion sickness and balance metrics, analysis of motion sickness response data from the same study was conducted. Adapted from Jones et al. [5], Figure 2.4 shows the distribution of mean motion sickness ratings reported at 1-min intervals along with standard error (SE) corridors throughout the scripted drive [5]. The Wilcoxon Kruskal–Wallis test of the rank sum of self-reported motion sickness ratings at each 5-min interval revealed significant differences between the *No-Task* and *Task* conditions ($p < 0.01$ for all intervals).

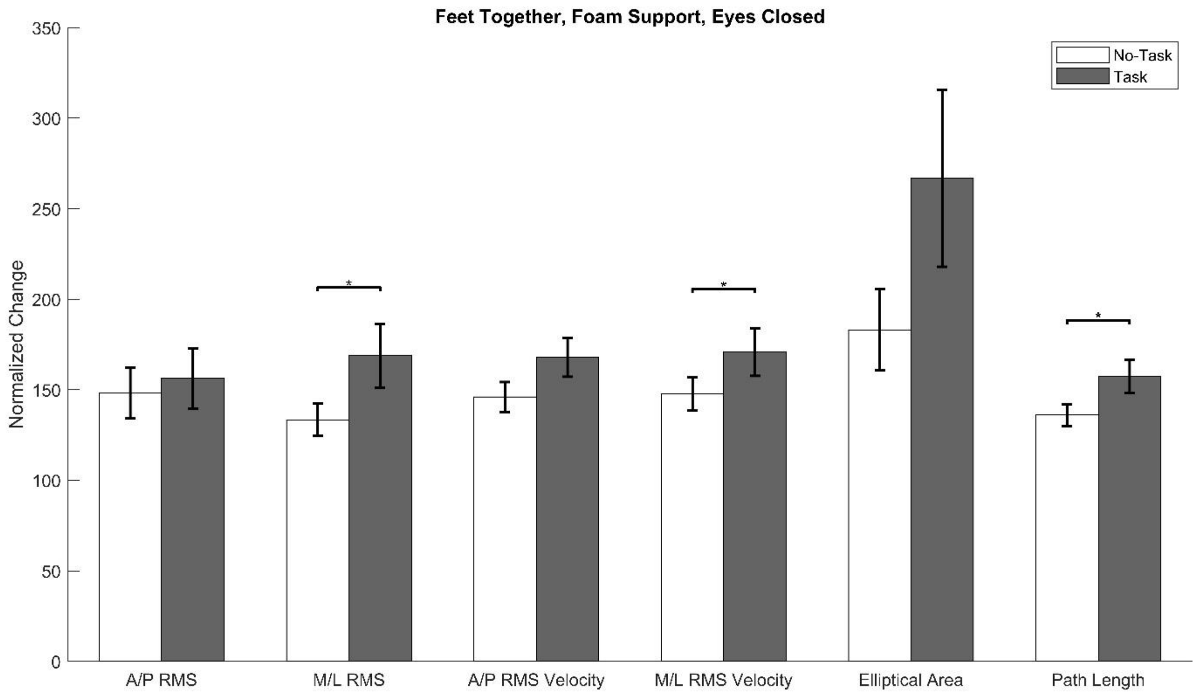
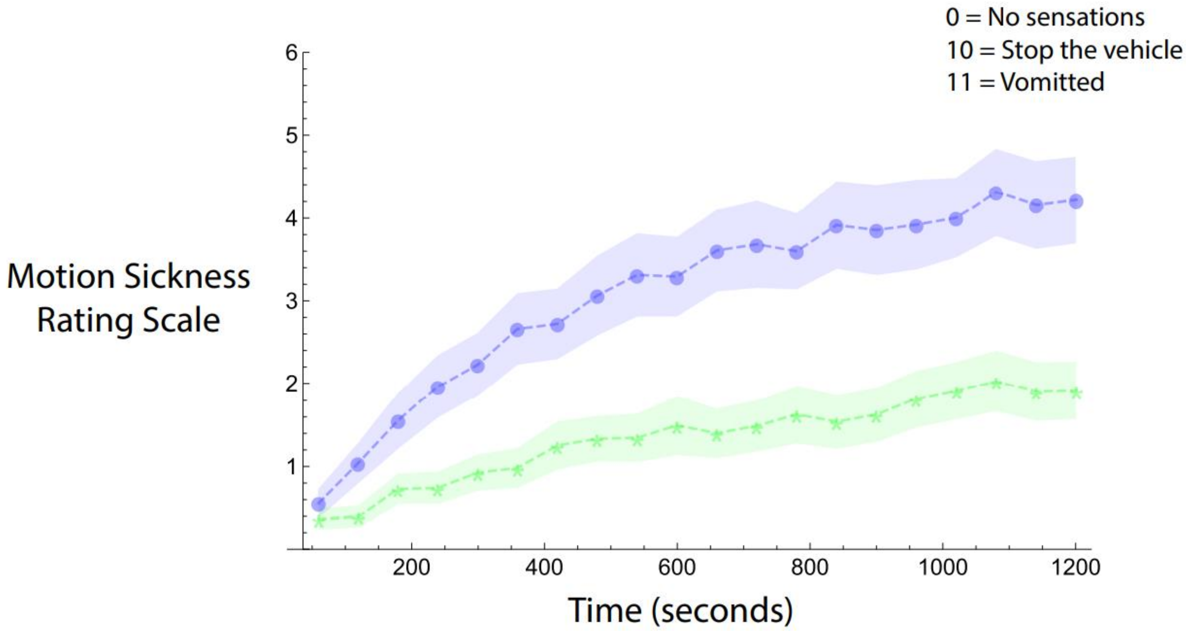


Figure 2.3: Bar plot showing the means of the six normalized balance metrics grouped by the task condition for the feet together, foam support, eyes closed exercise. The error bars represent standard error. A/P RMS and M/L RMS are in degrees. A/P RMS and M/L RMS velocity are in degrees per second. Elliptical Area (EA) and Path Length are in degrees^2 and degrees, respectively. The measurements were normalized by dividing the first post-drive balance trial by the last baseline trial preceding the drive. An asterisk denotes a significant p-value less than 0.05.

2.4. Discussion

In the current study, balance was negatively affected following a drive. Although not all comparisons were significant, the averages of the non-normalized post-drive values were greater than pre-drive across all metrics and exercises. The greatest change in non-normalized balance was observed in path length, increasing by 20.1° and by 36.0° post-drive in the *No-Task* and the *Task* conditions, respectively. Non-normalized post-drive postural sway increased from pre-drive for all but one of the balance metrics for the more challenging exercise (feet together, eyes closed, foam support). For the same exercise, there was also a general trend towards greater normalized postural sway following drives that involved a task (differences ranged between 8% and 86% for A/P RMS and EA). Likewise, participants reported higher motion sickness ratings in the *Task* condition. However, the current study did not observe a strong relationship between motion sickness susceptibility and balance. There was also no effect of vehicle acceleration or participant covariates.

Figure 2.4: Subjective rating data has been collapsed across the acceleration condition (low, moderate) to illustrate the difference in mean 1-min. subjective ratings between *No-Task* (light green, asterisk) and *Task* (blue, circle) test conditions. The y-axis is the subjective rating scale and the x-axis illustrates time history (20 min.). Each data point represents the mean rating and the corridor represents the mean ± standard error.



Prior to the current study, no studies have explored the effect of the motion of a vehicle on a closed test track on post-drive balance. However, similar to the current study, increases in path length and sway velocity have been observed among motion-based driving and flight simulator studies. Keshavarz et al. [9] observed increased COP path length following a simulated drive (specific values were not provided, but the estimated increase based on the published figure was 21% for older adults). In comparison, the current study measured approximately an average 40% increase in the non-normalized path length of the trunk following a vehicular drive. Although a direct comparison between Keshavarz et al. [9] and the current study is not possible (i.e., Keshavarz et al. [9] measured sway using the COP during a feet together, eyes open stance while the current study measured trunk sway during tandem stance), both studies observed increases in sway following the drive. Similar to the increased M/L RMS velocity measured post-drive in the current study (~50% at the trunk on average), Kennedy & Stanney [24] reported ~45% increase in M/L sway velocity of the head following a 2-hour motion-based, simulated flight.

In the current study, both postural sway and motion sickness ratings were more pronounced in the *Task* condition following a drive, suggesting an association between motion sickness and balance. In contrast to the motion sickness ratings reported in Jones et al. [5] (who reported a correlation with self-reported motion sickness susceptibility), postural sway was not expressively related with motion sickness susceptibility. Although some studies have correlated motion sickness measurements and balance [9], [15], the variations in motion sickness rating scales and balance metrics make comparisons across these studies difficult.

One of the limitations of this study is that participants did not practice the balance protocol or complete any training trials prior to the pre-drive balance trials, which means that the pre-drive and post-drive balance trials may still be capturing a learning effect. Second, the balance trials were also not performed in the same location. While the pre-drive trials were performed indoors in a laboratory, the post-drive trials were performed outdoors immediately upon exiting the vehicle, which may have introduced environmental effects. However, a reference visual target was provided to control for differences in the visual field. Additionally, since the frequency of the vehicle maneuvers was greater than that of naturalistic driving, the closed test track used in this study was a scaled exposure of naturalistic driving conditions [19]. Participants were also only passengers during the scripted drive, so it is uncertain whether these effects on balance apply to drivers as well. Lastly, the sample size in some of the bins of the participant sampling strategy were lacking when stratified by the covariates.

During a drive, drivers can make anticipatory postural adjustments because they can control the vehicle dynamics and are attentive of the road ahead [25], [26]. As a result, drivers experience less severe motion sickness symptoms compared to passengers [2]. Given that the motion sickness severity and postural sway have been shown to be correlated, passengers may experience greater changes to their balance [27], [28]. However, most driving simulator studies feature participants as drivers rather than front-seat passengers. The current study captures a more realistic representation of the effects of the front-seat passenger experience. This is especially important for AVs, where users are more likely to be passengers.

One implication of the current study raises a potential concern for at-risk populations using AVs and ride-sharing services in that they may be at risk of falling post-drive. Johansson et al. [29] found that an increased COP path length exceeding 402 mm (average COP path length was 338.23 mm) during a 60-s eyes open exercise was predictive of a 90% increase in the risk of falling in community-dwelling older adults. Future work will seek to adapt the protocol from the closed test track to real-time traffic on urban roads.

2.5. Conclusion

The current study performed a preliminary analysis of standing balance following exposure to the motion of a drive in a passenger vehicle on a closed test track. Similar to motion-based driving simulations, postural sway increased following the drive; users of AVs and other mobility solutions may be at risk of poorer balance. Further analysis showed that those who performed a task exhibited even larger changes in balance. Given that passengers are more likely to perform tasks while in a vehicle, a larger population of AV passengers (especially at-risk populations) may experience the negative effects of vehicle motion on standing balance.

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Chapter 3 Post-Drive Standing Balance of Vehicle Passengers Using Wearable Sensors: The Effect of On-Road Driving and Task Performance

3.1. Introduction

Urban transportation is anticipated to transform through the development of autonomous vehicles (AVs) and other mobility solutions (e.g., ride-sharing services). These transportation alternatives have the potential to reduce traffic congestion, increase user productivity, and provide greater access to transportation to a broader population [1]. Since AV users will be passengers, the widespread adoption of mobility solutions will likely result in an increased number of on-road vehicle passengers compared to drivers. Moreover, accessibility to AVs for broader populations will increase the diversity of passengers on the road. Accessibility is especially beneficial to older adults for increasing mobility, independence, and autonomy [2]. Across all population segments, users of mobility solutions will be freed from having to drive and will be able to engage in non-driving related tasks. However, studies of simulated driving and of in-vehicle passengers on a closed test track have demonstrated that postural control can be negatively affected by motion exposure [3–8]. Control of postural sway (especially of the trunk) is crucial for maintaining upright standing balance [9]. A substantial increase in postural sway may increase the risk of falling after an in-vehicle exposure associated with mobility solutions or AVs [10,11]. Given a larger and more diverse passenger population, those already susceptible to falling (e.g., older adults) or those not accustomed to frequent transportation may encounter an increased risk of injury. Older adults with a history of previous falls are also more likely to experience subsequent falls and injuries [12]. In the worst case, the resulting injuries from a non-fatal fall can significantly impact quality of life, reduce social and physical activity, and raise medical costs [13–16]. Therefore, it is necessary to understand how passenger vehicle transport affects the control of standing balance as increased fall risk may be a significant deterrent for certain users.

In-vehicle measurements of posture and balance have been collected using various sensors such as on-board depth cameras for head and upper body posture/orientation [17,18], as well as magnetic tracking systems for the trunk position [7,19]. When measuring post-drive postural sway, laboratory-based studies of simulated driving have leveraged typical laboratory-based instrumentation (e.g., force plates [6] and passive or active motion tracking). Options for instrumentation are constrained during in-the-field or naturalistic studies as equipment must be portable to facilitate measurements immediately following the exit from the vehicle. Although cameras mounted within the vehicle allow for accurate tracking and analysis of occupants' movements [20], they are restricted to in-vehicle data collections. Alternatively, wearable sensors are suitable for wireless data collection and enable the measurement of in-vehicle and post-drive postural sway.

Prior studies that have quantified postural sway before, during, and after exposure to driving have mainly used surrogates of on-road driving (i.e., driving simulations, head-mounted displays, fixed-base, and a 6 degree-of-freedom (DOF) motion platforms). These surrogates can be limited by technical and physical factors such as latency, graphical fidelity, and motion scaling factors [21–23]. Several studies have measured postural sway at the trunk or head during a simulated (driving, flight), physical driving, or gaming exposures, and some of these studies have reported significant differences relative to pre-exposure postural sway [7,19,24–28].

Among the existing studies that have quantified post-drive standing balance performance, only simulated driving routes have been used with participants as the drivers. Using a 6 DOF driving simulator, Keshavarz et al. (2018) [6] observed increases in the path length of drivers' sway following a simulated drive with varying sensory cues. In another study, Reed-Jones et al. (2008) [29] investigated driver behavior using a fixed-base driving simulator and found the inverse relationship, i.e., drivers' path velocity decreased following a simulated drive [29]. Other researchers observed increases in drivers' post-drive sway velocity following exposure to a fixed-base driving simulator, though the differences were not statistically significant [3]. Using a head-mounted display for a simulated drive, Mourant and Thattacherry (2004) [4] observed that drivers' time in a single-leg stance decreased following the exposure to the simulation. Overall, different metrics of standing balance have been shown to be affected by a simulated drive despite differences in experimental modalities across the studies.

To our knowledge, our previous study conducted in a passenger vehicle on a closed test track [8] is the only study that has quantified the effects of vehicle motion and task performance on passengers' post-drive standing balance performance. The scripted route consisted of many instances of longitudinal and lateral acceleration profiles similar to those observed in naturalistic driving datasets [30,31]. We analyzed the participants' performance on two balance exercises performed prior to and following the 20 min continuous drive in a passenger vehicle. The participants completed two driving sessions in randomized order as front-seat passengers. During one of the driving sessions, they completed a non-driving-related task that was administered on a handheld tablet. Throughout the other drive, the participants did not complete a task and rode in a standardized posture (unrestricted gaze and head orientation, hands on lap, or feet resting on heels). Following both driving sessions, passengers' trunk postural sway increased significantly, especially when participants performed a task throughout the driving session. We observed large increases in sway velocity and path length that were consistent with some findings of previous studies in simulated driving environments [3,6].

Comparison studies between surrogates of driving environments and naturalistic on-road driving have typically focused on the fidelity of the experimental context or the validity of the occupant's behavior. Simulator fidelity is critical as increased fidelity has been demonstrated to affect driver performance [32,33]. As it pertains to this on-road study, a lack of contextual vehicle features (e.g., vehicle seat, interior configuration, field of view, and accurate representation of vehicle motion) may influence postural sway. Physical fidelity (how a surrogate looks) and functional fidelity (how a surrogate operates) varies across different driving surrogates [34]. For example, virtual desktop vehicle simulations have reasonable functional fidelity (e.g., steering controls) but low physical fidelity (e.g., lack of vehicle cabin or accurate sensory stimuli). In-vehicle simulations use a variety of approaches to improve fidelity including motion cueing strategies [35,36], virtual environment tools [37], use of more realistic sensory cues and stimuli [38], and enhanced mechanical capability of the motion platform to generate tilts and displacements more representative of acceleration profiles experienced during naturalistic driving conditions [23]. In our previous closed test track study, passenger behavior was quantified during an in-vehicle exposure conducted on a closed test track with high physical fidelity. This in-vehicle exposure provided moderate functional fidelity given that the frequency of the vehicle events during the scripted route greatly exceeded the number of vehicle events that typically occur during naturalistic driving conditions. Additionally, a closed test track environment does not fully replicate the sensory, environmental and contextual cues, and psychological factors associated with an on-road environment that can affect occupant behavior

[39]. For instance, passengers experience naturalistic driving dynamics within the context of other on-road actors and vehicles interacting in real-time traffic.

Given the multi-faceted characteristics of on-road driving, the lack of prior work, and limitations of driving simulators, it is necessary to understand how different types of vehicle motion and task performance in an on-road environment affect post-drive standing balance performance among passengers. Therefore, the objective of this on-road study was to evaluate passenger behavior directly in the actual environment of study (an in-vehicle exposure conducted on-road under realistic driving conditions) and to compare these results to those previously gathered within the surrogate environment (i.e., the closed test track). This work contributed to our understanding of the potential risks associated with passengers' standing balance and will inform the design and implementation of future mobility solutions and testing platforms.

3.2. Materials and Methods

3.2.1. Experimental Design

In this on-road study, participants rode in the front passenger seat of a midsize sedan that was operated by a trained driver. The driving routes consisted of various driving events or maneuvers (e.g., turning, braking) under real-time driving exposure set in midday traffic throughout Ann Arbor, MI, USA. Participants were assigned to one of two routes: an urban route that consisted of neighborhood streets and main city roads (Urban, Figure 3.1), or a highway route that included lengthy passages on local freeways (Highway, Figure 3.2). The urban route consisted of the same range of vehicle speed, number, and type of vehicle maneuvers (e.g., left and right turns, braking, lane changes, and roundabouts) as the scripted route conducted on the closed test track [8]. However, the duration of exposure differed between the closed test track and on-road studies. For the closed test track study, the scripted route was 20 min in duration; in contrast, the time required to complete the same maneuvers on-road was approximately 2.5 times longer, approximately ~55 min in duration. The Highway route was designed to evaluate the effect of longitudinal acceleration control and higher vehicle speed (~65–70 mph) under conditions of minimal lateral acceleration.

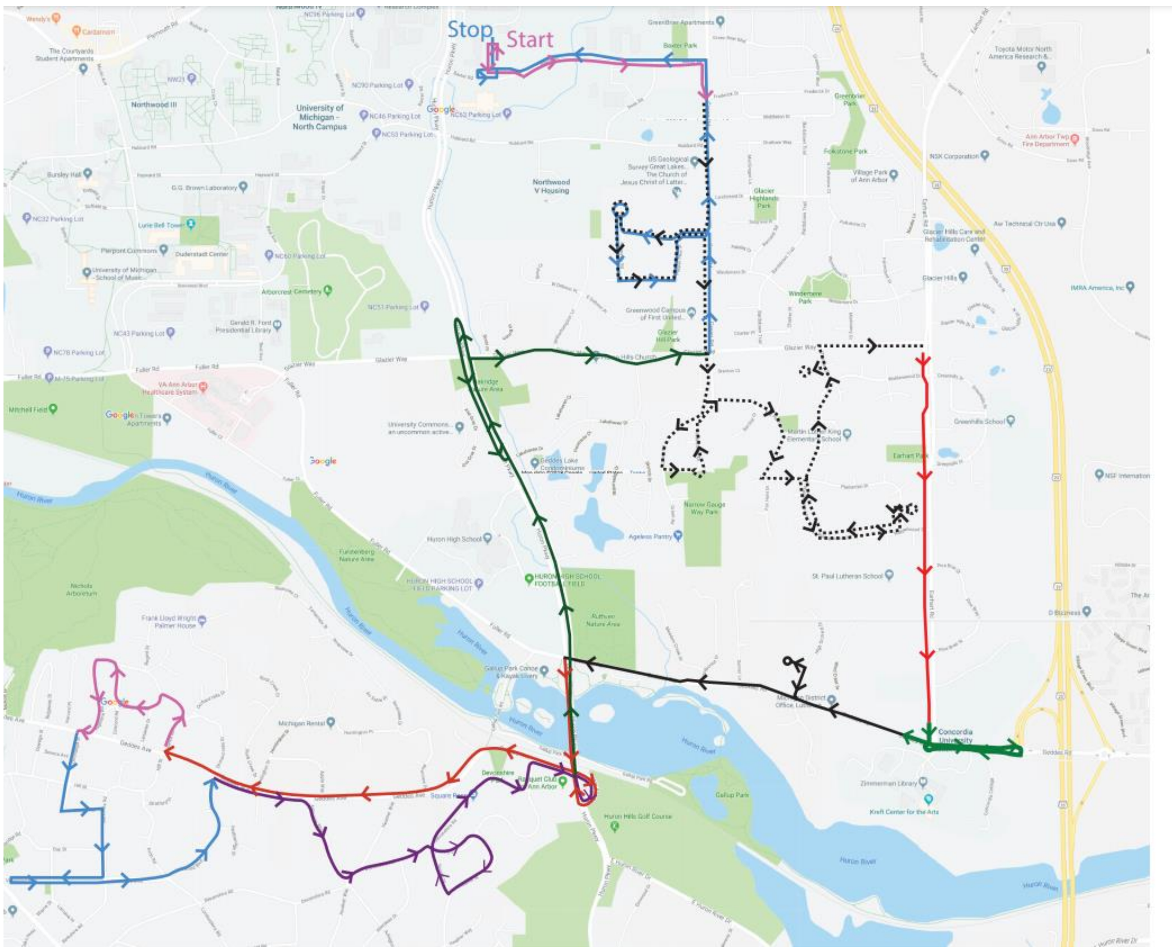

Figure 3.1: Map of the scripted Urban route throughout Ann Arbor.

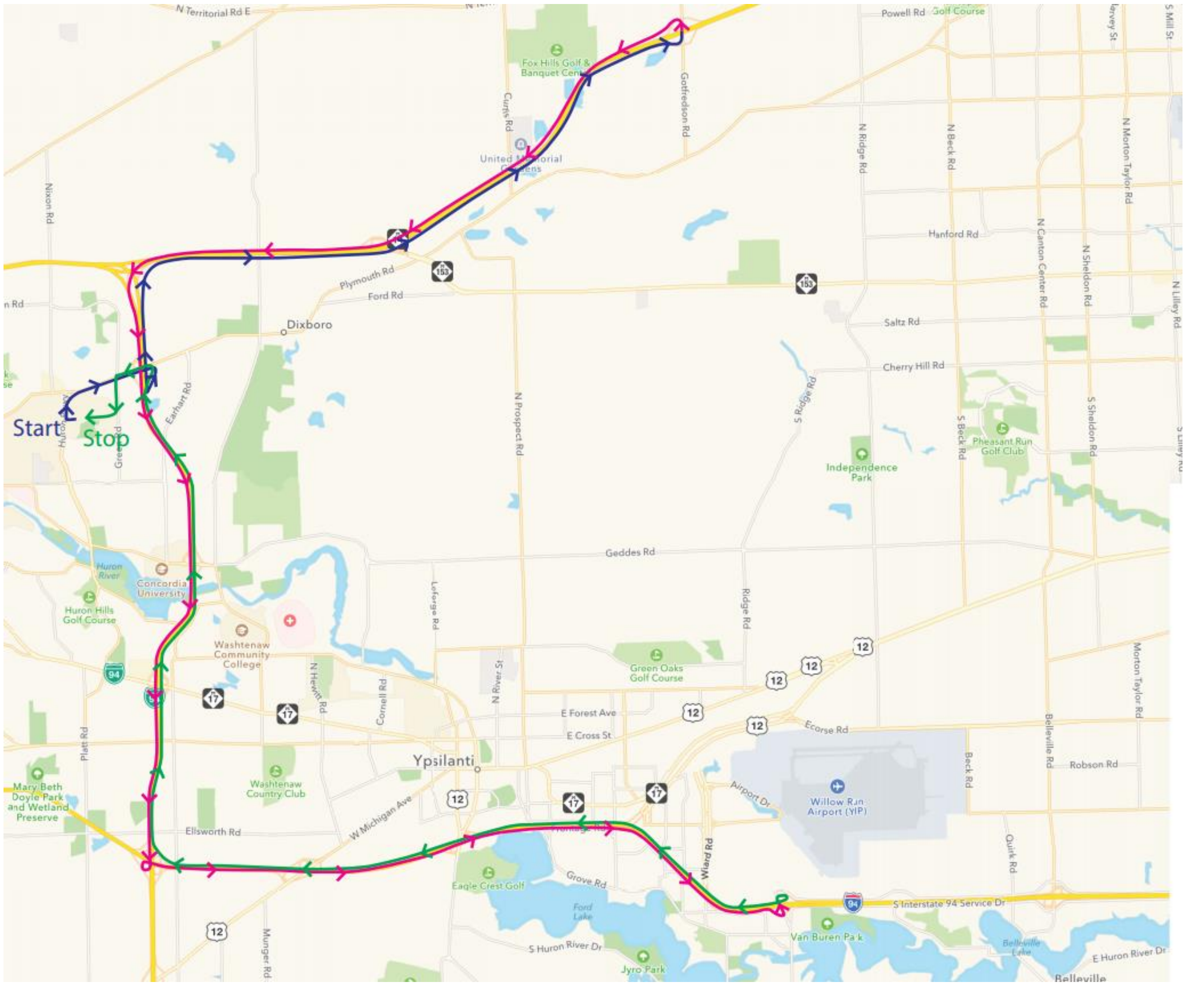

Figure 3.2: Map of the scripted Highway route.

Two levels of task performance were used as repeated tests during the on-road routes [31]. During the *Task* condition, participants completed a series of ecologically relevant, visual-based tasks on a handheld tablet-based device throughout the duration of the driving session. Otherwise, participants were instructed to exhibit normative passenger behavior with an unrestricted gaze (*No-Task* condition). A mixed between/within participant design was used. Participants were assigned to one of the on-road routes and were tested on the route twice, with and without the task. The order of these repeated tests on the *Task* condition was randomized. In total, there were four test conditions: Urban, *Task* (UT); Urban, *No-Task* (UN); Highway, *Task* (HT); and Highway, *No-Task* (HN).

3.2.2. Participants

The participants included 106 adults (47 males and 59 females) between the ages of 18 and 89 years (34.2 ± 18.5 years). The participant sample was further stratified by age: 82 were aged < 60 years (24.5 ± 4.3 years) and 24 were aged ≥ 60 years (67.0 ± 6.9 years). Adults under the age of 60 were classified as younger adults, while those greater than or equal to 60 years old were classified as older adults. Prior to the experiment, participants were screened and self-reported that they did not have diagnosed balance disorders, heart conditions, neurological conditions, migraines, cerebral or vascular disease, and did not use medications that might affect balance or cause dizziness (e.g., antidepressants or barbiturates) that would alter their motion sickness response or post-drive balance ability. The analysis presented in this paper was part of a larger study that explored motion sickness and on-road driving. Although descriptive data on participants' motion sickness were gathered, the effect of motion sickness on post-drive balance performance was not included in this paper.

To facilitate comparisons between the Urban and Highway routes, a non-parametric Wilcoxon rank-sum test and a chi-squared test was performed, indicating no significant differences between the two participant samples in terms of age ($p = 0.44$, $Z = 0.77$) or sex ($\chi^2 = 0.1361$, $p = 0.71$). Participants provided written informed consent and the study was conducted in accordance with the Declaration of Helsinki. The study was reviewed and approved by the University of Michigan Institutional Review Board (HUM00128751).

3.2.3. In-Vehicle Test Protocol

During the in-vehicle exposure, participants were asked to maintain a standardized, neutral posture in the passenger seat; more details can be found in Jones et al. [31]. Each driving session lasted until either the route was completed (55 min on average (SD = ± 4 min)) or until the participants opted to discontinue the driving session. In total, eight participants requested to stop the vehicle prior to the end of the route; however, they ended the driving session relatively close to the end of the scripted route and were able to perform the balance protocol. Participants completed a total of two driving sessions, one for each *Task* condition. The *Task* and *No-Task* driving sessions were scheduled on two separate days with a minimum of 24 h between sessions. For the *Task* condition, participants were additionally asked to complete a visual-based task administered on a handheld tablet-based device held in their lap during the drive. Participants were instructed to complete as much of the task as possible throughout the driving session and were allowed to take breaks at their own volition.

3.2.4. Balance Exercises

Participants performed a series of balance exercises immediately prior to and following the driving session in outdoor conditions beside the stopped vehicle. Two trials of each of the following three exercises that increased in difficulty were performed:

- Exercise 1: Feet together/eyes open/firm support;
- Exercise 2: Feet together/eyes closed/firm support; and
- Exercise 3: Feet together/eyes closed/foam support, using a compliant support surface (Airex, New York, NY, USA).

We chose these exercises because they were representative of real-world stances and visual and somatosensory scenarios (e.g., standing outside of a vehicle on paved or grassy surfaces during day and night conditions). Participants practiced this series of exercises in a laboratory setting prior to performing the pre-drive trials. During balance testing, participants were instructed to cross their arms and stand tall but avoid being stiff or tense. A visual reference target was placed at eye-level in front of the participants to control for changes in the surrounding visual field (e.g., if the participants opted to terminate the driving session before completing the route, they were asked to perform the balance exercises beside the parked vehicle). Each trial was 30 s long unless the participants either stepped out of the prescribed position or lost their balance (i.e., grabbed a nearby walker, failed to complete the exercise as described, or required intervention by a spotter to prevent a potential fall). Figure 3.3 illustrates this series of balance exercises.

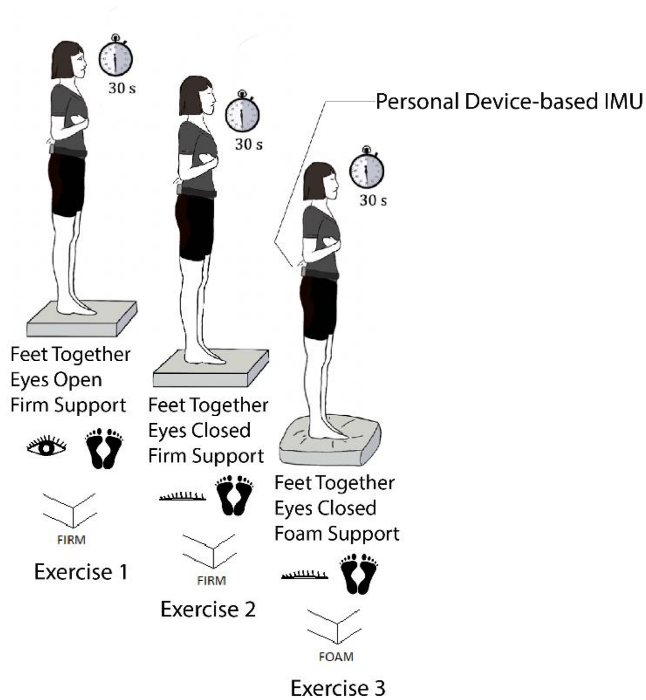

Figure 3.3: Balance exercises are shown in the order in which they were performed.

3.2.5. Balance Measurements and Instrumentation

A surrogate smartphone (6th generation iPod Touch, 2015) secured at the participants' lower back with an elastic waistband was used to measure anteroposterior (A/P) and mediolateral (M/L) postural sway [40,41]. Custom software installed on the smartphone extracted raw inertial measurement unit (IMU) data at a sample rate of 50 Hz from the embedded accelerometers and gyroscopes [41]. These data served as inputs into an extended Kalman filter from which tilt angle and tilt velocity were estimated. Tilt data were then processed in MATLAB (version 2020a, The MathWorks, Natick, MA, USA) and the following six balance metrics were computed [40,42]:

1. Root-mean-square (RMS) of trunk tilt in the A/P direction (A/P RMS);

$$AP\ RMS = \frac{1}{N}\sum_{i=1}^{N}[x_{AP}]_i^2$$

2. RMS of trunk tilt in the M/L direction (M/L RMS);

$$ML\ RMS = \frac{1}{N}\sum_{i=1}^{N}[x_{ML}]_i^2$$

3. RMS of trunk sway velocity in the A/P direction (A/P RMS Velocity);

$$AP\ RMS\ Velocity = \frac{1}{N}\sum_{i=1}^{N}[v_{AP}]_i^2$$

4. RMS of trunk sway velocity in the M/L direction (M/L RMS Velocity);

$$ML\ RMS\ Velocity = \frac{1}{N}\sum_{i=1}^{N}[v_{ML}]_i^2$$

5. Path Length of the trunk sway trajectory (Path Length); and

$$Path\ Length = \sum_{i=1}^{N-1}\sqrt{([x_{AP}]_{i+1} - [x_{AP}]_i)^2 + ([x_{ML}]_{i+1} - [x_{ML}]_i)^2}$$

6. Elliptical Area, which is the elliptical fit of the sway trajectory (Elliptical Area),

$$Elliptical\ Area = \pi \mathrm{ab} = 2\pi F_{0.05[2,n-2]}\sqrt{(s_{AP}^2 s_{ML}^2 - s_{AP,ML}^2)}$$

where N is the number of samples; x_{AP} and v_{AP} are the trunk position and velocity in the A/P direction, respectively; x_{ML} and v_{ML} are the trunk position and velocity in the M/L direction, respectively; s_{AP} and s_{ML} represent the standard deviation of the A/P and M/L trunk positions, respectively; $F_{0.02[2,n-2]}$ is the F statistic at 95% confidence for a bivariate distribution, and $s_{AP,ML}$ is the covariance of the A/P and M/L trunk positions.

As expressed by the equations above, RMS was calculated by taking the square root of the average of the squared tilt values. To compute the Elliptical Area of sway, a 95% confidence ellipse was fit around the tilt values for each trial before computing the area [41,42]. Path Length was computed by summing the Euclidean distance between consecutive samples of the A/P and M/L tilt angles [42]. We also computed the RMS of the acceleration signals for Exercise 1 to directly compare with prior work that measured trunk sway as a function of age and other pathologies [43–46]. The methods for computing the RMS of the A/P acceleration signal were consistent with those used by Moe-Nilssen and Helbostad (2002) [9], Kosse et al. (2015) [47], and Mancini et al. (2012) [48].

3.2.6. Data Analysis

In order to make comparisons between different groupings of the data, we only considered data from balance trials that were completed for the full 30 s. Out of 2544 pre- and post-drive trials, 29 trials were excluded from the subsequent analysis due to either step-outs or participants' inability to safely complete the exercise. Twenty-four trials were excluded due to environmental factors during the balance exercises (e.g., windy conditions). Lastly, 188 trials were excluded due to missing data, resulting in a total of 2303 trials included in the analysis. Given that the data were non-normal, non-parametric statistical tests were used for all statistical comparisons.

3.2.6.1. On-Road Analysis

Due to individual intra-variability in pre-drive balance performance, we normalized the post-drive measurements to analyze relative changes in the balance metrics across participants for each balance exercise [49,50]. Analysis of the normalized changes in balance metrics allowed for more direct comparisons between the on-road route and *Task* conditions. To compute a normalized change, participants' post-drive measurements were divided by the average of their pre-drive measurements for each balance exercise. To isolate the effect of the driving session, the first post-drive measurement and the average of the pre-drive measurements were used.

Firstly, to assess the effect of drive on standing balance performance, Wilcoxon signed-rank tests were performed to determine if post-drive measurements increased relative to participants' pre-drive measurements for Exercises 1–3, while collapsed across covariate descriptors. Normalized balance metrics were analyzed to determine if they were significantly different from a value of 1 that represented no change from pre- to post-drive. Additionally, statistical analysis of these normalized balance metrics was performed between the on-road route and *Task* conditions for each exercise. Specifically, Wilcoxon signed-rank and rank-sum tests compared the pre-drive and post-drive balance metrics for Exercises 1–3 within and across the Highway, *Task* (HT); Highway, *No-Task* (HN); Urban, *Task* (UT); and Urban, *No-Task* (UN) conditions. Due to the number of balance exercises, a Bonferroni correction factor or adjusted alpha level of 0.0167 per test (0.05/3) was applied for these comparisons.

We also examined the changes in post-drive standing balance performance across the two post-drive trials. In particular, we focused on Exercise 3 because it was the most challenging balance exercise and exhibited the largest changes in post-drive standing balance performance. Similar to the analysis in previous sections, balance metrics were grouped by the *Task* condition.

In order to compare across participants, the balance metrics were normalized by dividing the second post-drive balance measurement by the first post-drive balance measurement. This normalization captured the changes in balance performance relative to the first trial of Exercise 3 following a driving session. Wilcoxon signed-rank tests were used to determine if the relative changes were significantly different from a value of 1 that represented no change from the first trial to the second trial. Wilcoxon rank-sum tests were also used to investigate differences across the *Task* conditions. These statistical comparisons were evaluated at a level of significance of 0.05.

3.2.6.2. Comparative Analyses

Given that the Urban route was a scaled version of the scripted route used during the closed test track study, we compared the post-drive standing balance metrics across these conditions [8,31]. Although full details can be found in Jones et al. (2019) [31] and Le et al. (2020) [8], a brief description is provided here. Fifty adults participated in a similarly designed experiment. The previous closed test track study consisted of a concentrated 20 min driving exposure on a controlled scripted route [8,31] at two levels of acceleration (Moderate or Low) and repeated under the same *Task* condition. We selected one out of the two balance exercises from the closed test track study to use in this comparative analysis because it allowed for direct comparison with Exercise 3 (feet together/eyes closed/foam support) from this on-road study. To ensure valid comparisons across study populations, a non-parametric Wilcoxon rank-sum test and chi-squared test were performed across the test conditions for the closed test track study and this on-road study, finding that age ($p > 0.1$, $Z < 1.65$) and sex ($\chi^2 = 9.25$, $p = 0.97$) were not significantly different between study participant samples. Wilcoxon rank-sum tests ($\alpha = 0.05$)

were used to compare normalized changes in postural sway for Exercise 3 across conditions for the Urban and closed test track routes (Moderate and Low acceleration).

Prior to comparing the RMS of trunk acceleration to other reported values in the literature, we first established that our study participants exhibited similar baseline standing balance values with respect to the values reported by Park et al. (2016) [43]. Although their participants performed a variant of Exercise 1 (i.e., feet apart vs. feet together with eyes open on a firm support surface), prior studies have demonstrated there to be minimal differences in A/P sway between these two stances [51,52]. In comparison to the findings reported in Park et al. (2016) [43], the pre-drive values of the younger and older adult participants for our on-road study fell within the ranges specified by their respective age categories.

3.3. Results

3.3.1. On-Road Driving Analyses

3.3.1.1. Learning Effect

Prior to analysis, we observed a learning effect among pre-drive trials using a mixed model approach that informed which trials to include in our data analysis. To enable comparison with the work by Diamantopoulos et al. (2003) [53], we chose Path Length as the representative balance metric to conduct the learning effect analysis. The fixed effects were the trial number and the day of the session; participant identifiers were implemented as random variables. Estimates of the model coefficients revealed a significant difference between the first and second trials for Exercise 3 ($p < 0.001$). In contrast for Exercise 1 and Exercise 2, Path Length did not differ between trials ($p = 0.72$, 0.96, respectively). Moreover, an analysis of the practice trials performed in the laboratory revealed that the Path Length for the practice trials was significantly greater than the pre-drive trials for Exercise 3, indicating a learning effect. Therefore, for Exercise 3 only, we subsequently compared changes between the last pre-drive trial and the first post-drive trial. The analyses for Exercises 1 and 2 included all pre-drive trials.

3.3.1.2. Effects of Route, Task Conditions and Participant Covariates

The effects of the on-road routes, *Task* conditions, and participant covariates were also quantified using mixed models that were fit to the normalized Path Length of the sway trajectory. In addition to the fixed and random effects described in Section 3.1.1, we included additional fixed effects as categorical variables representing participant covariates (i.e., age or sex); route (Urban or Highway); and *Task* condition (*Task* or *No-Task*). For each exercise, the main effect of the route was insignificant ($p = 0.41$, $p = 0.40$, $p = 0.34$ for Exercises 1–3, respectively). Additionally, the effect of age or sex was not found to be significant. Therefore, all subsequent analyses were conducted on the combined dataset, combined across the Urban and Highway routes and the participant covariates.

3.3.1.3. Pre-Post Drive Analysis

Table 3.1 outlines the results from the pre-post analysis of the normalized changes in balance metrics as a function of the *Task* condition for each exercise. Across all the exercises, there were significant increases in nearly all of the balance metrics for the *Task* condition. For the final, most difficult balance exercise (Exercise 3), we found significant post-drive increases across all balance metrics during both *No-Task* and *Task* conditions. With the exception of A/P RMS for the *No-Task* condition ($p < 0.01$, $Z = 3.16$), the p-values for the comparisons among the other metrics were <0.001, with the largest Z-statistic reported for Path Length ($Z = 7.35$) and M/L RMS sway velocity ($Z = 7.01$).

Many of the balance metrics associated with Exercise 1 were also significant. For the *No-Task* condition, M/L RMS ($p < 0.01$, $Z = 2.62$), M/L RMS sway velocity ($p < 0.01$, $Z = 3.14$), and Elliptical Area ($p < 0.01$, $Z = 3.29$) increased significantly following the driving session. Similarly, for the *Task* condition, M/L RMS sway ($p < 0.001$, $Z = 4.04$), M/L RMS sway velocity ($p < 0.001$, $Z = 3.97$), and Elliptical Area ($p < 0.001$, $Z = 4.25$) increased significantly. In contrast, for Exercise 2, fewer balance metrics increased following a driving session, with only Elliptical Area ($p < 0.01$, $Z = 3.21$) increasing significantly following a driving session for the *No-Task* condition.

Table 3.1: Normalized values of the pre-post balance metrics for all exercises by *Task* condition. Median values (1st quartile and 3rd quartile) are shown. An asterisk (*) denotes a significant difference between pre-drive and post-drive postural sway for a specific *Task* condition. RMS = root mean square; A/P = anteroposterior; M/L = mediolateral; and EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per second. Elliptical Area and Path Length are in degrees^2 and degrees, respectively.

	No-Task	*Z*	*p*	*Task*	*Z*	*p*
Exercise 1: Feet Together/Eyes Open/Firm Support						
A/P RMS	1.15 (0.72, 1.68)	2.84	*<0.01	1.07 (0.69, 1.78)	2.34	0.019
M/L RMS	1.13 (0.77, 1.48)	2.62	*<0.01	1.23 (0.76, 1.92)	4.04	*<0.001
A/P RMS Velocity	1.03 (0.82, 1.33)	1.87	0.061	1.03 (0.88, 1.34)	2.80	*<0.01
M/L RMS Velocity	1.07 (0.89, 1.34)	3.14	*<0.01	1.10 (0.93, 1.38)	3.97	*<0.001
Elliptical Area	1.13 (0.76, 1.82)	3.29	*<0.01	1.28 (0.75, 2.56)	4.25	*<0.001
Path Length	1.04 (0.90, 1.21)	2.07	0.038	1.03 (0.91, 1.28)	2.68	*<0.01
Exercise 2: Feet Together/Eyes Closed/Firm Support						
A/P RMS	1.07 (0.77, 1.46)	2.14	0.033	1.15 (0.78, 1.57)	3.30	*<0.01
M/L RMS	1.00 (0.71, 1.44)	1.19	0.235	1.08 (0.73, 1.42)	1.88	0.060
A/P RMS Velocity	1.03 (0.86, 1.29)	1.95	0.052	1.14 (0.87, 1.30)	3.49	*<0.001
M/L RMS Velocity	1.05 (0.88, 1.24)	2.31	0.021	1.15 (0.94, 1.40)	3.57	*<0.001
Elliptical Area	1.13 (0.82, 1.55)	3.21	*<0.01	1.21 (0.74, 1.73)	3.45	*<0.01
Path Length	1.02 (0.90, 1.22)	2.06	0.040	1.06 (0.91, 1.27)	3.13	*<0.01
Exercise 3: Feet Together/Eyes Closed/Foam Support						
A/P RMS	1.14 (0.81, 1.79)	3.16	*<0.01	1.24 (0.79, 2.11)	4.09	*<0.001
M/L RMS	1.22 (0.80, 1.76)	3.70	*<0.001	1.37 (0.95, 1.99)	5.79	*<0.001
A/P RMS Velocity	1.23 (1.04, 1.52)	6.15	*<0.001	1.26 (1.01, 1.53)	6.01	*<0.001
M/L RMS Velocity	1.38 (1.13, 1.74)	7.01	*<0.001	1.27 (1.05, 1.63)	6.44	*<0.001
Elliptical Area	1.35 (1.08, 2.04)	5.83	*<0.001	1.35 (0.92, 1.98)	5.18	*<0.001
Path Length	1.23 (1.10, 1.55)	7.35	*<0.001	1.28 (1.05, 1.55)	6.99	*<0.001

3.3.1.4. Effect of Task Conditions

For Exercises 1 and 2, the normalized balance metrics were not statistically different between the two *Task* conditions. For Exercise 3, normalized RMS sway in the M/L directions increased significantly for the *Task* condition compared to the *No-Task* condition (p = 0.0014, Z = 3.19). The median, quartiles, Z-statistics, and p-values associated with the statistical comparisons are presented in Table 3.2.

Table 3.2: Normalized values of the balance metrics for all exercises by *Task* condition. Median values (1st quartile, 3rd quartile) are shown. An asterisk (*) denotes a significant difference between the *No-Task* and *Task* conditions for an exercise. RMS = root mean square; A/P = anteroposterior; M/L = mediolateral; and EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per second. Elliptical Area and Path Length are in degrees^2 and degrees, respectively.

	No-Task	*Task*	*Z*	*p*
Exercise 1: Feet Together/Eyes Open/Firm Support				
A/P RMS	1.15 (0.72, 1.68)	1.07 (0.69, 1.78)	0.90	0.37
M/L RMS	1.13 (0.77, 1.48)	1.23 (0.76, 1.92)	1.80	0.07
A/P RMS Velocity	1.03 (0.82, 1.33)	1.03 (0.88, 1.34)	1.03	0.31
M/L RMS Velocity	1.07 (0.89, 1.34)	1.10 (0.93, 1.38)	0.65	0.52
Elliptical Area	1.13 (0.76, 1.82)	1.28 (0.75, 2.56)	2.19	0.03
Path Length	1.04 (0.90, 1.21)	1.03 (0.91, 1.28)	1.02	0.31
Exercise 2: Feet Together/Eyes Closed/Firm Support				
A/P RMS	1.07 (0.77, 1.46)	1.15 (0.78, 1.57)	1.14	0.25
M/L RMS	1.00 (0.71, 1.44)	1.08 (0.73, 1.42)	-0.01	0.99
A/P RMS Velocity	1.03 (0.86, 1.29)	1.14 (0.87, 1.30)	1.65	0.10
M/L RMS Velocity	1.05 (0.88, 1.24)	1.15 (0.94, 1.40)	1.65	0.10
Elliptical Area	1.13 (0.82, 1.55)	1.21 (0.74, 1.73)	0.86	0.39
Path Length	1.02 (0.90, 1.22)	1.06 (0.91, 1.27)	1.54	0.12
Exercise 3: Feet Together/Eyes Closed/Foam Support				
A/P RMS	1.14 (0.81, 1.79)	1.24 (0.79, 2.11)	2.16	0.03
M/L RMS	1.22 (0.80, 1.76)	1.37 (0.95, 1.99)	3.19	<0.01*
A/P RMS Velocity	1.23 (1.04, 1.52)	1.26 (1.01, 1.53)	1.01	0.31
M/L RMS Velocity	1.38 (1.13, 1.74)	1.27 (1.05, 1.63)	-0.83	0.41
Elliptical Area	1.35 (1.08, 2.04)	1.35 (0.92, 1.98)	0.86	0.39
Path Length	1.23 (1.10, 1.55)	1.28 (1.05, 1.55)	0.05	0.96

3.3.1.5. Changes in Post-Drive Standing Balance Across Trials

To investigate the change in standing balance performance across the two post-drive trials, we analyzed the normalized balance metrics for Exercise 3 because it was the most challenging balance exercise and demonstrated the largest post-drive changes. All normalized balance metrics exhibited significant differences between the first and second trial for the *Task* condition. For the *No-Task* condition, sway velocity in the A/P ($p < 0.001$, $Z = -5.46$) and M/L ($p < 0.001$, $Z = -5.97$) directions, and Path Length ($p < 0.001$, $Z = -7.03$) decreased significantly as a function of post-drive trial number. Normalized post-drive measures of M/L RMS sway were significantly different ($p < 0.001$, $Z = 3.35$) when comparing between the *No-Task* and *Task* conditions. All statistical comparisons are shown in Table 3.3.

Table 3.3: Changes across post-drive trials described by normalized values for the post-drive trials and grouped by the *Task* condition for Exercise 3 (feet together/eyes closed/foam support). Median values (1st quartile and 3rd quartile) are shown. An asterisk (*) denotes a significant change in the second trial from the first trial. RMS = root mean square; A/P = anteroposterior; M/L = mediolateral; and EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per second. Elliptical Area and Path Length are in degrees^2 and degrees, respectively.

	No-Task			*Task*			*Task vs. No-Task*	
	Trial 2 / Trial 1	Z	*p*	Trial 2 / Trial 1	Z	*p*	*Z*	*p*
A/P RMS	0.95 (0.67, 1.36)	0.48	0.63	0.76 (0.52, 1.16)	-2.35	*0.02	1.81	0.07
M/L RMS	0.91 (0.58, 1.26)	-0.80	0.42	0.76 (0.52, 1.06)	-4.03	*<0.001	3.35	*<0.001
A/P RMS Velocity	0.86 (0.79, 0.98)	-5.46	*<0.001	0.86 (0.72, 0.98)	-5.55	*<0.001	0.98	0.33
M/L RMS Velocity	0.83 (0.70, 0.94)	-5.97	*<0.001	0.83 (0.69, 0.96)	-6.07	*<0.001	0.93	0.35
Elliptical Area	0.88 (0.61, 1.13)	-1.86	0.06	0.77 (0.52, 1.05)	-3.81	*<0.001	1.58	0.11
Path Length	0.85 (0.78, 0.95)	-7.03	*<0.001	0.85 (0.76, 0.96)	-6.67	*<0.001	0.63	0.53

3.3.2. Comparative Analyses

To facilitate comparisons between our previous closed test track study (a driving surrogate characterized as having high physical and moderate functional fidelity) and the current on-road study (naturalistic on-road driving environment), here we report the common balance exercise (Exercise 3) results from our closed test track study (further detailed in Le et al. (2020) [8]). The analysis of normalized balance metrics from the previous closed test track study revealed a significant effect of the *Task* condition on: M/L RMS sway ($p = 0.023$, $Z = 1.99$), M/L RMS sway velocity ($p = 0.047$, $Z = 1.68$), and Path Length ($p = 0.025$, $Z = 1.96$). Figure

3.4 presents the statistical comparisons, means, and standard errors for all the balance metrics spanning the Urban and closed test track routes (Moderate and Low Acceleration) for Exercise 3. Comparisons between the studies revealed no significant differences in normalized balance metrics across the routes for each *Task* condition. Although the normalized M/L RMS sway velocity for the *Task* condition was greater in the closed test track study, this difference was not significant ($p = 0.08$, $Z = 1.75$). Overall, there were no meaningful differences between the normalized changes in postural sway across the Urban route and the two acceleration levels of the closed test track route.

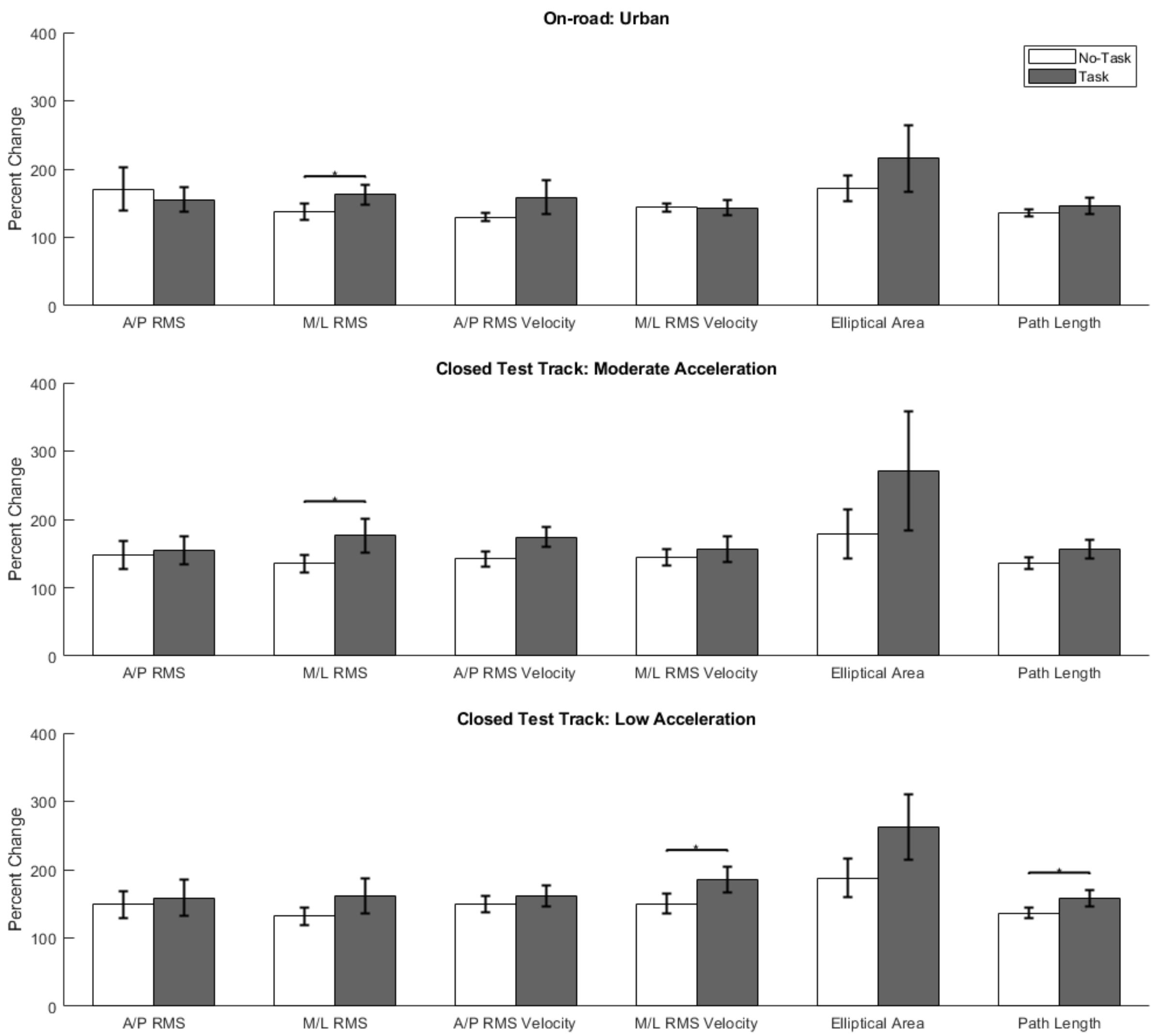

Figure 3.4: Bar plot illustrating the means and standard errors for the six normalized balance metrics for Exercise 3 (feet together/eyes closed/foam support) across studies. Abbreviations: RMS = root mean square; A/P = anteroposterior; M/L = mediolateral; and EA = Elliptical Area. A/P and M/L RMS are in degrees. A/P and M/L RMS velocity are in degrees per second. Elliptical Area and Path Length are in degrees^2 and degrees, respectively. An asterisk (*) denotes a significant difference for the non-parametric comparisons between the *No-Task* and *Task* conditions for that metric.

3.4. Discussion

3.4.1. On-Road Driving Analyses

Across all three balance exercises, postural sway increased following the driving session for each participant, regardless of participant covariates (i.e., age or sex). More specifically, the median values of the normalized metrics were either equivalent to or greater than pre-drive values across the route and *Task* conditions. For the most challenging balance exercise (Exercise 3), all the post-drive balance metrics were observed to increase significantly. Moreover, for Exercises 1 and 2, there were only two balance metrics that did not demonstrate significant increases following a driving session. These balance metrics were the normalized A/P RMS for Exercise 1 and normalized M/L RMS for Exercise 2. However, when comparing across the Urban and Highway routes and *No-Task* and *Task* conditions, there were only minimal differences among the normalized balance metrics. The only significant increase in balance metrics as a function of the *Task* condition was normalized M/L RMS sway for Exercise 3 (37% vs. 22% increase).

For Exercise 3, many balance metrics changed between the two post-drive trials. On average, the relative measures of all balance metrics decreased during the second trial. For the *Task* condition, all changes in the second trial differed significantly from the first trial, with the largest change being a 24% decrease in the median A/P and M/L RMS sway. Moreover, the decreased median value for M/L RMS sway during the second trial (0.83 deg) was similar to the median pre-drive value (0.80 deg), suggesting that post-drive standing balance ability may return to pre-drive levels within a short period of time following egress from a vehicle. However, there were some metrics that increased significantly post-drive but did not significantly decrease in the second post-drive trial. For example, for the *No-Task* condition, we observed significant post-drive increases in A/P and M/L RMS sway and Elliptical Area but no meaningful decreases in those metrics for the second trial, implying that some directional changes in postural sway may be sustained longer than others following a driving session. M/L RMS sway and elliptical area exhibited some of the largest post-drive changes among the six balance metrics (increases of 22% and 35%, respectively, for the *No-Task* condition and increases of 37% and 35% for the *Task* condition) that may explain why changes between the post-drive trials may take longer to recover to pre-drive values. Balance performance that did not fully recover by the second post-drive trial may potentially be a function of the specific postural strategies used for given standing postures [54] and/or explained by potential sensory adaptation [29]. Future work is needed to determine why some metrics were affected more than others and whether in-vehicle exposures lead to measurable sensory adaptations.

Among the published simulated studies that have investigated post-drive balance, Keshavarz et al. (2018) [6] demonstrated that the COP path length of drivers increased during a feet together/eyes open exercise following a simulated driving session on a 6 DOF motion platform. Although a direct comparison was not possible, the directional change of the Path Length (i.e., consistent increase) was similar between this on-road study and the Keshavarz et al. (2018) study, which we report here as a percent change for context. In this on-road study, the percent change between the medians of the non-normalized Path Lengths for Exercise 1 were 6% and 16% for the *No-Task* and *Task* conditions, respectively. In contrast, Keshavarz et al. (2018)

[6] found that there was roughly a 21% increase in the COP path length among older adults and a 17% increase among young adults. These similarities between passengers' and drivers' postural sway responses warrant additional investigation using direct comparisons.

3.4.2. Comparative Analyses

3.4.2.1. On-Road vs. Closed

This on-road study was the first to explore passengers' standing balance performance following a driving session in a naturalistic on-road environment. The changes in post-drive standing balance performance for Exercise 3 were consistent with the findings from our previous closed test track study [8] that found that all balance metrics increased following an in-vehicle drive. Additionally, there were minimal differences observed between the normalized post-drive postural sway metrics for the closed test track study and this on-road study, suggesting that the in-vehicle exposures scale similarly. The findings from the pre-post analyses across studies also provide further evidence that the closed test track is a representative experimental platform and surrogate for naturalistic on-road driving exposures.

The closed test track study reported a significant effect of the *Task* condition on more than one balance metric; specifically, normalized M/L RMS sway, normalized M/L RMS sway velocity, and Path Length were greater for the *Task* versus the *No-Task* condition. However, the balance metrics were not observed to differ between the *Task* conditions in this on-road study. Disparities between the findings may be attributed to the differences in the in-vehicle exposures. Although the number of vehicle events and the acceleration associated with each individual vehicle event were standardized, the overall in-vehicle exposure time differed between the closed test track (~20 min) and on-road (~55 min) studies. The association between task performance and increasing post-drive balance metrics observed during the closed test track study may suggest an interaction between task performance and the concentrated driving exposure.

3.4.2.2. Implications of Post-Drive Standing Balance for Falls

To contextualize the changes in post-drive balance, we chose to compare the RMS of the A/P acceleration with findings from a study by Park et al. (2016) [43] who reported normative RMS trunk acceleration data per decade of age. Following the driving sessions performed with a task, the average RMS A/P acceleration among the younger adult (0.0594 m/s^2) and older adult (0.0589 m/s^2) participants reflected measurements likely to be observed in older adults above the age of 60 from the Park et al. (2016) study. In a study conducted by Doheny et al. (2012) [55], RMS A/P acceleration was 20% larger among older adult fallers versus non-fallers. In comparison, the average percent change of post-drive RMS A/P acceleration among older adults in this on-road study was 14% and 42% for the *No-Task* and *Task* conditions, respectively. Hence, following in-vehicle exposures with task performance, the relative change in postural sway suggests that a rider susceptible to balance issues (e.g., an older adult) may be more likely to be at an increased risk for falls [56,57]; an increasingly likely scenario given the anticipated use of AVs and mobility services. However, there is large variability among RMS A/P acceleration data reported in the literature that may be due to a combination of heterogeneity among the sensors, post-processing techniques, and experimental conditions (e.g., vision and stance conditions) used [44,46,48,55], which makes such comparisons challenging.

3.4.3. Limitations

The current study is not without limitations. The balance exercises were performed in different locations. We assessed pre-drive balance outdoors near the laboratory facility, while post-drive balance exercises were performed next to the vehicle immediately upon exiting. However, to partially control for the variation in the visual surroundings, a visual reference target was provided for participants to use during both pre- and post-drive balance exercises. The order of the balance exercises was fixed as well with each subsequent exercise increasing in difficulty; therefore, order may have introduced a learning effect throughout the session. Even with a predetermined route and time of day (midday), we did not fully control for variations in traffic flow given that the driving sessions were affected by real-time traffic conditions. Furthermore, a 60 min driving exposure does not reflect the average time that participants normally spend in a passenger vehicle. Lastly, this analysis only considers standing balance performance before and after a driving session; thus, in-vehicle postural sway of the trunk should be included in future work to close the gap in continuous monitoring and the effects on gait should be explored.

3.5. Conclusion

This on-road study was the first to analyze the relationship between vehicle motion in an on-road setting, task performance, and post-drive balance performance. Postural sway was measured using a personal device-based IMU worn on the lower back. Parameterized using different metrics, postural sway increased post-drive, especially for the most difficult balance exercise. The pre-post changes in normalized postural sway on the Urban route did not differ significantly from a previous study conducted on a closed test track environment. However, the effect of task performance was less significant in this on-road study. Future work should continue to evaluate how an on-road driving exposure affects the standing balance ability of populations already susceptible to falling.

3.6. References

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Chapter 4 Motion sickness affects passengers' standing balance performance

4.1. Introduction

Motion sickness is a common illness experienced among vehicle passengers. Symptoms include nausea, drowsiness, fatigue, and stomach awareness, all of which can lead to travel discomfort and discourage the performance of in-vehicle, non-driving-related tasks [1]–[3]. With the growing use of urban on-road transportation (especially with automated vehicles), there is a greater need to understand and quantify the risk and severity of motion sickness incidence. One potential approach involves leveraging the relationship between postural instability and motion sickness, as there may be potential for using pre-drive balance assessments for predicting the motion sickness response. However, the association between standing balance performance and motion sickness has not yet been fully studied in an on-road driving environment, and few studies in the simulation space have explored the response among vehicle passengers. Moreover, there is a lack of work exploring the responses of passengers performing normative in-vehicle activities during on-road exposures.

The sensory conflict theory states that visual-vestibular sensory inputs that are incompatible with what is expected by the brain's "internal model" (developed through prior experience) lead to motion sickness [1], [4]. In one particular example, Reason (1978) [5] described how reading a book while in a moving vehicle causes sensory conflict between the static visual of the object and the dynamic motions of the vehicle. Other theories claim that reflexive eye movements or even the novelty of new modes of transportation explain motion sickness incidence [6]. Other works have added further nuance by claiming that motion sickness is observed alongside sensory conflict, postural instability, reflexive eye movements, and the interaction of these factors [7]. Riccio and Stoffregen (1991) [8] challenged the sensory conflict theory and proposed another theory based on postural instability, claiming that motion sickness develops as a result of a person's inability to adapt their posture during a motion exposure. Moreover, those who can minimize their amount of postural sway can reduce the severity of motion sickness [8]. Thus, the postural instability theory suggests that postural sway should be greater among those who are motion sick, and that these differences should be observable prior to the onset of motion sickness. Studies using visual-based motion exposures have typically found significant changes in postural sway prior to the onset of motion sickness [9]–[14]. However, most of these studies are based on empirical data of seated, in-vehicle postural sway in simulated driving and motion platforms, with limited works exploring post-drive standing balance.

Many studies have explored the postural instability theory of motion sickness during simulated drives by measuring seated postural sway at the head and torso during an exposure [14]–[19]. Using a fixed-base, open-cab driving simulator, Mackrous et al. (2014) [16] measured participants' head displacement while they maneuvered a continuous 26 km route with multiple intersections, and found no association with the severity of motion sickness symptoms. However, Curry et al. (2020) [20] measured the positional variability of the head and torso during a 15-min drive using a video game and a head-mounted-display, and found significant interactions between motion sickness incidence, participants' sex, and the axis of body motion. Similarly, two studies by Dong et al. (2011) [14] and Chang et al. (2021) [18] used a driving video game exposure; their findings were consistent with one another and suggested that seated postural activity in the torso increased over the length of the exposure, particularly for participants who self-reported motion sickness incidence. Moreover, participants who would later report motion sickness exhibited greater postural activity prior to the onset of symptoms, which aligns with the postural instability theory of motion sickness. A study by Chang et al. (2013) [19] used passive restraints during exposure, but participants who reported motion sickness still exhibited greater positional variability during the 50-min driving game exposure. Although studies using in-vehicle exposures are limited, a study by Irmak et al. (2021) [15] found that head roll of back-seat passengers increased over the course of a 30-min exposure to slalom driving; however, there was not a strong relationship with the MISC scale (misery scale as described in Bos et al. (2005) [21]). In general, seated postural instability has been shown to increase throughout the duration of simulated exposures; in contrast, that relationship between motion sickness and postural instability has not been found during in-vehicle exposures.

Previous studies have also explored how motion sickness affects pre- and post-drive standing balance performance in many different virtual and motion-based environments [22]–[27]. For example, virtual-based studies have investigated motion sickness and balance ability using virtual moving rooms, head-mounted displays, console video games, virtual environments, and virtual simulations (e.g., flight simulators) [10], [13], [28]–[30]. However, prior studies focused on simulated driving [24], [25], [27] or on closed test tracks [26] have found inconsistent results. For example, Keshavarz et al. (2018) [24] observed that the path length of participants' postural sway increased following a session in a driving simulator. However, no correlation was found between path length and subjective motion sickness ratings on the Fast Motion Sickness Scale. A study by Reed-Jones et al. (2008) [25] also used a fixed-base driving simulator, but found that path velocity of postural sway during a single-leg stance decreased following a session. Moreover, the changes to path velocity were inversely related with increasing motion sickness severity, which was quantified using the Simulator Sickness Questionnaire (SSQ). Using a head-mounted display as their simulated driving exposure, Mourant & Thattacherry (2000) [27] found that drivers' time in single-leg stance decreased and motion sickness ratings on the SSQ increased significantly following the exposure. However, there were no reports of how these data were correlated. A study by Curry et al. (2020) [11] demonstrated that pre-drive postural sway measures (i.e., multifractality) differed significantly between susceptible participants prior to a driving game exposure. Overall, studies of pre- and post-drive standing balance performance have suggested that there may be a relationship between motion sickness severity and changes in postural sway.

In our previous studies of on-road driving, we looked primarily at the change in passengers' standing balance performance following a drive on a closed test track [26] and a realistic, urban on-road driving environment [31]. In both studies, passengers exhibited large relative increases in the balance metrics after a drive, especially when participants were instructed to perform a non-driving-related task during the in-vehicle exposure. Moreover, participants self-reported higher ratings of motion sickness during the drives that involved a task. This positive trend between a non-driving-related task and substantial post-drive changes in balance metrics suggested that motion sickness may have been an underlying factor. Although we collected data on passengers' motion sickness throughout the drive, we did not consider them in these prior analyses.

To the best of our knowledge, the relationship between motion sickness and post-drive standing balance has not been fully explored in an on-road, in-vehicle environment. There is a need to study this relationship beyond simulated driving because the motion sickness response may be substantially different between in-vehicle exposures to on-road, simulated, or closed test track driving. This may be due to experiential differences in the visual field, physical and functional fidelity, the driver workload, or the intensity of the motion during the drive [32], [33]. Such work would be particularly relevant to all types of vehicle passengers because motion sickness can affect user performance [2], especially as automated vehicles and mobility solutions become further normalized in urban transportation.

Therefore, we seek to formally evaluate the effects of motion sickness on changes in standing balance performance following in-vehicle exposures conducted on a closed test and a realistic, on-road driving environment. Moreover, we perform a preliminary analysis for predicting motion sickness incidence using balance metrics and other relevant participant demographics.

4.2. Methods

4.2.1. Dataset

The data included in this study are sourced from two previous on-road driving studies. These studies explored the relationship between the standing balance performance of vehicle passengers following in-vehicle exposures on a closed test track and in realistic urban on-road driving conditions [26], [31]. In the following sections, a description of the experimental protocols is provided. The relevant data collected across studies include: i) self-reported ratings of overall motion sickness throughout a drive, ii) pre-drive and post-drive balance metrics, iii) drive conditions, and iv) participant demographics (i.e., age, sex).

4.2.2. Participants and Experimental Design

In the on-road study, 106 adults (47 males, 59 females) between the ages of 18 yr. and 89 yr. (34.2 ± 18.5 yr.) participated in a mixed factorial design experiment: 82 were age < 60 yr. (24.5 ± 4.3 yr.), 24 were age ≥ 60 yr. (67.0 ± 6.9 yr.). As for the closed test track study, 50 adults (23 males, 27 females) between the ages of 18 and 78 years (40.0 ± 20.6 yr.) participated in a similarly designed experiment: 33 were age < 60 yr. (28.3 ± 8.5 yr.), 17 were age ≥ 60 yr. (66.4 ± 4.8 yr.). Participants in both studies were asked to assess their prior history with motion sickness as well as their level of motion sickness susceptibility. Motion sickness susceptibility was categorized into four levels (never, rarely, sometimes, and frequently) based on how often participants experienced motion sickness in the past.

In both studies, participants rode in the front passenger seat of a midsize sedan operated by a trained driver. However, different routes were used in the closed test track and on-road studies. In the on-road study, participants were assigned to be driven on one of two routes: an urban route that exclusively used local neighborhood streets and main city roads, or a highway route that involved extended bouts on local freeways. These routes were referred to as the Urban and Highway routes, respectively. Each route involved real-time driving exposure with various driving events (e.g., braking, lane changes) set in midday traffic throughout Ann Arbor, MI, USA. In contrast, the closed test track study consisted of a concentrated driving exposure on a controlled, scripted route on a closed test track [26], [34]. The scripted routes were designed to include many different latitudinal and longitudinal acceleration profiles that would likely be observed in naturalistic driving datasets [34], [35]. The frequency of driving events was designed to be similar across both studies (e.g., similar number of left turns); however, to distinguish two different routes, participants were driven at two levels of acceleration (referred to as Moderate or

Low Acceleration). Further details about the in-vehicle exposures and the route designs can be found in Jones et al. (2019) and Le et al. (2020) [26], [34].

Participants performed repeated tests on their assigned route (i.e., either one of Urban, Highway, Low Acceleration, or Moderate Acceleration) using two different levels of an ecologically relevant task. During a drive with *Task*, participants completed a visual-based task administered on a handheld tablet during the drive, as seen in Figure 4.1. In another drive (*No-Task*), participants were instructed to exhibit normative passenger behavior with an unrestricted gaze. The order of these repeated tests on the *Task* condition was randomized. In total, there were four test conditions for the on-road drive: Urban, *Task*; Urban, *No-Task*; Highway, *Task*; and Highway, *No-Task*. Similarly, the four test conditions for the closed test track study were: Moderate Acceleration, *Task;* Moderate Acceleration, *No-Task*; Low Acceleration, *Task*; and Low Acceleration, *No-Task*. To facilitate comparisons between study participants, a non-parametric Wilcoxon rank sum test and a chi-squared test was performed and observed no differences between groups in terms of age, sex, and motion sickness susceptibility. Each participant provided written informed consent and the study was conducted in accordance with the Declaration of Helsinki. The studies were reviewed and approved by the University of Michigan Institutional Review Board (HUM00128751)**.**

4.2.3. Experimental Protocol

4.2.3.1. Balance Testing

Participants completed a series of balance exercises before entering the vehicle, and immediately after egress. In the on-road study, participants performed three trials of each balance exercise, whereas only two trials were performed for each exercise in the closed test track study.

Although a different set of balance exercises were used in each study, all participants performed a feet together/eyes closed/foam support exercise using a compliant surface (Airex, New York, NY); this balance exercise was used for direct comparisons across studies. During the exercises, participants were instructed to cross their arms, stand tall, and avoid being too stiff or tense. A visual target was placed in front of the participant to provide a consistent reference point, especially when the surrounding visual field was different (i.e., depending on where the vehicle was parked during the test). Each trial lasted 30 seconds, unless the participant lost their balance. Losses of balance were considered as either 1) stepping out of the feet together stance, 2) needing to grab a nearby walker, or 3) a spotter intervening to prevent potential falls.

4.2.3.2. In-Vehicle Protocol

Throughout the drives, participants were asked to maintain a neutral posture in the passenger seat while being driven on the assigned driving course. In the on-road study, each drive lasted until either the route was completed (55 minutes on average), or until the participant opted to discontinue the test within that time frame. In contrast, the maximum time for a drive was limited to 20 minutes in the closed test track study. The repeated tests were scheduled with a minimum of 24 hours between drives to minimize the influence of lingering symptoms of motion sickness on the second test. To assess the level of motion sickness, participants self-reported an overall motion sickness rating every minute during the drives using an 11-point integer scale (with 0 representing "no motion sickness” and 10 representing “stop the car”).

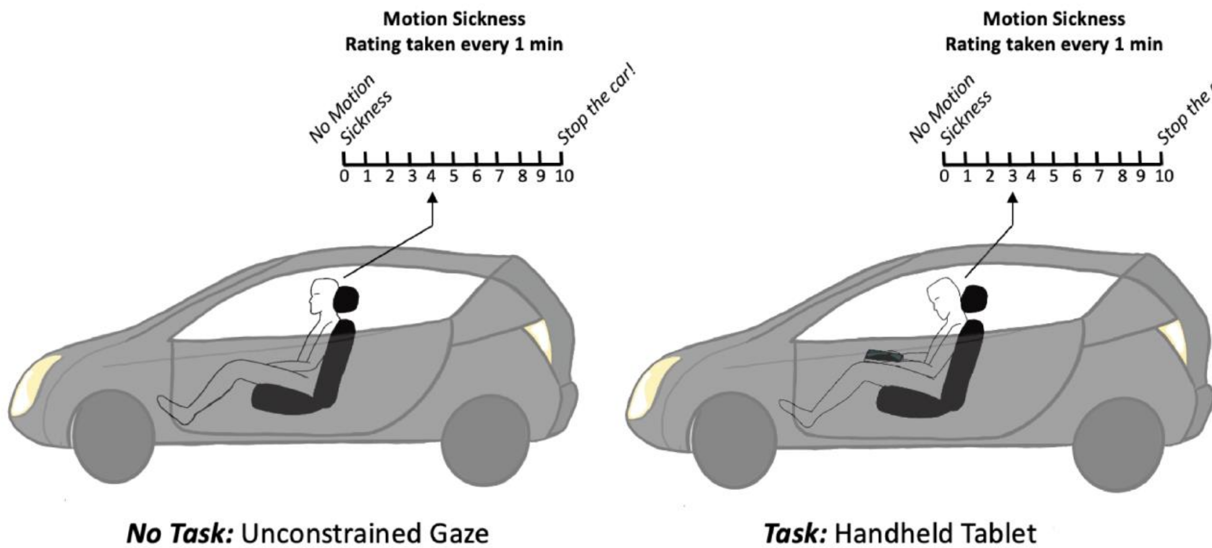

Figure 4.1: Participants performed repeated tests on their assigned route in either a *Task* or *No-Task* condition. In the *No-Task* condition, participants exhibited an unconstrained head position, orientation, and gaze. In the *Task* condition, participants were instructed to hold a handheld tablet in their lap. Every minute, participants self-reported an overall rating of the motion sickness on a scale between 0 and 10.

4.2.4. Balance Measurements and Instrumentation

Standing balance performance was measured by using an inertial measurement unit (IMU) embedded in a surrogate smartphone (6th generation iPod Touch, 2015) [36], [37]. The device was secured at the participants' lower back with an elastic waistband throughout the balance exercises. Accelerometer and gyroscope data were collected at a sample rate of 50 Hz, after which a Kalman filter was used to fuse and decompose the signals into measures of anteroposterior (A/P) and mediolateral (M/L) trunk postural sway position and sway velocity. These tilt data were then processed in MATLAB (The MathWorks, Natick, MA) to calculate the following six balance metrics: root-mean-square (RMS) of trunk tilt in the A/P (A/P RMS) and M/L (M/L RMS) directions, RMS of trunk sway velocity in the A/P and M/L directions, path length of the sway trajectory, and the elliptical fit of the sway trajectory area [36], [38]. RMS was calculated by taking the square root of the average of the squared tilt values. To compute the elliptical area of sway, a 95% confidence ellipse was fit around the trunk tilt values in each trial before computing the area [37], [38]. Path length was computed by summing the distances between consecutive samples in the signals capturing the tilt angles [38].

4.2.5. Data Analysis

4.2.5.1. Mixed Models of Balance Metrics

A mixed model approach was used to explore the relationship between metrics of standing balance and motion sickness. A model was fit to each balance metric for the feet together/eyes closed/foam support exercise, leading to a total of 6 fitted mixed models. Participant age, sex, motion sickness response, route (Urban, Highway, Low, or Moderate), *Task* condition, and their interactions acted as fixed effects in the model. The subject code was treated as a random variable.

To further elaborate on the fixed effect representing motion sickness, participants were labeled as either a non-responder, a mid-level responder, or a high-level responder based on their self-reported motion sickness ratings. If their maximum motion sickness rating belonged in the lowest quartile relative to other pooled participants in their test condition, they were labeled as non-responders. If their self-reported maximum rating fell in the highest quartile, they were labeled as a high-level responder to motion sickness. Otherwise, they were labeled as mid-level responders. The thresholds that defined responders and non-responders of motion sickness were computed for each individual test condition across both data sources. In the current study, the lower and upper quartiles of motion sickness ratings for each test condition were: Highway, *No-Task* (0, 3); Highway, *Task* (1, 5); Urban, *No-Task* (1, 4); Urban, *Task* (2.25, 8.75). In the closed test track study, the lower and upper quartiles of motion sickness ratings for the test conditions were: Low Acceleration, *No-Task* (1, 4.5); Low Acceleration, *Task* (2.5, 7.5); Moderate

Acceleration, *No-Task* (0, 4); Moderate Acceleration, *Task* (5, 10). These thresholds are shown in Table 4.1. In order to make comparisons between our previous studies, only data from the first trial in the common balance exercise were used. Consequently, the on-road data set consisted of only 212 data points, while the closed test track data set consisted of only 100 data points.

Route	***Task***	**Lower Quartile**	**Upper Quartile**
Highway	*No-Task*	0	3
Highway	*Task*	1	5
Urban	*No-Task*	1	4
Urban	*Task*	2.25	8.75
Low Acceleration	*No-Task*	1	4.5
Low Acceleration	*Task*	2.5	7.5
Moderate Acceleration	*No-Task*	0	4
Moderate Acceleration	*Task*	5	10

Table 4.1: Thresholds for defining a participant as a non-responder or responder to motion sickness for each test condition across both studies. Ratings were reported on a continuous scale with a range between 0 and 10. The on-road study used a Highway and Urban route. The closed test track study used a Low Acceleration and Moderate Acceleration route.

4.2.5.2. Binary Classification of Motion Sickness

We framed part of the analysis as a supervised binary classification task, where the goal was to predict whether or not a participant would experience motion sickness during the drive using a combination of pre-drive balance metrics and participant demographics. Participants' data were labeled as "sick" or "not sick" depending on the maximum motion sickness rating reported during the drive. The threshold for determining "sick" or "not sick" was chosen such that the data were split roughly evenly. Other covariates included the values of the balance metrics, the independent conditions of the drive (i.e., the route and the *Task* condition), and participants' age and sex.

During model development, we randomly split the data into a training set (80%) and a held-out test set (20%) and repeated this 5 times for the entire dataset. When splitting the data, repeated tests from a single participant (i.e., during *Task* and *No-Task* condition) were grouped together to prevent label leakage. During each iteration, we learned a nonlinear tree-based model known as a random forest, selecting model hyperparameters (i.e., number and depth of trees, the number of features assigned to each tree, and the number of samples needed to split a node) using 10-fold cross-validation on the training data and optimizing for the area under the receiver operating characteristic curve (AUC). In brief, the AUC captures the ability of a model to rank a randomly selected example from the "sick" group higher than a randomly selected example from the "not sick" group. An AUC of 0.5 indicates that the model performs no better than chance, while an AUC of 1.0 indicates perfect classification of the data. Moreover, the AUC was used as the primary performance metric because the data were roughly balanced, and overall model performance can be determined without specifying model structure [39].

To characterize model performance, the AUC was computed for each held-out test set. Error bars were computed using the AUC's computed during the 10-fold cross-validation of the training set. Lastly, to assess the contribution of different covariates towards prediction, permutation importance of each covariate was computed for the final models by permuting correlated groups of features with $\rho > 0.7$. We measured the drop in AUC after 100 permutations in the test set.

4.3. Results

4.3.1. Mixed Models of Balance Metrics

Being a responder to motion sickness played a significant role in the mixed models fitted to normalized M/L RMS sway velocity ($\beta = 0.20 \pm 0.06$, $p < 0.01$), and path length ($\beta = 0.14 \pm 0.05$, $p < 0.01$). Performing a task throughout the drive was also significantly correlated with increased M/L RMS ($\beta = 0.27 \pm 0.11$, $p = 0.01$) and A/P RMS velocity ($\beta = 0.24 \pm 0.11$, $p = 0.03$). The results for the mixed model of normalized path length and M/L RMS sway velocity are reported in Table 4.2. A visualization of the path length as a function of responders to motion sickness and the different routes are shown in Figure 4.2.

Path Length					
Fixed Effect	**Estimate**	**Standard Error**	**df**	***t***	***p***
(Intercept)	1.28	0.07	201.53	18.90	*<0.001
Responder	0.14	0.05	233.04	2.73	*<0.01
Random Effect	0.30				

M/L RMS Velocity					
Fixed Effect	**Estimate**	**Standard Error**	**df**	***t***	***p***
(Intercept)	1.32	0.08	205.15	15.7	*<0.001
Responder	0.20	0.06	242.77	3.27	*<0.01
Random Effect	0.44				

Table 4.2: Results of the reduced mixed model for path length and sway velocity in the M/L direction, exhibiting a significant effect of motion sickness. A * denotes that the estimate of the coefficient for a fixed effect was significantly different from 0 ($p < 0.05$).

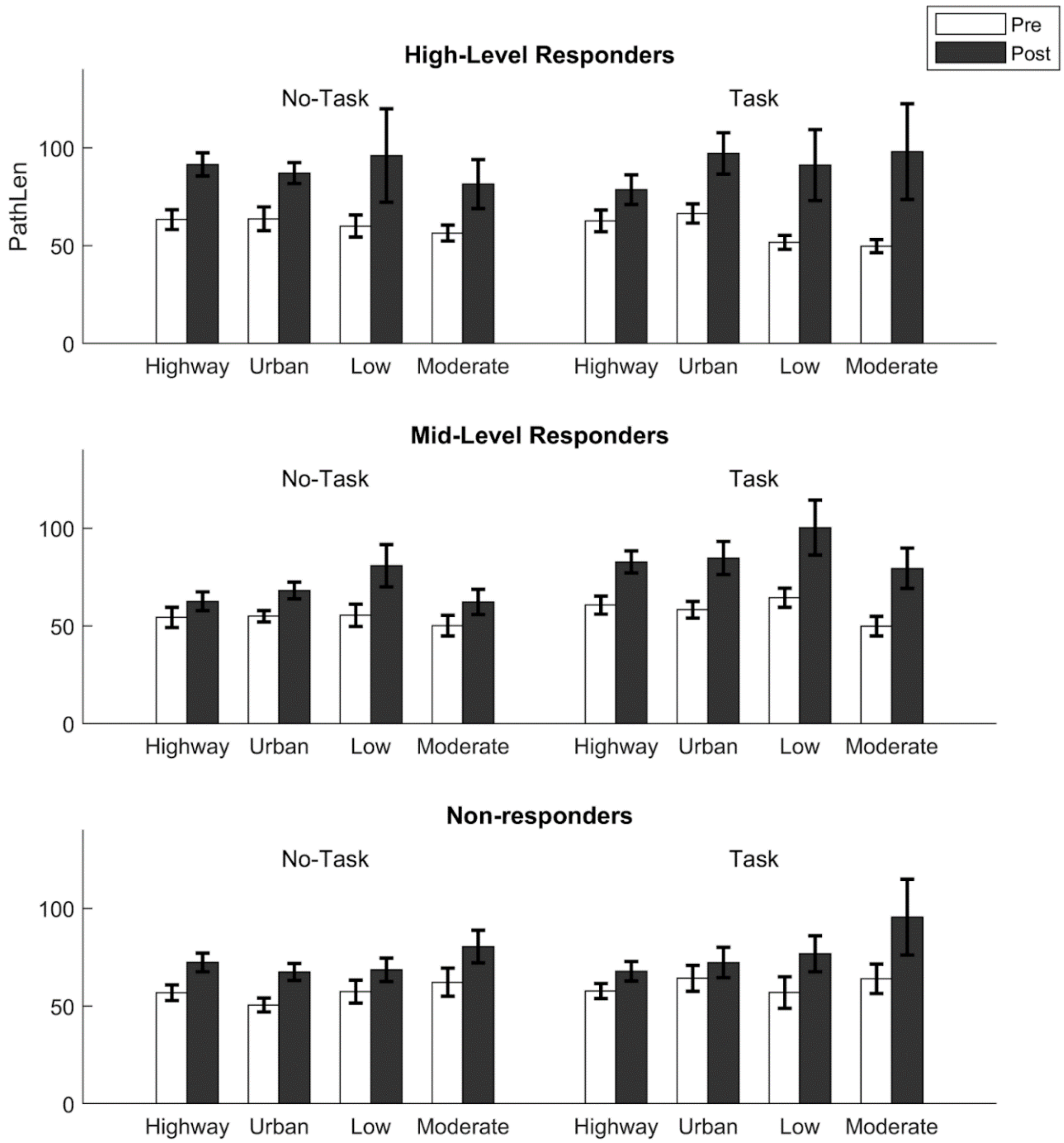

Figure 4.2: Path length grouped by the four test conditions, and pre-drive versus post-drive across both data sources for different levels of motion sickness responses. The balance exercise is feet together/eyes closed/foam support.

4.3.2. Binary Classification of Motion Sickness

A rating of 3 on the motion sickness rating scale was used as a threshold for labeling participant data as “sick” and “not sick”. Out of 300 complete data points, 178 were labeled as “sick”. The AUC’s for the 10-fold cross-validation for each train-test split are shown in Table 4.3, as well as averages for each train-test split. For each train-test split, the AUC computed for the held-out test sets were 0.68, 0.79, 0.64, 0.65, and 0.69. The average AUC across all held-out test sets was 0.69, indicating fair performance for this classification task. A plot of the AUC for one of the held-out test sets is included in Figure 4.3.

	Fold										
Split	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**Avg. (S.D.)**
1	0.700	0.733	0.604	0.696	0.614	0.600	0.549	0.607	0.603	0.729	0.644 (0.061)
2	0.659	0.643	0.555	0.607	0.729	0.594	0.676	0.508	0.650	0.586	0.621 (0.061)
3	0.511	0.521	0.738	0.600	0.857	0.625	0.539	0.563	0.607	0.808	0.637 (0.116)
4	0.563	0.733	0.664	0.860	0.514	0.630	0.785	0.725	0.664	0.713	0.685 (0.097)
5	0.719	0.629	0.715	0.692	0.518	0.671	0.773	0.521	0.663	0.842	0.674 (0.096)

Table 4.3: Area under the receiver operating curve computed for the 10-fold cross validation of the training set for each train-test split.

A plot of the permutation importance for each of the features in the model is also shown in Figure 4.4. The top five most important features were the Task condition; the correlated group of M/L RMS sway velocity, elliptical area, and sway path length; the Highway route; the age of the participant; and the sway position in the A/P direction.

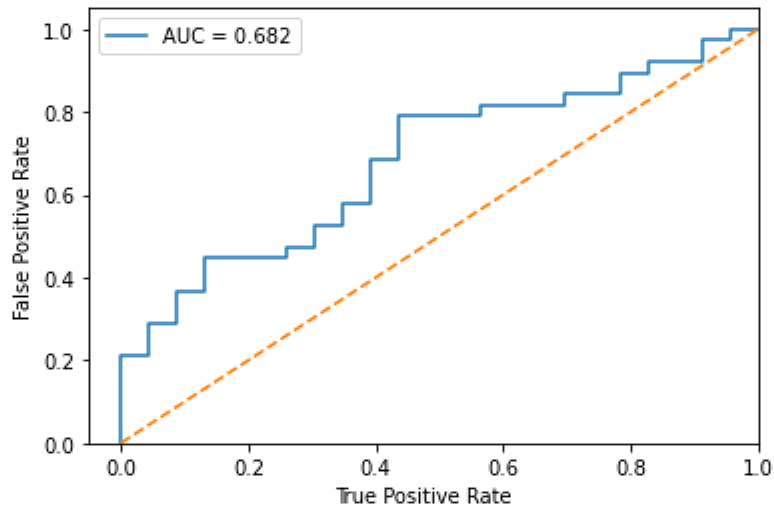

Figure 4.3: Receiver operating characteristic curve for the model predicting motion sickness on one of the held-out test sets.

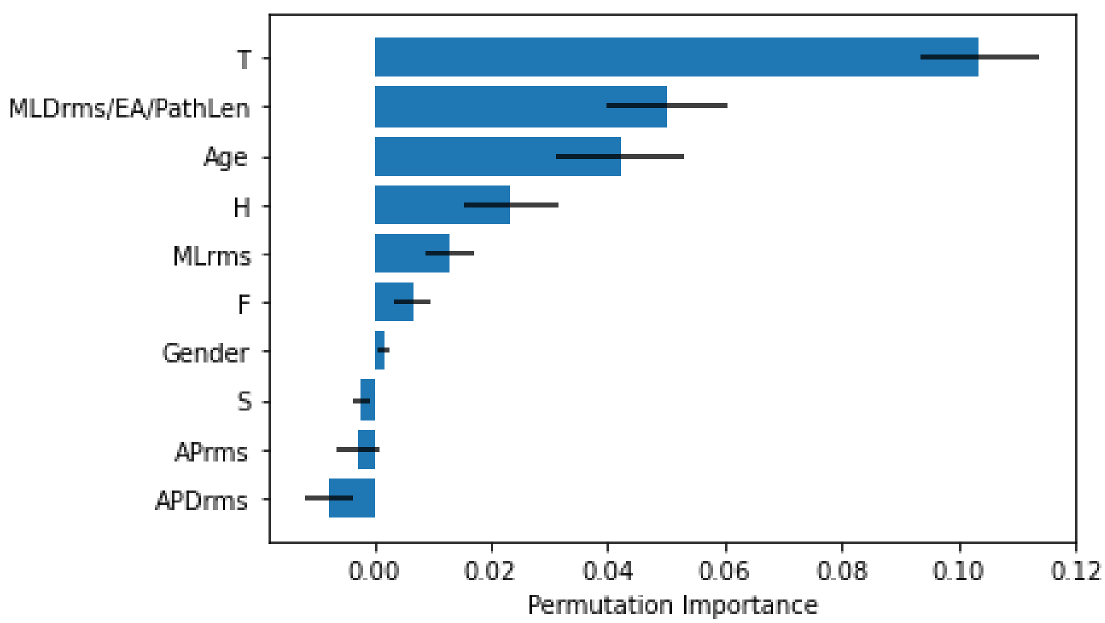

Figure 4.4: Permutation importance of the different features in the model, defined as the drop in AUC for all the held-out test sets. Error bars represent the standard deviation of 100 iterations. *Task*, Highway Route, Moderate Acceleration Route, and Low Acceleration Route represent the respective independent drive conditions. M/L RMS Velocity/Elliptical Area/Path Length represent the correlated group of M/L RMS sway velocity, elliptical area of sway, and the path length of the sway trajectory. Age and Sex represent participant demographics. A/P RMS, A/P RMS Velocity, and M/L RMS represent the RMS of sway position/velocity in the A/ P direction, and the RMS of sway position in the M/L direction, respectively.

4.4. Discussion

Motion sickness was significantly related to the metrics of standing balance, as seen in the mixed models. The fixed effect representing motion sickness responders had a relatively large effect for sway velocity and path length. For instance, evaluating standing balance performance among motion sickness responders corresponded with a 14% and 20% increase in M/L RMS sway velocity and path length, respectively. However, the effect of motion sickness did not seem to correlate with any metrics of RMS sway position. Physically, "sick" participants exhibited less control of their posture (i.e., increased sway velocity) while simultaneously minimizing increases to the area of sway, which might be achieved by adapting different control strategies to compensate for disorienting effects of motion sickness. For example, higher stiffness around the ankle joint is associated with higher frequencies of postural sway and fast, small adjustments of posture [40]. Overall, larger changes were observed among those who experienced greater levels of motion sickness during the drive.

When classifying participants as either "sick" or "not sick", the random forest model obtained an average AUC of 0.69 on the held-out test sets. Given that an AUC of 0.5 indicates performance no better than chance, the predictive model shows adequate performance for classifying motion sickness using this specific set of covariates [41]. Based on the permutation importance, the *Task* condition exhibited the largest influence on the model's prediction of motion sickness. This is consistent with previous experimental studies that have found higher motion sickness severity that perform non-driving related tasks during a drive. This is supported by the fact that the distribution of the motion sickness ratings tended to be centered around a larger rating for the *Task* conditions. For example, in the Moderate Acceleration, *Task* condition, the lowest quartile corresponded to a motion sickness rating of 5, which was higher than some of the upper quartiles in other conditions. However, in contrast to previous findings in our closed test track study, the age of the participant had a somewhat substantial amount of influence on the predictive performance of the models. Though, more data may be needed to make firm conclusions given the large standard deviation.

Findings from previous studies of motion sickness and standing balance have been inconsistent. As mentioned earlier, the study by Keshavarz et al. (2018) [24] found significant increases in path length following simulated driving, but there was no meaningful relationship with reported ratings of motion sickness. In contrast, Reed-Jones et al. (2008) [25] found a negative correlation between pre-drive path velocity (r = -0.344), post-drive sway area (r = -0.476), and the measurements from the SSQ in a driving simulator. One potential explanation for the inconsistency in these findings is the methodological variations in motion sickness assessment and standing balance exercises. The SSQ quantifies specific dimensions and symptoms of motion sickness, while the rating scales reflect an overall assessment of motion sickness. Although the FMS functions similarly to the rating scale used in the current on-road study, a max rating of 20 may skew the results differently for participants. Moreover, the types of balance exercises performed vary greatly (i.e., single-leg stance vs. feet together/eyes open/firm support), such that the sensitivity of balance metrics to motion sickness ratings may be lower in certain exercises. More importantly, in this on-road study, analysis of the motion sickness ratings in the mixed models only included the most responsive and least responsive participants. Therefore, changes to balance metrics may only be significantly related to the most severe levels of motion sickness, which could explain why findings in previous studies have been inconsistent.

The findings of this study revealed the importance of participants’ age and sex in making predictions of motion sickness. However, postural sway (using normalized balance metrics) was not found to be correlated with either participant demographic. Previous studies on the relationship between motion sickness, postural sway, and participant demographics have reported inconsistent results. Some virtual-based studies have found significant effects of age and sex on the severity of motion sickness responses [42], [43], while others have found no such relationships [44], [45]. In one virtual driving study among older adults, motion sickness incidence (based on SSQ) was greatest among older females, and lowest among younger males [42]. In another virtual-based study, motion sickness responses among older adults increased after a session in a driving simulator, though any effects of sex were insignificant [46]. With respect to postural sway, a pair of virtual-based studies found participant sex to be expressively related to the amount of in-vehicle sway [17], [20]. It is possible that participants' lack of exposure to vision-based, virtual systems may have contributed to stronger motion sickness responses, especially among older participants [6], [47]. Conversely, in on-road environments, the effects of age and sex on motion sickness or postural sway may not be as strong due to participants’ familiarity with the motion modality (i.e., urban transportation). In our previous study on closed test tracks, post-drive postural sway was not associated with participant age or sex [26]. Overall, the effect of participant demographics on motion sickness and postural sway are varied among different driving environments. Additional work is needed in a realistic on-road environment to understand how motion sickness responses and standing balance ability might change for different passenger populations.

Studies that have predicted motion sickness from in-vehicle exposures are still limited. One study by Lin et al. (2013) [48] used electroencephalogy (EEG) to estimate the continuously changing level of motion sickness in a dynamic driving simulator. Although their neural network architecture obtained promising results, the prediction task was not a binary classification task. Still, their work demonstrated that EEG-based features may be valuable for improving the prediction accuracy of motion sickness during a drive. Another study by Dennison et al. (2019) [49] used a combination of sensor data to optimize a model for classifying four levels of motion sickness in a virtual environment on a head-mounted display. Postural sway measured with a Wii Balance Board during the 30-minute exposure was able to achieve ~83% predictive accuracy on 10-fold cross-validated data.

The current study is not without limitations. The amount of data used for the analyses were limited because only the first trial from the common exercise was used. The balance metrics were also computed from balance trials performed before and after a drive, as opposed to trunk postural sway during the drive. Moreover, no features in the models captured motion sickness throughout the course of the drive. Consequently, the findings in the mixed model analysis captured discrete states of motion sickness, rather than its development or onset. Additionally, the “sick” and “not sick” labels were based on the maximum motion sickness ratings; there could be other potential metrics for characterizing the data.

4.5. Conclusion

In this study, the relationship between postural sway, participant covariates, and motion sickness were explored in on-road driving. Mixed models of the balance metrics revealed that participants who were more responsive to motion sickness exhibited the larger changes in post-drive postural sway. When training a prediction model, task performance and the balance metrics were the two most predictive features of motion sickness during the drive. These findings support the relationship between postural instability and motion sickness, and further work can inform future approaches for estimating motion sickness during urban transportation.

4.6. References

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Chapter 5 Noninvasive Estimation of Hydration Status in Athletes Using Wearable Sensors and a Data-Driven Approach Based on Orthostatic Changes

5.1. Introduction

Exercise-induced dehydration is typically a result of insufficient replenishment of fluids lost mainly to sweat. Dehydration of up to 2 to 3% of one's body weight in athletic settings is common for healthy individuals, especially when competing in the heat [1]. Dehydration can predispose individuals to a variety of heat illnesses, including heat stroke and heat exhaustion [2]–[5]. Heat stroke for example, is the third leading cause of death in high school athletes and is regularly reported among other occupations that encounter heat stress [5].

To lower the potential risk of heat-related injuries, it is important to monitor hydration status and rehydrate during exercise [6]–[8] (e.g., drinking to thirst [9]–[11] or planned drinking programs to minimize bodyweight loss [6], [7], [10], [12], [13]. Laboratory-based approaches for monitoring dehydration status (e.g., serum chemistry panels), while accurate, require specialized equipment and can be difficult to administer during athletic activities due to low portability [10], [14], [15]. Measuring changes in bodyweight is one of the most common means of assessing hydration status, primarily due to its simplicity and low cost [10], [15], [16]. However, in athletic settings, it is often difficult to get accurate assessments of fluid loss without nude bodyweight measurements. Clothed bodyweight measurements may be rendered inaccurate over time due to sweat captured in clothes and other parts of the body [10], [17]–[19]. Other confounders affecting bodyweight measurements include the time of day, respiratory water loss, and substrate oxidation [19], [20]. Therefore, to improve hydration assessments during exercise, there is a need to develop complementary approaches to current field-based bodyweight measurements [20]. There exists a potential opportunity to leverage the data that are already collected in athletic contexts for estimating hydration status. Many professional and collegiate athletes are equipped with wearable technologies in the field that inform training and performance (some athletic programs include Duke Basketball; University of Michigan Basketball, Soccer, and Field Hockey). Devices like the Catapult Optimeye (catapultsports.com) can continuously collect data such as heart rate and position during games and practices [21]–[23]. The specific types of data and their accessibility create a promising opportunity for developing a noninvasive, complementary approach for assessing hydration status.

In this study, we explore the potential for utilizing data from existing wearables to detect early levels of dehydration. We aim to develop an approach that performs sophisticated analyses of available data to make informed estimations of hydration status. Such an approach could be integrated into future wearables to complement existing techniques and improve overall assessments of hydration status in athletic settings. In particular, we are interested in wearable devices that measure heart rate and postural orientation over an extended period of time. Using these data, we leverage the relationship between hydration and cardiovascular responses to orthostatic changes for assessing hydration status: when an individual is dehydrated, heart rate increases significantly as part of an overall compensatory response to a decreased cardiovascular return due to orthostatic changes [24], [25].

Previous work has investigated orthostatic movements to measure exercise-induced dehydration. However, prior work only used summary statistics (e.g., peak heart rate response) [26], considered the delayed effects of exercise-induced dehydration [27], or focused on standard postural movements (e.g., supine-to-stand or sit-to-stand) [27], [28], leading to only modest diagnostic results and a limited capacity for field applications. In a study by Cheuvront et al. (2012) [26], the difference between the averaged heart response of the final 10 seconds of 3 minutes of sitting and 1 minute of standing provided fair discrimination of dehydration of 3% bodyweight loss. Owen et al. [27] aimed to estimate 2% bodyweight loss and achieved moderate accuracy by measuring the heart rate change one minute after standing from supine. Though, participants in both studies performed the post-dehydration postural tests in the day following their exercise session, which raises further uncertainty as to how their methods might translate to a field application. In contrast, in this study, we leverage the longitudinal heart rate response, monitor hydration immediately after exercise, and consider non-standard and shorter postural movements (e.g., toe-touches)—ultimately with a goal to develop an approach more suitable for field applications. We hypothesized that we could accurately detect exercise-induced dehydration using a combination of wearable technology that currently exists in the field and a varied set of postural movements, especially those more amenable to athletic environments (e.g., toe-touches).

5.2. Materials and Methods

5.2.1. Study Design and Setting

This study employed a controlled crossover design. The protocol was reviewed and approved by the University of Michigan Institutional Review Board (HUM00011582). Each participant provided written informed consent and the study was conducted in accordance with the Declaration of Helsinki.

5.2.2. Study Population

Physically active volunteers (10 male, 25.0 ± 6.6 years; 10 female, 27.8 ± 4.3 years) were recruited using the University of Michigan's online recruitment tool (https://umhealthresearch.org) from May 2019 to February 2020. Using the area under the receiver operating curve (AUROC), a sample size calculation determined that 20 samples would be sufficient for detecting hydration status with a discriminative performance of at least AUROC = 0.74 ($\alpha = 0.05$, $\beta = 0.2$) [29]. Given a randomly selected pair of positive and negative examples, the AUROC represents the probability of ranking the positive example higher than the negative example. For reference, an AUROC of 0.5 describes a model performance no better than random chance, whereas an AUROC of 1.0 represents perfect discrimination. Healthy volunteers were screened for any history of cardiovascular, gastrointestinal, or musculoskeletal pathologies prior to enrollment. Volunteers were included if they were between ages 18 and 45, had a body mass index (BMI) below 30, and were not taking blood pressure or diuretic medication. Volunteers were screened for a minimum level of fitness and weekly activity; the inclusion criteria required an estimated VO2 max rating above the 70th percentile for adults of their age and sex [30]. We estimated VO2 based on a previously validated approach that relies on self-reported BMI, Perceived Functional Ability (PFA), the Physical Activity Rating Questionnaires (PAR-Q), and sex [31].

5.2.3. Study Interventions

Participants completed two experimental sessions scheduled 1-2 weeks apart within in a laboratory setting. To ensure euhydration upon arrival, participants were instructed to drink a prescribed amount of water before their session (7 mL/kg of bodyweight 4 hours before the experiment, and 5 mL/kg of bodyweight 2 hours before the experiment) [7]. Additionally, participants were instructed to fast by avoiding solid foods 2 hours before the session. Upon arrival, participants voided, and a urine strip was used to measure urine specific gravity and verify hydration status. Nude bodyweight was then captured to the nearest 50 grams using a Seca 703 (Hamburg, Germany) scale. Participants were provided a set of loose, moisture-wicking, athletic clothing.

During the first session, no fluids were provided during exercise. Using a Monark 928e (Vansbro, Sweden) cycle ergometer, participants warmed up for 5 minutes at 70 watts and subsequently exercised in 15-minute bouts (with ~1 minute between bouts) in-side an enclosed, heated environment until they either 1) lost 2% of their initial nude bodyweight, or 2) completed 90 minutes of total exercise. Changes to bodyweight were repeatedly measured after each 15-minute bout to track the percentage of bodyweight lost due to exercise. Participants toweled off and wore clothing during weight measurements until they lost roughly 1% of bodyweight, after which nude bodyweight measurements were taken until exercise ended. During the second session, participants exercised for the same number of bouts, and losses in bodyweight were measured and replenished with a prescribed amount of commercially available sports drink (Gatorade, Chicago, IL). After drinking, participants' bodyweight was measured again to verify that participants attained their original bodyweight. The heated environment consisted of a 6.5' x 10' walk-in greenhouse with a 1500-watt commercial feedback-controlled space heater (Patron, Cheektowaga, New York) set to 86° F. Participants were asked to maintain a heart rate equivalent to 75% of their estimated maximum heart rate throughout exercise. Maximum heart rate for each participant was estimated by subtracting their age from 220 [32]

Prior to and following the exercise portion, participants exited the heated environ-ment and performed a series of five scripted postural movements (i.e., “pre-exercise” and “post-exercise” movements) (Figure 5.1). In order, they were:

- supine-to-stand test (2 minutes supine, 1 minute standing; three repetitions),
- short supine-to-stand test (1 minute supine, 1 minute standing; one repetition),
- toe-touch stretch (2 minutes stretching, 1 minute standing; two repetitions),
- short toe-touch stretch (30 seconds stretching, 30 seconds standing; three repetitions)
- “tired runner” pose (bending down with hands on knees, 30 seconds stretching, 30 seconds standing; three repetitions)

The supine-to-stand test was chosen because of its prominent use as a clinical tool for grossly screening dehydration [33]. We included the canonical version of the test, as well as a variation where we reduced the amount of time participants laid in the supine position. Other postural tests (i.e., toe-touch and “tired runner” pose) were included as they represented postures that are expected to be seen in an athletic setting.

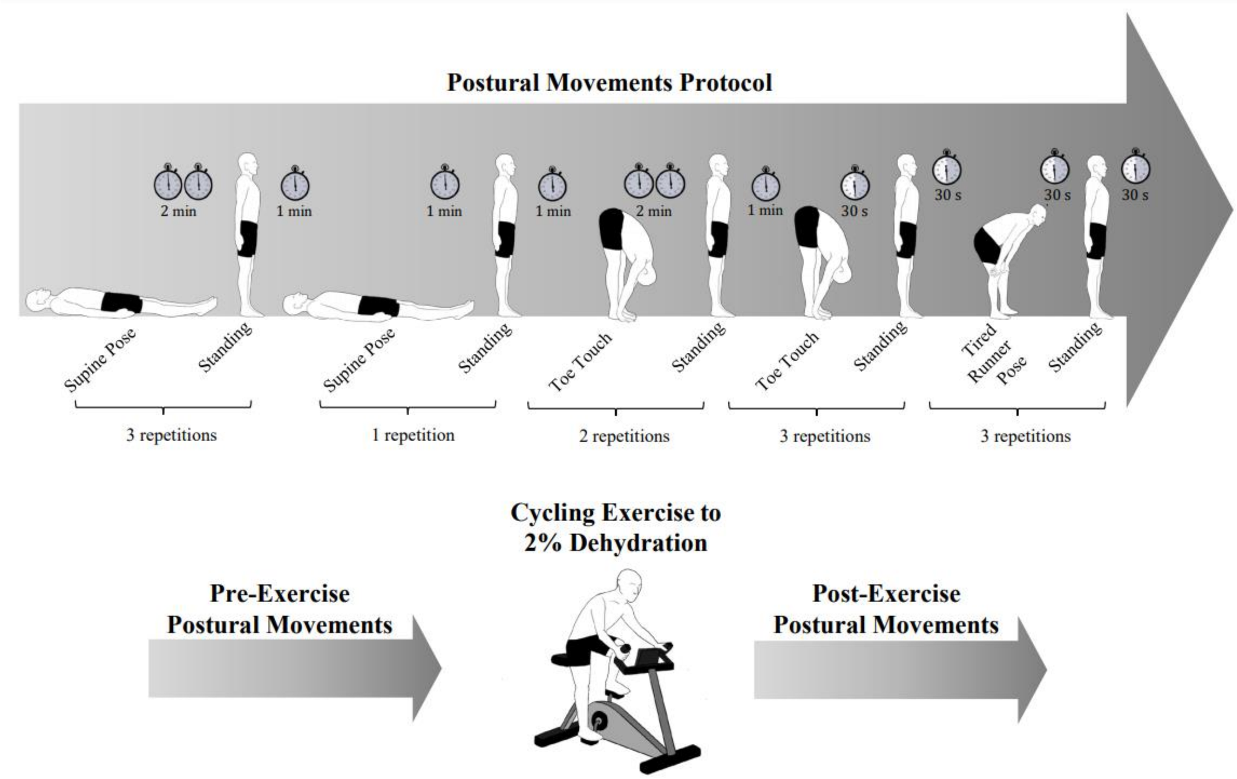

Figure 5.1: Scripted postural movements. Overall, 11 postural movements were performed before, and after exercise (2% dehydration) during the dehydrated session with a varying number of repetitions. For the hydrated sessions, participants performed the postural movements following the same amount of exercise that was needed to lose 2% bodyweight during the dehydrated sessions. The timing of the full postural movement sequence and the number of repetitions are shown in the top panel. The bottom panel shows the timing of the postural movements relative to the exercise component of the protocol. After transitioning to a standing position and completing a repetition, participants sat for 1 minute.

Between repetitions, participants sat on a chair for 1 minute to allow their heart rate to return to the level prior to the postural movement. Afterwards, participants stood up, returned to the center of the lab, and remained in the initial standing position for a few seconds before performing the next postural test. Participants completed the series of scripted postural movements in approximately 40 minutes. Throughout the scripted postural movements, participants were instrumented with a chest strap heart rate monitor (Polar H10) to monitor heart rate and a wearable inertial measurement unit (Catapult OptimEye S5) to measure postural orientation at 100 Hz.

5.2.4. Data Processing

We framed the hydration estimation task as a binary classification problem, where an accurate model would map the heart rate response during a postural movement to an estimate of the participant's hydration status. Postural movements were labeled 'dehydrated' if they were performed after exercise during the first session (no fluids). All other postural movements were labeled "euhydrated" given that they were performed either before exercise, or after an exercise session with fluid replenishment. To develop our model, we focused on the relative change in heart rate evoked by the transitions to standing during the postural movements.

To compute relative change in heart rate, we started by smoothing the heart rate signal using a moving average (4-second window), and then dividing the heart rate signal into a pre-transition response, and a post-transition response. The transitions between postural positions were automatically detected based on the velocity of the pitch of the trunk during the postural movement. We then segmented the post-transition heart rate into three segments of equal length (e.g., divide 30 seconds of standing into three 10-second segments). As seen in Figure 5.2, the features used in our model were based on the difference between the average heart rate within each post-transition segment and the average pre-transition heart rate (i.e., average heart rate during 10 seconds prior to transition). This scheme effectively adjusted for inter-individual variances in resting heart rate and captured orthostatic effects rather than effects of exercise and recovery.

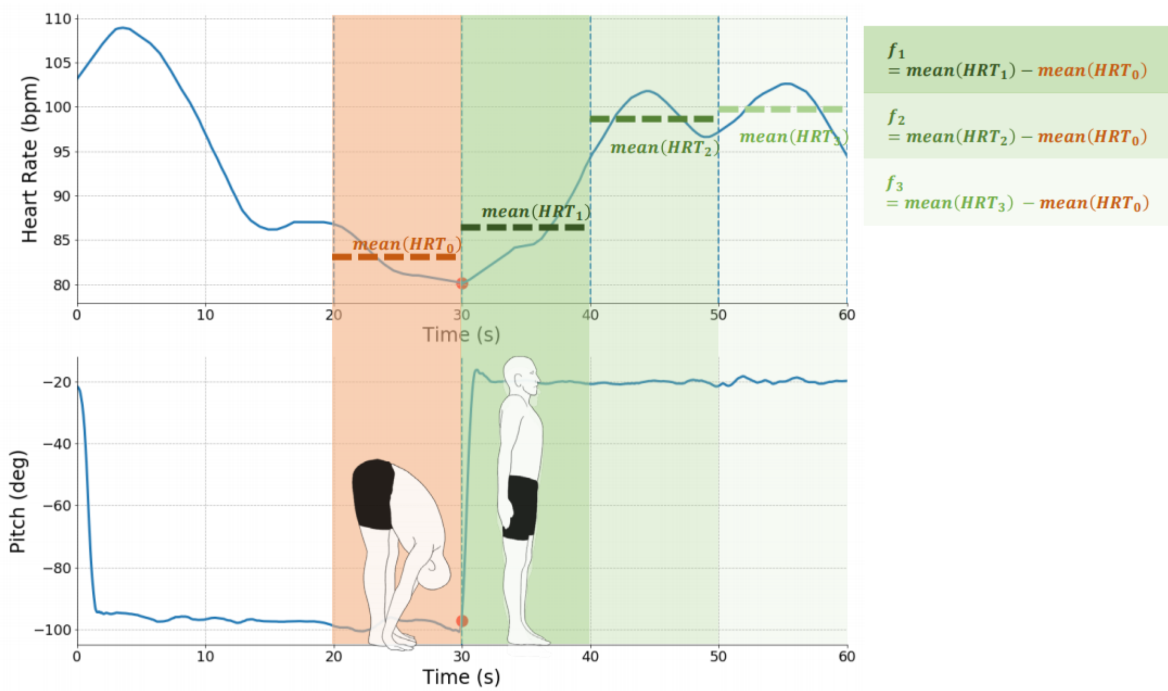

Figure 5.2: Feature extraction from a single postural movement. The differences between the mean heart rate in each segment and the mean pre-transition heart rate focus on the heart rate response to the transition in the postural movement. By subtracting the mean heart rate before the transition occurs, we removed the magnitude of the heart rate and focused on the response to the postural movement.

5.2.5. Model Training and Validation Scheme

To train and evaluate a model for assessing dehydration status based on extracted features, we iteratively split the data into training and testing sets. In each iteration, we re-served one participant's postural movements for the test set, and the postural movements of all other participants were used to train the model. Compared to a random split, this approach estimates how the model will generalize to new participants. As postural movements that were labeled ‘dehydrated’ only occurred after bouts of exercise, we focused our evaluation on post-exercise postural movements to ensure that the model was learning the effect of dehydration rather than exercise.

To construct our model, we used L2 regularized logistic regression to learn a mapping from our computed features of heart rate to estimate hydration. We selected model hyperparameters based on the training data by maximizing the leave-one-out cross-validation AUROC [34].

Applied to each held-out participant, we evaluated the model's ability to distinguish between hydrated and dehydrated examples based on the AUROC. We reported the AUROC averaged across participants, along with the interquartile range (IQR). To qualitatively evaluate the AUROC of our model, we referred to the descriptors outlined by Obuchowski et al. [35]. In addition to evaluating on all post-exercise postural movements, we evaluated on subsets of postural movements (e.g., toe touches only). Finally, we explored the importance of each feature by calculating Shapley values with respect to all post-exercise postural movements, using AUROC as the value function [36]. We reported the average and standard deviation of the Shapley values across all held-out participants. A larger Shapley value indicates a more important the feature. To visualize these different segments, we computed and illustrated the heart rate responses for the post-exercise toe-touches between the hydrated and dehydrated sessions. We averaged the heart rate measurements at each sample (every 0.01 seconds) across all participants. Furthermore, we subtracted the average heart rate measured at the time of transition from the dehydrated and hydrated signal. Consequently, the signals were aligned at the time of transition, which facilitated fair comparisons between the post-transition responses. We specifically chose to present the post-exercise toe-touches to show the potential of shorter postural movements.

5.3. Results

5.3.1. Participant Characteristics

Participants lost 2.0% ± 0.3% of their bodyweight following exercise without replenishing fluids. Male participants weighed 75.4 ± 9.9 kg before exercise and 73.9 ± 9.7 kg after exercise (dehydrated sessions); female participants weighed 63.8 ± 5.5 kg before exercise and 62.5 ± 5.4 kg after exercise (dehydrated sessions). Self-reported PFA-1, PFA-2, and PAR-Q are shown in Table 5.1. Using a published regression formula [31], the average VO2 max for males and females were 53.4 ± 2.11 and 46.6 ± 3.61 $ml \cdot kg^{-1} \cdot min^{-1}$, respectively. Each subject met the 70th percentile of VO2 max for their age and sex for inclusion in the study.

Table 5.1: Characteristics for each participant. BMI = Body Mass Index, BW = Nude Bodyweight, PFA-1 = Perceived Functional Ability First Rating (assesses ability to run 1 mile), PFA-2 = Perceived Functional Ability Second Rating (assesses ability to run 3 miles), PAR-Q= Physical Activity Readiness Questionnaire, DEH = Dehydrated Session, HYD = Hydrated Session

ID	Age [yrs.]	Sex	Height [cm]	Initial BW, DEH [kg]	Body-weight Lost [%]	Initial BW, HYD [kg]	BMI [$kg \cdot m^{-2}$]	PFA [1, 2]	PAR-Q	VO2max [$ml \cdot kg^{-1} \cdot min^{-1}$]
1	23	M	182	85.60	1.52	88.50	25.8	11, 9	9	51.7
2	25	M	195	98.10	2.14	98.40	25.3	11, 10	7	51.4
3	27	F	165	66.10	1.21	65.00	23.8	11, 9	7	51.9
4	27	M	172	66.40	1.58	66.30	22.9	12, 9	7	54.1
5	23	M	182	70.45	2.20	70.60	21.7	13, 11	8	57.3
6	19	M	163	70.85	1.98	70.50	26.6	11, 10	7	50.4
7	27	F	178	65.95	2.43	65.00	20.8	11, 10	7	48.1
8	25	M	165	76.50	2.09	76.15	25.5	11, 11	9	53.4
9	42	M	195	76.80	2.28	75.75	22.1	11, 11	8	55.5
10	24	F	175	75.80	2.31	75.65	24.4	10, 8	7	42.9
11	27	F	155	59.45	1.93	59.35	25.3	9, 9	7	42.2
12	23	F	167	66.50	2.03	67.50	24.2	11, 10	7	45.3
13	28	F	170	59.00	2.03	59.35	20.8	12, 12	8	51.0
14	38	F	160	58.55	2.04	57.60	22.7	9, 7	7	42.8
15	18	M	180	75.20	2.53	75.10	24.0	11, 9	7	51.8
16	30	F	170	59.95	1.83	59.25	20.4	9, 9	7	46.2
17	26	M	178	67.35	2.15	65.95	20.8	11, 9	7	54.4
18	22	M	163	66.75	1.95	68.25	24.9	12, 11	8	53.9
19	30	F	170	67.10	2.01	67.10	23.8	11, 9	7	44.9
20	24	F	170	59.70	2.09	59.80	19.6	11, 11	8	50.5

5.3.2. Model Performance

Our algorithm achieved an average AUROC of 0.79 (IQR: 0.75, 0.91) when evaluating on post-exercise postural movements (Figure 5.3). Applied to the two-minute post-exercise supine-to-stand movements for the full population, performance improved (mean AUROC: 0.89, IQR: 0.89-1.0) (Table 5.2). Applied to the shorter 30-second toe-touches, the model achieved similarly strong discriminative performance (mean AUROC: 0.89, IQR: 0.89-1.0). In comparison, performance decreased slightly for the two-minute toe-touches (mean AUROC: 0.82, IQR: 0.81-1.0). For the one-minute supine-to-stand movement, the model achieved a mean AUROC of 0.79 (IQR: 1.0-1.0). Lastly, the 30-second "tired runner's" pose achieved the lowest discriminative performance among the individual postural movements (mean AUROC: 0.77, IQR: 0.67-1.0).

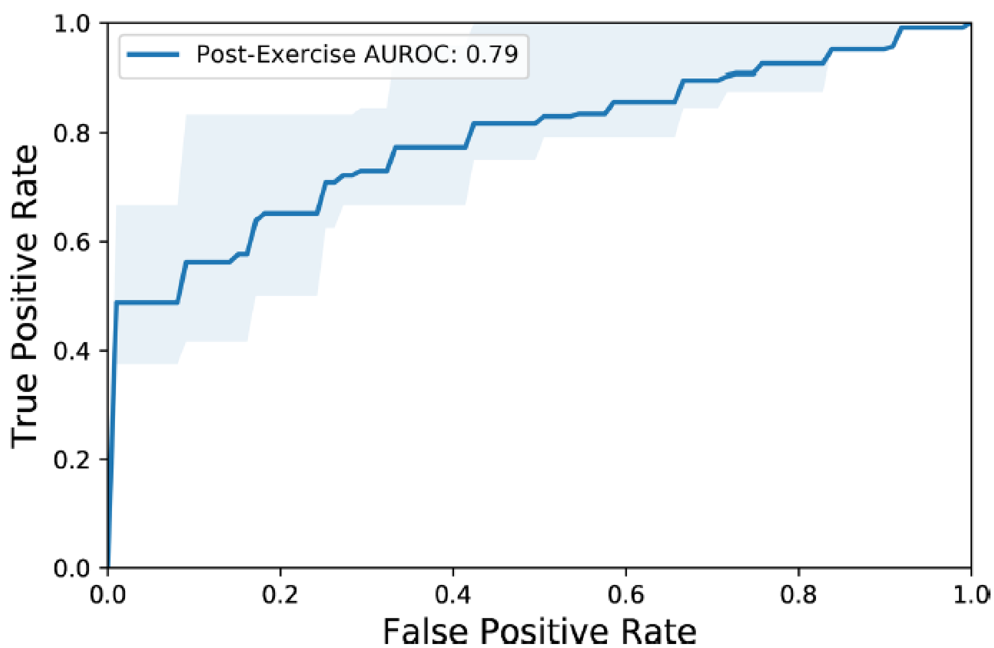

Figure 5.3: AUROC curve for the model when evaluating on post-exercise postural movements. The results were averaged across all participants as the test set. The shaded portion represents the IQR of the performance across the test participants.

Table 5.2: Distribution of classification performance when evaluating on specific postural movements post-exercise. AUROC = Area Under Receiver-Operating-Curve, IQR = Interquartile Range

Evaluated Postural Movements	**Mean AUROC (IQR)**
All	0.79 (0.75, 0.91)
2-Minute Supine-to-Stand	0.89 (0.89, 1.00)
1-Minute Supine-to-Stand	0.79 (1.00, 1.00)
2-Minute Toe-Touch	0.82 (0.81, 1.00)
30-Second Toe-Touch	0.89 (0.89, 1.00)
30-Second Runner's Pose	0.77 (0.67, 1.00)

5.3.3. Feature Importance

The Shapley values for the first, second, and third heart rate segments were 0.02 ± 0.05, 0.11 ± 0.07, and 0.15 ± 0.10, respectively. The heart rate responses during the first segment of the post-transition appeared similar in the hydrated and dehydrated sessions (Figure 5.4). The difference between the two heart rate responses was most pronounced in the final segment.

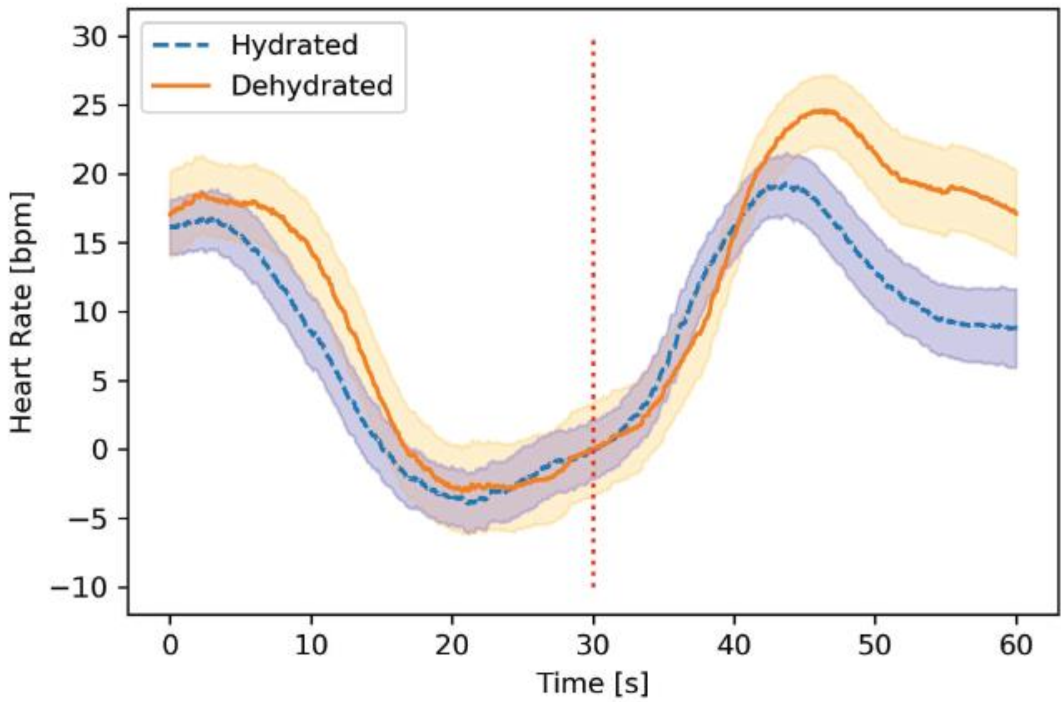

Figure 5.4: Average heart rate response to post-exercise toe-touches. The hydration session and dehydration session heart rate responses are shown, averaged across all participants and post-exercise trials. The vertical dashed line is halfway between the toe-touch and standing positions. Standard error is shown for each signal.

5.4. Discussion

Our results demonstrate that mild dehydration of at least 2% body weight loss can be detected noninvasively using readily available data from commercial wearables (i.e., heart rate and postural data), which is consistent with findings in prior lab-based studies that found orthostatic changes to be sensitive to levels of exercise-induced dehydration [26], [27]. Moreover, accurate assessment does not necessarily require the longer clinical-based supine-to-stand movement. Instead, postural movements common in athletic settings, such as shorter toe-touches, may be used to detect mild.

At a level of 2% bodyweight loss, our model achieved between fair to high average AUROC for all the postural movements. Notably, the canonical 2-minute supine-to-stand test and the 30-second toe-touches achieved the highest average AUROC (0.89). Although the 30-second “tired runner’s pose” had the lowest average AUROC (0.77, IQR: 0.67-1.00), the performance would still be considered fair [35]. The model’s performance on the shorter postural movements (i.e., toe-touches and “tired runner” pose) indicate that postural changes with movements closer to what is more commonly seen in athletic settings have the potential to be used for hydration assessments, and these postural changes are likely to be seen when individuals are maximizing their recovery between repeated bouts of activity (e.g., during games/practices) [37]. The high average performance and tight interquartile ranges across participants also demonstrated the robustness of our algorithm. In fact, the upper bound of the IQR for each postural test equaled 1.00, indicating a perfect classification for some individuals. When classifying all 24 post-exercise postural tests for a participant, our model achieved moderate performance (0.79, IQR: 0.75-0.91), demonstrating that data from wearables can be used for reliable predictions of mild dehydration.

Few studies have quantified the discriminative ability of the clinical orthostatic test, and even fewer studies have incorporated varied postural movements for diagnostic approaches [26], [27]. Previous works exploring the relationship between postural movements and the post-transition heart rate responses have achieved only modest AUROCs. At an average dehydration of 2% bodyweight loss, Owen et al. [27] reported an AUROC of 0.66 for their supine-to-stand assessments. However, their dehydration protocol account-ed for effects of exercise by assessing hydration two days after the exercise with a fluid re-striction protocol. As a result, their participants reached a steady-state whereby orthostatic changes in heart rate may not be as useful for discriminating hydration status. In comparison, we processed relative change in heart rate to address the immediate effects of exercise and obtained a higher AUROC (0.89), while also exploring different postural movements that are more commonly seen in athletic settings. Moreover, our assessment of hydration following the end of exercise (especially in heated environments) may be more valuable for early interventions of mild dehydration. At 3% bodyweight loss minimum, Cheuvront et al. [26] reported an AUROC of 0.67 using sit-to-stand movements and measurements of the absolute difference in the peak heart rate responses. Similar to the study Owen et al. [27], they assessed hydration status during the following day after exercise, which may have diminished the ability for orthostatic changes in heart rate to discriminate hydration status. Although our study assessed a lower percentage of bodyweight loss, our model still achieved a higher AUROC for different postural movements (i.e., 0.89 for the 30-second toe-touches). Our improved values of AUROC may be explained by our modified approach, which leveraged the longitudinal heart rate response to extract useful information and estimate dehydration. Furthermore, we tested immediately following exercise, which may have decreased the general variability in heart rate [38]. The authors have cited heart rate variability contributing to the insensitivity of their approach. Ultimately, it is not possible to make direct comparisons to these methods as we assessed hydration status immediately following exercise.

The heart rate response closer to the end of the postural tests influenced the model more heavily, as indicated by the Shapley values. Studies that measured the change in participant heart rate 1 minute after a supine-to-stand postural transition similarly found a significant effect of dehydration [27], [28]. Owen et al. [27] reported a change of 26 ± 12 bpm while dehydrated to 2% bodyweight loss, and 14 ± 8 bpm when hydrated. In an ultramarathon setting, Holtzhausen and Noakes [28] reported the change in heart rate 30-60s after standing from supine (17 ± 8 bpm) to be significantly greater after the race than before (7 ± 9 bpm). However, their study participants had a greater bodyweight loss percentage (4.6% ± 1.3%). The severe level of dehydration, intensity of the exercise, and environmental factors may have factored into the differences in reported values between the related studies. Overall, these studies' findings are consistent with the results of our feature importance analysis; the heart rate response closer to the end of the postural tests provided the most useful information for classifying mild dehydration of 2% bodyweight loss.

When evaluating on all postural movements, the model achieved random or worse than random performance for two participants (9 and 17). We hypothesize that these differences were due to moderate changes in baseline bodyweight between experimental sessions (Table 1). Both subjects weighed more at the beginning of their dehydrated session than their hydrated session by 1.40 kg and 1.05 kg, respectively. Given that they lost 1.75 kg and 1.45 kg after exercise, their final post-exercise weight in the dehydrated sessions would have been relatively close to their baseline weight during their hydrated sessions, which may have led to similar orthostatic responses. Although we restricted fluid and food intake prior to the experiment, daily mass variability may have factored into the differences in baseline bodyweight. Our study did not account for participants' daily mass variability, which may have introduced some uncertainty to bodyweight measurements as a proxy for hydration status. However, changes in daily mass have been estimated to be less than 1% in active men [39].

Lab-based detection methods that typically involve samples of bodily fluid, while accurate, are expensive and may be difficult to collect continuously in a fast-paced athletic context [10], [14], [15], [20]. In contrast, clothed bodyweight measurements provide one of the quickest and most accessible assessments of hydration with minimal equipment in the field (e.g., a scale situated on the sidelines). However, if nude bodyweight measurements are not feasible, excess sweat in the clothing and on the athlete should be minimized to obtain the most accurate and precise measurements [40]. In our lab-based study, we used nude bodyweight measurements throughout a cycling exercise to train a model and make predictions of dehydration. As such, our model learned how to weigh features based on accurate measurements of nude bodyweight, which improves the reliability of the model predictions. Therefore, our method may potentially complement clothed body-weight measurements by leveraging increasingly available data from wearable sensors. As recommended by Barley et al. [20], combining our approach and gross bodyweight measurements may therefore lead to an increase in overall reliability. In a practical setting, our method may inform athletes when they are approaching mild levels of dehydration and enable early interventions, such as taking additional informed measurements of bodyweight, before potentially reaching severe levels of dehydration.

Our study is not without limitations. First, cycling in a heated environment was used to dehydrate participants; it is unclear how our results might generalize to other methods of dehydration, especially passive approaches (e.g., heat exposure) [41]–[43]. Second, we relied on bodyweight to measure the level of dehydration. While blood sample analysis may be more accurate it is more difficult to obtain. Third, we designed the study such that the dehydrated session preceded the hydrated session in the case that, if participants dropped out after the first session, we would still have relevant data on dehydrated individuals. As a result, this could have caused habituation to the protocol, particularly for individuals with minimal cycling experience. However, we only included participants above an estimated level of fitness with no history of cardiovascular disease (though fit-ness was not directly measured). Fourth, postural movements were performed in the same order each time. Thus, heart rate following exercise may have recovered substantially during the later postural movements (e.g., “tired runner’s pose”). Additionally, participants sat between repetitions, which may have affected heart rate responses due to the dynamic shift in body fluids. Finally, fluids were replenished periodically throughout the experiment as well, meaning that fluids administered near the end of the exercise may not have been fully absorbed by the time participants performed the postural tests.

We note that some of these limitations are likely present, and have been present in the past, for many lab-based dehydration studies. For example, in lab-based settings, ecologically valid exercise conditions can be difficult to replicate, which raises some uncertainty when studying the effect of hydration on physical performance [9], [44]. Despite these limitations, our approach provides a meaningful step towards potentially automating non-invasive measurements of dehydration, which may eventually improve hydration practices and health monitoring. In addition to reducing the risk of heat-related injuries, prop-er hydration may also maintain physical performance during activity [4], [45]–[47]. In its current form, our method may not be directly applicable to natural field settings. However, this work illustrates the efficacy of using increasingly readily available data from wearable sensors for detecting hydration status, while also using shorter and more diverse postural movements than previously considered.

5.5. Conclusion

Overall, our method for detecting mild dehydration (2% bodyweight loss) leverages increasingly common wearable sensors and varied postural movements. Using heart rate and postural orientation data, a reliable and accurate prediction could be made after 30 seconds of a postural transition. Moreover, the approach required minimal, noninvasive, commonly used wearable sensors. In future implementations, such an approach would complement existing bodyweight measurements, and potentially allow earlier interventions of dehydration. Future work should incorporate more ecological exercise conditions to validate the efficacy of such an approach in natural field settings.

5.6. References

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Chapter 6 Discussion

6.1. Dissertation Overview

This dissertation explored the potential for translating physical and physiological wearable-based signals for secondary prevention of health conditions beyond a clinical setting. Chapters 2 through 5 focused on developing models of vehicular motion sickness and mild dehydration, such that measurements from wearable sensors (i.e., standing balance, heart rate) could be leveraged to estimate the progression and onset of a health condition. Chapters 2 and 3 evaluated post-drive postural sway as a function of in-vehicle task performance and continuous vehicular motion on closed test tracks and realistic driving conditions, respectively. In Chapter 4, motion sickness ratings were correlated with pre-drive balance metrics of postural sway to develop a predictive model. Chapter 5 illustrated the feasibility of existing wearable sensors for developing novel methods of assessing dehydration. The following sections of this chapter will contextualize these findings with respect to prior work, and further discuss the next steps in translating these relationships for field applications using wearable technology.

6.2. Scalability and fidelity of simulation-based findings to realistic environments

In this dissertation, the methodology in Chapter 3 was an iteration of the methodology described in Chapter 2, adapting the experimental protocol from a closed test track to a realistic on-road driving environment. The on-road drive conducted in Chapter 3 operated at the highest level of physical and functional fidelity. The sample sizes for both studies (N = 50, 106 participants, respectively) were larger in comparison to previous driving-related studies, which suggests that the data set collected and analyzed in this dissertation were more representative of normative in-vehicle behavior. To further highlight the fidelity of the data set, the motion sickness ratings were self-reported on a continuous scale with anchors at 0 and 10. Although the ratings themselves were subjective, excluding descriptive levels of motion sickness allowed more salient measurements of motion sickness. In comparison, the scripted route on the closed test track in Chapter 2 lacked certain contextual factors (e.g., other actors on the road), limiting its functional fidelity.

Nevertheless, the scripted routes in Chapter 2 were designed to reflect a scaled version of the Urban on-road route in terms of the frequency of driving events. As such, with similar in-vehicle motion exposures, the changes in post-drive standing balance performance were expected to be relatively consistent across studies. However, the comparative analysis found no substantial differences between the normalized balance metrics. At first glance, the similarities suggest that there is absolute validity in the balance metrics between the closed test track and realistic on-road driving. Moreover, normalized balance metrics were greater for the *Task* condition than for the *No-Task* condition in both studies, suggesting relative validity of these balance metrics.

The effect of the *Task* condition was significant across both studies; specifically, changes to balance metrics were largest for the *Task* condition. Performing an in-vehicle task likely introduced a provocative level of sensory conflict between the moving vehicle and the view of the handheld device. Furthermore, participants were instructed to hold the device in their lap, which implies that participants held their head downward to complete the task. Studies in other types of motion exposures have shown that head position can influence motion sickness incidence and severity [1]–[4]. In a study by Baumgarten et al. (1980) [5], participants that tilted their head forward during rollercoaster flight always reported motion sickness symptoms earlier than participants that sat in an upright position. In contrast, in a study of rally car co-drivers, there were fewer occurrences of motion sickness among passengers that frequently shifted their view between the road and their notes (15.3%) in comparison to passengers that read a book in the car (25.9%) [4]. However, passengers' notes or books may not have been strictly placed in their lap during the experiment. Overall, in addition to the sensory conflict introduced by the handheld task, the position of the head may have had an integral, additive role in causing motion sickness incidence during drive, which subsequently affected post-drive standing balance.

However, the effect of the *Task* condition was less prevalent among the on-road balance metrics compared to the closed test track balance metrics. In the on-road driving study, for the feet together/eyes closed/foam support exercise, only normalized M/L RMS sway differed as a function of the *Task* condition. In contrast, for the same balance exercise, the *Task* condition was significant for M/L RMS sway, M/L RMS sway velocity, and path length. The inconsistencies in these findings may potentially be a result of the design of the in-vehicle exposure. Although the frequency of driving events was designed to be consistent between the two studies, the scripted route on the closed test track consisted of a shorter exposure (20 minutes maximum) in comparison to the on-road driving exposures (~55 minutes on average). Consequently, the amount and distribution of recovery time between the different driving maneuvers on the closed test track may have been much shorter, causing relatively larger changes in post-drive postural sway.

Nevertheless, comparisons for validity across Chapters 2 and 3 have some limitations. Studies on driving validity typically consist of repeated measurements on a sample population, where a single participant completes tests in both a simulator and an on-road environment. This was not the case in Chapters 2 and 3, as sample populations did not overlap. Still, there were no meaningful differences in the demographics between the study cohorts. Ultimately, there was consistency between the findings, which could imply that, when scaled properly, tests on a closed test track might offer meaningful approximations of the outcomes of in-vehicle exposures to on-road driving. Future work should directly compare the post-drive standing balance performance of passengers following an in-vehicle exposure during closed test track and on-road driving for individuals and aim to the quantify the role of head position on motion sickness and post-drive changes in standing balance.

6.3 Risk of falling due to in-vehicle exposures and motion sickness

When considering the populations that can benefit from increased access to transportation, the magnitude of the increases in standing balance performance may increase the risk of falling for certain segments of the population (e.g., older adults) [6]–[8]. Normalized changes in standing balance metrics from to pre- to post-drive were significantly greater across every balance exercise. Furthermore, for the *Task* condition, nearly every balance metric increased significantly post-drive. To facilitate comparisons to prior work, additional metrics needed to be computed. Namely, the RMS of the trunk's acceleration was computed given that it is commonly reported for comparing postural sway between non-fallers and fallers [9]–[13]. As described in Chapter 3, the relative changes in RMS acceleration exceeded what has been reported in prior studies of fallers. For the on-road study, RMS acceleration increased by 14.1% (*No-Task*) and 42.4% (*Task*) on average for older adults, whereas previous studies have observed relative differences of ~20.0% between non-fallers and fallers. Consequently, the changes in balance metrics suggest an increased level of fall risk following continuous in-vehicle exposures.

The effect of motion sickness must also be considered when discussing the risk of falling, as motion sickness incidence and susceptibility have been correlated with decreased postural stability across various virtual and motion-based platforms [14]–[18]. The studies in this dissertation were among the first to identify a positive correlation between motion sickness and increased postural sway following an on-road drive. However, self-reported ratings of motion sickness were lower among older adults [19], which has been observed in previous studies of passenger behavior [20]. Less motion sickness among older adults suggests that the increased risk of falling due to motion sickness may be minimal, which further implies that the main contributions to the increased postural sway among older adults could be due to sensory adaptations to in-vehicle motion. In short, sensory adaptation describes the change in how sensory information (i.e., from the visual, vestibular, somatosensory systems) is regulated for sensing the body's orientation in space due to changes in environmental conditions and tasks. Sensory adaptation has been observed to contribute to maintaining postural stability in different motion contexts [21]. Previous studies have investigated similar sensory adaptations in other motion modalities [3], [22]. In contrast, younger adults in the on-road driving studies reported larger ratings of motion sickness on average. Furthermore, normalized changes in RMS acceleration were comparable between younger and older adults, suggesting uncharacteristically large increases in postural sway for younger adults—perhaps due to potential increased susceptibility to motion sickness [23].

Additional work is needed to characterize the effects of worsened post-drive balance metrics and their implications on increased fall risk. Across the studies, post-drive balance metrics showed an increase in postural sway following a drive. In the closed test track study described in Chapter 2, nearly every balance metric for the common balance exercise (feet together, eyes closed, foam support) worsened following a drive, for both *Task* conditions. However, changes were especially large among balance metrics associated with sway velocity, which has been shown to be correlated with those with a history of falling [7]. Similarly, in Chapter 3, all normalized balance metrics (especially sway velocity) for the common balance exercise were significantly worse following a drive in an on-road environment. In Chapter 4, motion sickness response was significantly correlated with normalized M/L RMS sway velocity, which further emphasizes the effect of in-vehicle exposures on sway velocity. While postural sway position generally increased among participants, larger increases in sway velocity could be representative of a modified postural control strategy among passengers, whereby quicker postural adjustments were made to compensate for larger deviations from a stable posture. Passengers' sense of posture may have been challenged by the motion during the drive, and some may have been potentially minimizing in-vehicle postural sway as a countermeasure for motion sickness [24]–[26]. This dynamic change in environment may have caused sensory adaptations to the specific postural demands of in-vehicle motion. Upon egress, the sensory model used for maintaining seated postural stability in an in-vehicle context was likely retained in the short-term. When tasked with maintaining standing balance, this short-term adaptation likely hindered the shift in postural control strategy, producing larger increases in postural sway [3], [27], [28]. Therefore, when assessing standing balance performance immediately following egress from the vehicle, participants exhibited increased postural sway, potentially as a result of the subtle changes in postural control strategies.

The specific set of balance metrics that worsened following a drive help illustrate how individuals were maintaining stability to prevent falling during the balance exercises. The RMS of sway position and sway velocity captured the magnitude of trunk tilt and the speed of the postural adjustments to maintain stability. Elliptical area was most directly correlated with the RMS of the sway position, as larger deviations will increase the variance of the sway signals, which led to larger values of elliptical area. In contrast, path length captures the distance between consecutive samples of sway position at a fixed sample rate; therefore, larger values of RMS sway velocity will be associated with larger values of path length due to larger distances between samples. In the study described in Chapter 2, for the feet tandem, eyes open, firm support exercise, path length and sway velocity increased while sway position and elliptical area did not. In this scenario, participants may have been performing quicker postural adjustments within a similar area of sway, potentially in response to sensory adaptations following the drive. In the study described in Chapter 3, for the *Task* condition, nearly every normalized balance metric worsened significantly following the drive. Physically, participants exhibited an overall decrease in postural stability, as both sway position and velocity increased; participants experienced larger deviations from the vertical and had to make much quicker adjustments to maintain stability. Increased elliptical area and path length also indicated that there were substantial changes in sway regardless of the direction [29].

Overall, future work will need to perform direct observations of older adults with a known history of falling. In this dissertation, it is unknown if some older adult participants were already highly susceptible to falling, or if adults had no prior history of falling at all. Analyses of falls in this dissertation were only based on normative, average changes in standing balance performance among adults aged above 60. The results were intended to contextualize the potential risks associated with mobility solutions among specific populations.

6.4. Comparisons to other field-based, data-driven hydration assessment studies and methods

In Chapter 5 of this dissertation, a noninvasive, data-driven method for assessing dehydration was developed to complement current methods and inform the secondary prevention of severe dehydration. A predictive model achieved high diagnostic accuracy by leveraging data on posture and heart rate during various orthostatic movements. Below, the data-driven model approach developed in this dissertation is compared to other existing methods and approaches. Additionally, the appropriateness of the method for field-based assessments is explored.

Previous studies have used different combinations of sensor data and data-driven techniques. Some studies collected clinical data on participants dehydrated from medical conditions [30], [31], while other studies leveraged different types of sensor data (e.g., electrocardiograms, galvanic skin response) [32]–[34]. Among these studies, only one implemented an exercise protocol [33], and the highest accuracies (> 91%) were achieved using data about electrodermal activity [32], [34]. Although the reported accuracies were impressive, their models were trained on a different type of dehydration (i.e., fluid restriction), so it is unclear the extent to which the models would directly transfer to field-based assessments of exercise-induced dehydration. Moreover, some studies used specialized sensors that may not be suitable during intense physical activity or may be sensitive to body position [32]; furthermore, the design of wearable sensor systems themselves should not interfere with the intended task

[35]. In comparison, the method developed in Chapter 5 may be more amenable to field-based assessments given that off-the-shelf wearable sensors were used to investigate dehydration from aerobic cycling exercise.

Field-based assessments of hydration status embody a few key characteristics: portability, ease-of-use, and reliability. As such, athletic programs have relied on periodic measurements of losses in bodyweight and changes in urinalysis readings to assess dehydration [36]. Although they may be noninvasive and quick to administer, these methods use discrete measurements to estimate an individual's hydration status, which may interrupt the flow of activity. The method developed in this dissertation has the potential to address this limitation. Using commonly available wearable sensors, the method in this dissertation could eventually be adapted for real-time feedback, which would further improve the secondary prevention of severe dehydration. Considering the implementation, an individual's postural orientation and heart rate data could be harnessed using existing wearable devices (e.g., Catapult OptimEye S5). Following certain automatically-detected postural transitions, the trained model could transform the data to estimate hydration status. Given that 30-second toe-touches were feasible for accurate hydration assessments of 2% bodyweight loss (0.89 AUC), it is plausible that other naturalistic postural movements (during play, stretching, or downtime) could achieve similar performance. At worst, the recommendations of the model would complement other assessment methods and generally estimate the probability of mild dehydration. A future study with ecologically relevant, on-field data would inform how to improve the signal-to-noise ratio, and further develop a noninvasive, real-time feedback system.

6.5. Extending known physiological relationships with data-driven approaches

In this dissertation, wearable sensors (i.e., IMUs, heart rate monitors) served as a powerful, flexible platform for collecting user data. These data contributed to developing empirical models based on known physiological relationships that could be used to support health monitoring for secondary prevention strategies. In some cases, the reliability and application of current prevention methods were improved by leveraging modern data-driven approaches. For example, extensive analysis on the orthostatic response to postural movements demonstrated that other postural movements could feasibly be used for classifying hydration status. In addition to the traditional supine-to-stand test (which reasonably achieved the highest diagnostic performance), toe-touches or even “tired” runner’s poses showed comparable performance when supported by an analytical, data-driven approach. In Chapters 2 and 3, wearable sensors enabled wireless data collections of postural sway, allowing investigations of standing balance performance and motion sickness in an ecologically relevant on-road driving environment. In Chapter 4, a predictive model was trained on data pertaining to vehicular motion sickness, standing balance performance, drive conditions (i.e., route and *Task*), and participant demographics. Although the predictive performance could be improved with additional data, the results based on the balance metrics alone was promising.

6.6. Potential for these wearable sensors in translating these signals for secondary prevention

Wearable devices act as an unobtrusive tool that can collect various signals, such as heart rate, body temperature, and posture. This dissertation explored different relationships among wearable sensor-based signals that were measured in a non-clinical setting, laboratory-based settings. The chapters in this dissertation related changes across standing balance, motion sickness, or dehydration with inertial and physiological measurements (e.g., trunk acceleration and heart rate). The following sections outline feasible ways these relationships could be translated into applications for secondary prevention with current wearable systems, as well as potential challenges.

6.6.1. Capturing standing balance and postural sway with wearable sensors

Control of balance plays an important role in the coordination of body movements. Maintaining balance is critical for reducing the risk of fall injury; otherwise, the resulting injury could lead to rippling, detrimental effects such as lower quality of life, increased healthcare costs, and increased risk of subsequent—potentially fatal—falls [37], [38]. Fall injuries are especially prevalent among older adults and individuals with neurological disorders like Parkinson's disease [39], [40]. To reduce the risk of falling and life-altering injuries, it is important for adults to be cognizant of their ability to maintain balance throughout activities of their daily living, especially during ambulation and transportation [41].

In this dissertation, Chapters 2 and 3 focused on evaluating standing balance specifically prior to and following an on-road driving motion exposure. Given the prevalence of urban, personal vehicular transportation, the scenarios and the findings presented in these studies have direct applicability to activities of daily living. For example, postural sway velocity and path length were found to increase significantly (across nearly all balance exercises) following an on-road drive, regardless of whether or not an on-road drive took place on a closed test track or an urban environment. Based on these findings, it is recommended that standing balance be further evaluated after egress of a vehicle following a continuous drive (e.g., in an automated vehicle), especially among older adults. Outside of an experimental setting, wearable devices may serve as a potential platform for conveniently measuring standing balance performance given their increasing popularity and accessibility.

As explained in Chapter 1, wearables commonly implement inertial measurements units. In Chapters 2 and 3, inertial sensors that are, by design, embedded in a personal device were used to assess standing balance [42], exemplifying that existing technology can be adapted for different applications. Generally, with appropriate software, wearables devices could evaluate different metrics of postural sway during specific balance exercises [43], [44]. As an example of a use case, a post-drive balance assessment with a wearable device could deliver key information to adults about their ability to maintain balance, such that they could reduce the risk of fall injuries. Moreover, pre-drive balance assessments with wearable devices could provide assessments of a user's susceptibility to motion sickness [45]. Beyond isolated, standing balance exercises, wearable devices could also continuously monitor postural sway, which is valuable given that previous studies have similarly observed changes in postural sway during extended exposures to motion [46]–[49]. Given these use cases, it is straightforward for future wearable sensors to capture standing balance performance as an integrated feature of a ubiquitous product (e.g., smart watch, smartphone applications). Wearable devices for monitoring postural sway are already commonly used among field, clinical, and laboratory-based studies [50], [51]. Many studies have further explored the feasibility of remote in-home monitoring using a plethora of wearable sensors [52], [53]. In a recent study, a compact wireless inertial sensor was mounted superior to the right ear using either a headband or a two-sided adhesive. These wearable inertial sensors captured different metrics of postural sway, with sway power being highly indicative of concussions in athletes [51]. The study's authors envision the wearable sensors to be useful for making decisions about an athlete's ability to continue an activity following a concussion. Knowing this, a similar approach could be adapted for on-road driving. As an example of an embodiment, a smart watch could measure postural sway, compute balance metrics, compile the metrics into a model, and finally indicate the potential risk associated with the changes in balance control, or in comparison to normative values within the user's cohort. The user can then make informed decisions and take precautionary measures to reduce the risk of falling.

6.6.2. Improvements in motion sickness estimation and detection

As transportation becomes more accessible with automated vehicles and mobility solutions, motion sickness is expected to become an increasingly prevalent problem for passengers [19], [54], [55], which can detract from the perceived benefits of automated vehicles (e.g., increased task productivity, leisure, accessibility to transportation and independence). Previous studies have already shown vehicle passengers to be more susceptible to vehicular motion sickness in comparison to drivers [19], [56], [57], and to experience an increased severity of nausea and other associated symptoms. Changes in balance performance have been reported as being correlated with motion sickness as well [46], [47], [58], [59]. Chapters 2 and 3 focused on the specific changes to post-drive standing balance performance and the relationship with vehicular motion sickness and task performance. The findings showed that passenger behavior under realistic driving conditions led to increased motion sickness and decreased post-drive balance performance, which could ultimately increase the risk of falling and injury among susceptible populations. Therefore, it is important to discuss how wearables can support secondary prevention of motion sickness, thereby reducing the detrimental effects of motion sickness on standing balance, task performance, and other activities in daily living.

Wearable devices can leverage physiological and physical signals for various informative health applications, including motion sickness. Quantifying motion sickness would be useful given that motion sickness ratings can be highly subjective and unrepresentative of the severity of motion sickness symptoms [19]. Although subjective motion sickness ratings may be useful for directly assessing symptom profile and severity, wearable devices might be able to further estimate the development of motion sickness and determine when severer symptoms might occur. However, limited work exists on measuring and addressing motion sickness with wearable devices. On the commercial market, there are only a few wearable products available, such as the ReliefBand® (reliefband.com), that attempt to reduce the occurrence of nausea and prevent motion sickness. In brief, users are encouraged to activate the device once they are aware of their symptoms, or even as a preventative measure. Based on the prevention framework developed in Chapter 1, the wearable could be classified as either primary or secondary intervention because the goal is to prevent the manifestation and onset of symptoms, or reduce the severity of symptoms once they appear.

Among the published academic literature, very few studies have evaluated sensor-based signals from wearable devices for measuring motion sickness to inform prevention [60], [61]. In particular, the pilot study by Liu et al. (2015) analyzed a set of physiological signals that were collected using wearable devices (i.e., blood pressure, heart rate). Using a fixed-base virtual driving simulator, the authors compared statistical features of each physiological signal before and after the onset of visually induced motion sickness (VIMS), finding that a decreased correlation between heart rate and blood pressure may be indicative of a state of VIMS. The authors acknowledged that their analysis did not necessarily capture the onset of VIMS, and only compared differences in physiological sensor-based signals between non-VIMS and VIMS conditions. Thus, their results would be more appropriate for secondary prevention, in which symptoms have already appeared. Nevertheless, these studies illustrate the potential of combining multiple wearable sensors to capture and estimate motion sickness.

To that end, an ensemble of wearable sensors, models, and algorithms could potentially form a reliable system for quantitatively estimating the onset and severity of motion sickness throughout daily living. Given the findings of Chapter 3, assessments of balance performance could be a potential contributor to this proposed ensemble estimator of motion sickness. The study in Chapter 4 found a significant relationship between maximum motion sickness rating and specific balance metrics (i.e., RMS sway velocity and path length). Previous studies in motion sickness and standing balance have found increased postural sway during quiet standing to be a precursor to motion sickness symptoms [14], [58], [62]. To translate these findings, wearable devices could monitor postural sway, compute balance metrics, and feed a parameter into a larger system that could weigh the recommendation and make an improved estimate of a user's state of motion sickness. In the field, users could perform prescriptive balance screenings to estimate potential onset of motion sickness. Following a drive, an analysis of postural sway could provide a complementary measure alongside other motion sickness screening tools. However, during the onset of motion sickness, it might be infeasible to halt all activity to perform a balance assessment. Instead, another approach might consist of continuous monitoring of posture, as discussed in the previous section. A further improvement could be using an analysis of postural sway during dynamic gait and correlating the changes in different metrics with motion sickness. The relationship between dynamic balance and motion sickness requires additional study though, as correlations between standing balance and dynamic balance have not been strong [63]. As such, more work is needed to determine what types of balance assessments and metrics would be best suited for contributing to estimations of motion sickness.

6.6.3. Data-driven approaches to dehydration assessments with wearable devices

Dehydration plays an important role in reducing the risk of heat-related illness [64]–[66], especially among athletic individuals. To prevent severe levels of dehydration, individuals should engage in secondary prevention by monitoring their hydration status and rehydrating accordingly. However, current approaches can be limited by their reliability and/or access to equipment and technical expertise [36], [67]. For instance, salivary markers of hydration can be severely impacted by the ingestion of fluids [68]. In another case, invasive samples of blood can require expensive laboratory equipment and technical expertise. In field applications (e.g., games, practices), wearable devices can provide many opportunities for increasing the prevalence and accuracy of hydration assessments. In the case of the model developed in Chapter 5, postural movements detected by an algorithm could trigger the wearable device to analyze subsequent changes in orthostatic vital signs. A future implementation of the model would then accurately classify dehydration at a level of 2% based on the changes over a set amount of time. The predicted outcome would enable users to make more informed decisions on replenishing fluids and prevent excessive dehydration that might affect their health and performance.

Given the myriad of assessment methods, wearable devices can leverage different physiological principles to estimate hydration status. For example, some devices measure skin conductance at the wrist and are designed to be a long-term solution for monitoring hydration [69]; others may consist of a disposable adhesive patches that capture sweat rate [70]–[72]. In Chapter 5, a plausible method for noninvasive, semi-continuous monitoring of hydration status based on orthostatic measurements was developed using a combination of wearable devices in a laboratory setting. Using a multimodal, sensor-based approach, signals from a wearable heart rate monitor and an inertial measurement unit were extracted to train an accurate predictive model of 2% dehydration, achieving an average 0.79 AUC on the test sets. Prior laboratory-based studies have used similar orthostatic measurements to detect hydration status, but have reported lower discriminative performance [73], [74]. However, there are key differences between the study conducted in Chapter 5 and prior work on orthostatic measurements, which will be further discussed in the limitations. Overall, the model demonstrates the potential of wearable devices in a controlled setting; however, there are a few challenges to consider in order to translate the findings into a field-ready application.

A significant challenge to consider is how the laboratory-based observations translate to a field application. The overall accuracy and reliability of the predictive model may vary significantly given that the natural postural movements observed in a field setting may not induce sufficient orthostatic changes for useful predictions. Moreover, the duration of the poses may introduce noise and further distort the estimation of dehydration. Still, different types of postural movements were found to be effective for detecting dehydration, as evidenced by the performance (AUC) of the models when using a 30-second toe-touch or 30-second hands-on-knees pose. The lowest average AUC across all the different postural movements was 0.77 for the hands-on-knees pose, which is still considered to be significant given the statistical power of the study [75]. Moreover, the different types of postural movements were chosen to mimic common scenarios in the field. It is very likely that athletes would naturally perform similar movements as a form of recovery [76], or as part of a stretching routine. Future work should fit a similar model using data collected from an athletic field setting to evaluate the transferability of the findings from Chapter 5.

Hydration assessment methods also have to consider the physiological differences between different types of dehydration (i.e., hypertonic versus hypotonic), as some methods are more appropriate than others [36]. The study described in Chapter 4 investigated active dehydration through cycling exercise, where excessive sweat losses led to hypertonic dehydration. As a result, there was a decrease in the volume of blood (hypovolemia) and fluids throughout the body [77]. When making orthostatic movements, the lack of blood volume led to a compensatory cardiovascular response, demarcated by increased heart rate and blood pressure. The predictive model developed in Chapter 5 captured this relationship to make accurate estimations of hydration status. Although the data captured exercise-induced dehydration, it is anticipated that the model will perform similarly under scenarios during which individuals are passively dehydrated. For example, the cardiovascular response following dehydration due to sauna exposure has been found to be similar to the response observed in submaximal exercise [78]. Therefore, sauna-induced dehydration should result in similar orthostatic responses that can be predicted by the model. For wearable devices to be reliable in different scenarios, future work should focus on evaluating model performance for other types of dehydration and explore additional sensor-based physiological measurements, as other biomarkers may be more indicative and preferred for estimating passive dehydration [79]. A multimodal approach where multiple sensors and hydration assessments are used may be an option for increasing the overall reliability of a wearable system.

6.6.4. Populations that would benefit most from increased prevalence of wearables

The risks associated with poor control of balance, motion sickness, and dehydration are highly dependent on the user. One of the most salient examples is that falls affect older adult populations disproportionately due to age-related effects on balance ability [40]. It follows that a wearable device focused on health monitoring for secondary prevention of falls would significantly benefit older adults. Furthermore, wearable devices may be of great value for populations that experience similar losses of balance (e.g., because of vestibular disorders).

For motion sickness, wearable technologies that make progress towards estimating risk of onset would logically be useful for individuals with a known history of motion sickness incidence, as well as populations that are highly susceptible to motion sickness [23]. In the context of automated vehicles, drivers that are shifted into a passenger role may find themselves to be newly susceptible to motion sickness, contrary to their past travel experiences. In this case, wearable technologies for motion sickness would directly address these newer cases of passenger motion sickness. Generally, in an on-road driving environment, younger adults with less travel experience are more likely to experience motion sickness [20], with some studies reporting that females are more likely to be affected as well [23], [80]. Therefore, wearable applications for preventing motion sickness may be most beneficial to a younger adult population, who were found to report the highest motion sickness ratings in this dissertation. In a scenario where motion sickness does occur, increased fall-risk may be minimal as younger adults are much less likely to experience fall-related injuries [40].

Lastly, the role of dehydration in daily living typically depends on the individual's routine, environment, and occupation. Wearable technologies have been thoroughly researched for athletic and military applications due to their level of intense, physical activity [60], [81]–

[83]. In heated environments, it is especially critical to monitor hydration status to maintain physical and cognitive performance. In this dissertation, the study reported in Chapter 5 describes a new method that could complement current hydration assessment methods, and improve the overall approach to secondary prevention in many existing scenarios. Given the focus on real-time monitoring of hydration status, the method developed in this dissertation could easily be modified and adapted for both inpatient and outpatient settings. Furthermore, future work could explore other populations (e.g., less active individuals, clinical populations).

6.6.5. Leveraging commercially available devices for implementation

The translation of this dissertation's findings may be limited by the availability and prevalence of wearable sensors and devices. One strength of the studies in this dissertation is that the instrumentation for collecting sensor-based signals is highly accessible. In the case of detecting dehydration, a commercially available heart rate sensor (e.g., Polar H10) was used to collect heart rate data for developing the model. Many third-party applications and devices such as the Catapult OptimEye S5 interface with the transmitted heart rate signal through a common Bluetooth protocol. With the appropriate software, these applications can perform a transformation (e.g., filtering, computing metrics) and subsequently provide insights into the user's current hydration status.

The need for higher quality data from sensors may be dependent on the strength of the underlying relationship between model predictors and outputs. In Chapter 5, a commercially available chest strap heart rate monitor was sufficient for developing an accurate predictive model of dehydration. It is possible that aggregate metrics like the mean can sufficiently capture most of the variance between individuals' hydration statuses. Though, if a higher-grade sensor (e.g., higher sampling frequency and/or resolution) were to be used, additional features like higher-frequency components could capture dynamic signal behavior and potentially improve model performance. However, higher quality data may not necessarily lead to improved model performance. In a study by Alvarez et al. (2019) [33], an electrocardiogram was collected, sampled at 1000 Hz, to estimate the level of dehydration. Without using orthostatic movements, their best model, based on the time between RR intervals, only achieved an accuracy, precision, and recall of at most 0.68. Besides model performance, some technologies are currently limited when thinking about the design considerations for a wearable device. For example, a clinical electrocardiogram is currently infeasible for wearable applications. Similarly, when measuring postural sway, a force plate is simply not feasible for wireless data collections during daily living. Though, with advances in wearable technologies and sensors, it may be possible to make similar measurements (e.g., instrumented insoles in place of force plates). Although an IMU may not directly capture the center-of-pressure, prior work has successfully used IMUs to wirelessly assess risk of falling, detect gait abnormalities, and analyze changes to standing balance performance [9]–[11], [84], [85]. Ultimately, there is currently a tradeoff between having a higher-grade sensor (and a potentially improved model), and having a compact, inexpensive wearable system.

6.7. Implications

This dissertation illustrated specific health monitoring applications of wearable devices to support non-clinical, secondary prevention by studying 1) post-drive increases in postural sway using a mobile device, 2) the relationship between subjective ratings of vehicular motion sickness, task performance, and postural sway, and 3) noninvasive detection of mild dehydration using commonly available physiological data.

The study conducted in Chapter 2 revealed acute effects of a scripted, continuous driving exposure with task performance on passenger behavior. The study represented one of the first extensive explorations of postural sway in an on-road driving environment, and extends previous findings on postural instability in driving simulators and other motion modalities. Furthermore, the additive effects of performing a non-driving-related task imply that the magnitude of sensory conflict during the exposure may be proportional to the resulting changes to postural sway. For certain passengers, performing a task while using mobility solutions may decrease the level of comfort during transportation and, for certain segments of the passenger populations, increase the risk of injury due to falling.

In Chapter 3, the analysis of standing balance was extended to realistic on-road driving conditions, further nuancing the relationship between post-drive postural sway and in-vehicle exposures. Even in realistic driving conditions, the increase in postural sway following a drive provided additional evidence that intensive, continuous motion exposures temporarily alter standing balance ability. Similar to the findings described in Chapter 2, the relative change in post-drive postural sway varied as a function of the *Task* condition, implying that normative passenger behavior in urban transportation may be detrimental to standing balance control immediately following the drive. It is for this reason that wearable devices capable of measuring data throughout daily living are needed. Assessing postural sway during and after in-vehicle exposures could inform users about their postural instabilities, and could potentially reduce the risk of falling, and subsequently alleviate some of the effects associated with falls (i.e., medical costs, social anxiety, recurring injuries) [37], [86].

A large implication of the relationship between motion sickness and standing balance ability is that an unforeseen risk of injury may be present among different segments of passenger populations. The postural instability theory of motion sickness proposes that being in a continued state of postural instability leads to the onset of motion sickness [26]. In this dissertation, postural instability (parametrized through balance metrics of trunk sway) was found to be expressively related with high responders to motion sickness. As such, during an activity as common as personal transportation, one might expect postural instability to be both a precursor and a result of motion sickness incidence, among other effects of motion sickness (e.g., vomiting, fatigue) [87]–[90]. The predictive model of motion sickness developed in this dissertation identified which types of passengers and behaviors were most likely to contribute to motion sickness incidence. The predictive model could easily be supported by wearable devices, and users could be informed, with reasonable confidence, about their potential likelihood for experiencing motion sickness during an on-road drive. The model parameters also provide insight into specific behaviors that could be the focus of mitigation strategies (e.g., limiting amount of time in fixed head positions during task performance). More broadly, using wearable technology to develop personalized mitigation strategies would reduce the likelihood of motion sickness and promote more comfortable use of automated vehicles, mobility solutions, and personal transportation among passengers.

In Chapter 5, this dissertation demonstrated a multimodal approach using commonly available wearable sensors and machine learning to noninvasively detect mild dehydration. Data-driven, machine learning approaches were shown to be feasible for quantifying and improving upon the existing clinical orthostatic tests, such that they potentially could complement other assessment methods closer to real-time. Improvements to the predictive model (e.g., with more data, improved feature engineering, other types of algorithms) for a wearable device could increase individual awareness of dehydration, inform the user to replenish fluids, and prevent severe heat-related illnesses associated with dehydration. More specifically, in field applications, users could leverage the predictions of the model by taking additional assessments of dehydration (i.e., bodyweight measurements or urinalysis) to confirm the level of fluid loss. Furthermore, by detecting more naturalistic postural movements during physical activity, the model takes steps towards a real-time, long-term monitoring system based on simple ubiquitous wearable sensors.

Generally, when considering predictive models coupled with a wearable device, the user is given actionable recommendations based on their data. In theory, gathering data and having a human in the loop could further improve the models installed on wearable devices (online learning). Ultimately, it is up to the user to act on these recommendations to address any symptoms or potential health issues. This dissertation primarily focused on the feasibility of different wearable sensors for health monitoring applications. However, the interaction between the wearable device, the data being collected, and the decision-making of the human user remains to be explored.

6.8. Limitations

The findings presented in this dissertation only illustrate applications of different relationships that can be measured using wearable technology, rather than proposing and testing a preliminary design. As such, customized hardware could be developed to leverage the specific relationship revealed through this research to create a compact, wearable devices. In Chapters 2 and 3, assessments of balance were limited to quiet standing exercises; analysis of dynamic balance during gait could be useful for a more ecologically relevant context beyond passenger vehicular transportation. Although the relative changes in balance may have been indicative of increased risk of falling, there were no data collected that directly captured the probability of falling or retrospective/prospective falls. Because motion sickness ratings throughout the drive were indicated using a custom rating scale, it is unknown if the findings would directly map to measurements and tools used in related studies (e.g., the SSQ). However, in prior analyses of the ratings, combining participants' self-reported motion sickness susceptibility and ratings data revealed a strong correlation to similar descriptive rating scales. Still, the data on motion sickness ratings were used to classify motion sickness using pre-drive balance metrics and participant covariates. In Chapter 5, a larger sample size would be useful for capturing different levels of aerobic fitness and other participant demographics. The sample population included in the study was restricted to younger, athletic individuals without any history of cardiovascular diseases. With a machine learning approach, additional samples would lead to improved generalization of the model to various individuals. Although the model was trained to classify 2% loss of bodyweight, some participants did not actually achieve 2% bodyweight loss due to time constraints or fatigue. Moreover, the model developed in Chapter 5 was only based on data obtained through exercise-induced dehydration.

6.9. Future Work

6.9.1. Postural sway beyond quiet standing exercises

The balance metrics used for the studies in this dissertation were computed from trials that were performed prior to and following a drive. A significant body of work has examined postural instability over the course of an exposure, as opposed to before and after. As was discussed in Chapter 3, future studies should include measurements of postural sway throughout an in-vehicle exposure. Those findings would then elucidate whether or not the postural instability theory extends to physical, in-vehicle exposures during on-road driving. Given that metrics of trunk postural sway increased post-drive (and were significant with respect to the *Task* condition), it is likely that a similar trend would be observed for in-vehicle postural sway. Other studies have found that the postural sway of individuals with motion sickness increases over the length of an exposure [18], [58], [62]. It is possible then that, following an exposure, postural sway metrics might show increased postural sway compared to baseline measurements.

In addition to in-vehicle postural sway, measurements of dynamic balance should be studied as part of future work. Understanding dynamic balance following a drive would contribute to the design of a wearable device that could be used seamlessly throughout real-life, unscripted daily activities. These additional metrics of balance ability could then support the predictive model of motion sickness, and contribute to developing a prescriptive model for improved secondary prevention.

Investigating how sensory adaptation to different types of motion may have potential for further understanding the mechanisms of how on-road driving affects standing balance. A previous study has investigated sensory adaptation mechanisms following simulated driving by comparing sway metrics between different visual conditions and analyzing changes to the visual contribution to postural control [22]. Participants in that study were found to be more dependent on the visual sensory system for balance due to the mismatch between the visual and vestibular signals presented in a fixed-base driving simulator. A similar balance protocol could be performed to explore how dependencies on different sensory systems change throughout an on-road driving exposure, and potentially inform mitigation strategies.

6.9.2. Exploring different in-vehicle exposures among passengers

Throughout the studies of postural sway and motion sickness, participants only sat in the front passenger seat during the drives. Given that different seating configurations can lead to varying motion sickness responses [4], [91], [92], future studies should investigate how post-drive postural instability varies as a function of different in-vehicle passenger exposures. When considering the potential designs of automated vehicles, future studies can place participants in the back seat, or even have participants face rearward during in-vehicle exposures [93]. Moreover, it would be important to study participants' experiences in response to the motion profiles of an automated vehicle, instead of having a trained operator. Similar to the studies in this dissertation, it is likely that future studies would explore automated vehicle testing on a closed test track prior to adapting the protocol to an on-road, urban environment.

6.9.3. Additional wearable sensors for motion sickness detection and prediction

This dissertation investigated predicting motion sickness using a minimal number of wearable IMUs. However, based on the findings of related work, future work should explore additional physiological sensors in combination with wearable IMUs to determine if overall predictive performance could be improved. Some promising examples include blood pressure and heart rate monitors. Multiple metrics could be derived from each sensor to potentially improve predictive performance. With additional data and features, there is potential to re-frame the problem as a regression problem, where motion sickness ratings are estimated via other modeling techniques such as linear regression or neural networks.

Future work focused on predicting motion sickness onset should also investigate the relationships between different sensations and symptoms, as opposed to just overall subjective ratings. Current work on predicting motion sickness is limited because some studies incorporate data that has been collected after motion sickness onset. With the goal of predicting motion sickness, future work should shift towards only using data available prior to reaching a certain threshold of motion sickness.

6.9.4. On-field data collections of postural movement

This dissertation leveraged laboratory-based empirical data to build models to estimate dehydration using 20 participants (10 male, 10 female). Moving forward, a larger sample size is desirable, as more data would improve the generalization of the model to other individuals. Given that commercial wearable devices were used during data collection, future work could involve the adaptation of the laboratory-based protocol for an on-field study. Collecting kinematic postural data in real-time would be valuable for tuning the predictive model, and ultimately determine the practicality and viability of the noninvasive method. Furthermore, data should be collected in both active and passive scenarios (e.g., practices or saunas) to assess the generalizability of the model for different types of dehydration.

There may be significant challenges with mapping the laboratory-controlled, scripted postural movements with naturalistic postural changes seen in real-life scenarios and activities. In an athletic field setting, the tested postural movements may not appear as frequently as needed. Moreover, the depth of the movements may not be sufficient to elicit the orthostatic changes needed to classify hydration status. In that case, future studies should focus on analyzing data from scripted postural movements performed by athletes at specific times during a field activity, so that models can be trained using levels of hydration and exercise that are more typical of what is observed in a field setting. Such findings will be important for determining whether or not the method can function beyond scripted postural movements.

6.9.5. Developing a multi-modal estimation system of dehydration

Similar to the prediction of motion sickness, additional sensors should be explored as part of a multi-modal system for predicting dehydration. Existing methods of hydration assessment have their own limitations, whether it pertains to accuracy, reliability, and accessibility, among other criteria. As Barley et al. (2020) [94] suggested, multiple measurements are preferred for obtaining the most complete assessment of hydration status. Given the growth of wearable technologies in recent years, many other additional methods can be implemented (or already exist) as part of a wearable device as well. For example, certain wearable systems perform chemical sweat analysis while being completely housed in a watch worn on the wrist [95]. Therefore, future work should investigate combining and weighing the estimates from different systems to improve the overall quality and accuracy of the recommendations. In addition, these systems should focus on detecting mild dehydration so as to improve the effectiveness of secondary prevention. As a result, in a non-clinical setting, users of a wearable can be well-aware of their own hydration status, preemptively replenish lost fluids, and ultimately reduce the risk of injury associated with unaddressed dehydration.

6.9.6. Evaluating passive approaches of dehydration

The study described in Chapter 5 developed a model based on exercise-induced dehydration. For alternative modes and methods of dehydration (e.g., hypotonic, isotonic), there are distinct differences between the physiological changes in fluid balance and composition; these changes can affect the accuracy of hydration assessments [96], [97]. However, orthostatic measurements have been effective for assessing dehydration due to diuretics [74]. Heat stress and fluid restriction have been shown to affect orthostatic intolerance in older adults [98], [99].

Therefore, it is likely that the model developed in Chapter 5 will translate similarly for other passive approaches of dehydration, though predictive performance might vary. Future work should validate models using a similar experimental protocol; however, additional controls should be in place for heat acclimatization, and different exposure conditions should be used (e.g., fluid restriction, heat stress, saunas). Future analyses should further determine if any features and transformations are important for distinguishing between passive and active dehydration methods.

6.9.7. Incorporating other types of models for estimations

Physics-based models have been shown to be increasingly useful for estimating the behavior of different systems. Leveraging scientific theory and knowledge for developing physics-based models is useful because performance of data-driven models can be limited by the amount of available data, and they may not generalize well beyond the sample data used for training [100]. Moreover, a hybrid approach can be useful for improving overall performance [101]. Given that previous studies have developed mathematical and computational frameworks for motion sickness and dehydration [102], [103], future work should explore the use of physics-based models to improve data-driven models used for monitoring health conditions, especially when data that trains these models are sparse.

6.9.8. Technological requirements for supporting wearables for health monitoring

In this dissertation, data-driven models were developed using commercial sensors and large, comprehensive datasets. However, work is still needed to determine if current hardware and software embedded in wearable devices would be able to satisfy the computational demands of these models for implementation. Although these models can be simple, future work could incorporate more complicated models (e.g., neural networks) for health monitoring as data-driven approaches become more popular. Depending on the application, increasingly complex models can drive hardware and software requirements to meet higher demands on signal processing, sensor input/output, and model computations, among others [104]. With respect to motion sickness and dehydration, improved sensors that can capture high-fidelity representations of physiological signals (e.g., electrocardiograms) could enable more sophisticated features for modeling health conditions. In parallel, embedded computers in wearable devices must be able to host these data-driven models and process larger input data.

6.10. References

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