Fall Risk Classification in Community-Dwelling Older Adults Using a Smart Wrist-Worn Device and the Resident Assessment System-Home Care (RAI-HC)

by

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A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirements for the degree of
Master of Science
in
Public Health and Health Systems

Waterloo, Ontario, Canada, 2017

Authors Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Background: Falls are a serious problem especially in the aging population. To accurately identify individuals at risk for falls and mitigate the devastating effects caused by falls has become prominent to geriatrics and public health agencies. Leveraging wearable technologies and clinical assessment information may improve fall risk classification.

Objectives: The overall objectives of this thesis project are to: (1) investigate the similarities and differences in physical activity (PA), heart rate (HR) and night sleep (SP) in a sample of community-dwelling older adults with varying fall histories, using a smart wrist-worn device; and (2) examine the risk factors for falls in the target population, create fall risk classification models and evaluate classification performances based on: i) wearable data, ii) the Resident Assessment Instrument for Home Care (RAI-HC), and iii) the combination of wearable data and the RAI-HC system.

Methods: Two parallel studies were conducted in this project. Study I was a community-based cross-sectional study, utilizing the RAI-HC system to examine the risk factors for falls in older people. In the primary analysis, the ordinal attribute of previous falls (0, 1, and ≥ 2) was used as the outcome variable to build the proportional odds models (POM) for ordinal logistic regression. In the secondary analysis, the binary attribute of falls (yes/no) was used to distinguish fallers and non-fallers. Study II, a prospective, observational study was conducted to investigate the similarities and differences among three independent faller groups (*non-fallers*[1], *single fallers*[2], and *recurrent fallers*[3]) based on the number of previous falls in a sample of older

[1] People who have no (zero) falls in last 90 days.

[2] People who have one (1) fall in last 90 days.

adults living in community, with continuous measurements of PA, HR and SP using a smart wearable device. Descriptive statistics and simple statistical analyses were conducted to test the differences between groups. The wearable and RAI-HC assessment data were further analyzed and utilized to create fall risk classification models, with two supervised machine learning algorithms: logistic regression (LR) and decision tree (DT). The calculation of a set of performance metrics was performed to evaluate the classification performance of each final model.

Results: Study I: Of 167,077 individuals aged ≥ 65 in the RAI-HC data set, 113,529 (68.0%) had no history of falls, 27,320 (16.4%) had one fall, and 26,226 (15.7%) experienced multiple (≥ 2) falls. Unsteady gait, Activities of Daily Living (ADL) decline, ADL self-performance on transfer dependency, short-term memory problem, primary modes of locomotion (indoors), stair climbing, bladder continence, and limit going outdoors due to fear of falling were significant predictors of fall risk in both human and computer feature selection models derived from the Minimum Data Set-Home Care (MDS-HC). The Method of Assigning Priority Levels (MAPLe) (1 vs. 5: odds ratio (OR) = 0.20; 95% confidence internal (CI), 0.18-0.22), Changes in Health, End-Stage Disease, Signs, and Symptoms (CHESS) (0 vs. 5: OR = 0.27; 95% CI, 0.21-0.36), ADL Clinical Assessment Protocol (CAP) (0 vs. 2: OR = 0.21; 95% CI, 0.20-0.22), Cognitive CAP (0 vs. 2: OR = 0.33; 95% CI, 0.31-0.35), and Urinary Incontinence CAP (3 vs. 0: OR = 1.77; 95% CI, 1.62-1.94) were strong predictors in classifying older people with past fall histories based on the CAPs and a variety of summary scales and algorithms available within the RAI-HC assessment. The POM built on all available items on the RAI-HC data set achieved the

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[3] People who have two or more (≥ 2) falls in last 90 days.

best performance in classifying the three faller groups, with overall classification accuracy of 71.5%, and accuracies of 93.3%, 5.5% and 46.0% in classifying the non-faller, single faller and recurrent faller group, respectively. Likewise, the logistic regression model built on all available RAI-HC items achieved the best performance in distinguishing fallers and non-fallers, with the highest overall classification accuracy of 75.1%, the largest area under the curve (AUC) of 0.769, and the lowest Brier score of 0.171. **Study II:** Of 40 participants aged 65-93, 16 (40%) had no previous falls, while 8 (20%) and 16 (40%) had experienced one and multiple (≥ 2) falls, respectively. The wearable components of PA measurements extracted from the smart wrist-worn device were significantly different among three faller groups. Daily walking HR and daily activity time were identified as the best subset of predictors of fall risk with wearable data. Classification models derived from the RAI-HC data set containing 40 participants' latest assessments outperformed those based on wearable data only. The best classification model was a decision tree based on the combination of both data sets with 80.0% of overall classification accuracy, and accuracies of 87.5%, 50.0% and 87.5% in classifying the non-faller, single faller and recurrent faller group, respectively.

Conclusions: Continuous measurements of PA, HR and SP appear to supplement the RAI-HC system in facilitating fall risk stratification. Future fall risk assessment studies should consider leveraging wearable technologies to supplement resident assessment instruments.

Acknowledgments

I want to thank everyone who helped me throughout my second Master's program, which has proven to be one of my best learning experiences at the University of Waterloo (UW).

I would like to thank my supervisor, Dr. Joon Lee, for supporting me over the past two years, and for giving me so much freedom to design this thesis project. He had not only taught me numerous research skills but also illuminated a research field of which I find myself genuinely passionate about. I would be lost without his dedicated guidance. My other committee members have also been very supportive. Dr. John Hirdes, "the senior Canadian Fellow and a board member of interRAI"[4], has brought a useful perspective to this thesis, and encouraged me to make it more accessible to the Waterloo Wellington Community Care Access Centre (WW CCAC). Dr. Joel Dubin has long been an inspiration to me, providing valuable feedback and critical analyses for my study design, as I expected, and has kept me honest about all the details.

I would like to thank the interRAI group at UW, in particular, Julie Koreck, Leslie Eckel, Jonathan Chen, Nancy Curtin-Telegdi, Raquel Betini and Micaela Jantzi for giving me support whenever I was disoriented exploring the interRAI system or having a hard time identifying appropriate research institutes and recruitment methods at the beginning of this project. I also thank Dr. Paul Stolee for connecting me with the WW CCAC to kick-off the project and thank Dr. George Heckman and Dr. James Tung for their insights into my study design at the early stage.

[4] http://www.interrai.org/john-hirdes.html

I wish to thank the WW CCAC and community support of the Kitchener-Waterloo-Cambridge-Guelph (KWCG) region. In particular, thanks to Arsalan Afzal, the Project Manager for Partnership & Performance, as well as Valarie Alton, Anne-Elise Sauve-Jones and many other Care Coordinators, for providing valuable time and their own expertise in the field of fall risk assessment and my project with participant incentive. By chance, I was able to work as placement student during part of my time with the WW CCAC, for which I am truly grateful.

Thanks to my fellow colleagues in the Health Data Science Lab at UW, Arjun Puri, Anis Sharafoddini, Yingying Xu, Ben Kim, and Ken Tran for their assistance with my project, with whom I had the pleasure of working over the years. I also thank my undergraduate volunteers, Anna Staszewska, Ryan Chu, and Aein Zarrin for their dependable assistance with literature review and data collection.

Of course, I would like to thank my family and friends, whom have consistently supported me and put up with my mood swings when things were not coming out quite as smoothly as I would have hoped. Special thanks to my loving son, Andrew Yang for being a great kid with so much independence at his age, putting up with my weekends in the office and providing a welcome distraction from school.

This thesis project was supported by a research grant titled “Data-Driven Decision Making in Health Care” from AGE-WELL (Aging Gracefully across Environments using Technology to Support Wellness, Engagement and Long Life NCE Inc.), a national research network in technology and aging through the NCE (Networks of Centres of Excellence) program.

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List of Abbreviations

ADL	Activities of Daily Living
AGE-WELL	Aging Gracefully across Environments using Technology to Support Wellness, Engagement and Long Life
ANOVA	Analysis of Variance
AUC	Area Under the Curve
CAPs	Clinical Assessment Protocols
CHESS	Changes in Health, End-Stage Disease and Signs and Symptoms of medical problems
CI	Confidence Interval
DT	Decision Tree
ECG	Electrocardiography
HC	Home Care
HR	Heart Rate
HRV	Heart Rate Variability
IADL	Instrumental Activities of Daily Living
IQR	Interquartile Range
IV	Information Value
LED	Light-Emitting Diode

LR	Logistic Regression
LTC	Long-Term Care
MAPLe	Method for Assigning Priority Levels
MDS	Minimum Data Set
NCE	Networks of Centres of Excellence
NN	Neural Network
NPV	Negative Predictive Values
OR	Odds Ratio
PA	Physical Activity
POM	Proportional Odds Model
PPG	Photoplethysmography
PPV	Positive Predictive Values
QoL	Quality of Life
RAI	Resident Assessment Instrument
RF	Random Forest
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SEN	Sensitivity

SPE	Specificity
WOE	Weight of Evidence
WW CCAC	Waterloo-Wellington Community Care Access Centre

1. Introduction

1.1 Background

Falls are a serious problem especially in the aging population. The high prevalence and negative impact of falls in older people have become a general issue from public health and social care perspectives. Due to the multi-factorial nature of risk factors for falls, current fall prevention strategies are comprehensive and multifaceted [12, 13, 21, 23, 25-27, 42]. To accurately predict falls and mitigate physical and psychological damages caused by falls has become an important goal for geriatrics and public health agencies.

The characteristics of fallers and non-fallers among older people in community settings and long-term care (LTC) facilities have been identified in previous research [1-4]. Most studies involved in fall risk assessment have focused on discrimination between non-fallers and fallers [1-4]. However, few studies have attempted to further differentiate *single fallers* and *recurrent fallers* in older adults living in community [5-7], and examine the unique characteristics of each faller group.

Evidence-based fall risk assessments determine proper interventions for individuals who are at risk for falls. Conventional fall risk assessment tools often use questionnaires or functional assessment tests, taking assessment scores to classify older people into high risk (fallers) or low risk (non-fallers) [8, 9]. However, the fall risk in older adults is more accurately classified using fuzzy boundaries between multiple risk categories, compared to defining fall risk as a binary outcome [8].

Recent technological advances have incorporated wearable sensor-based systems into fall risk assessment protocols [8-10]. A wearable sensor system can continuously monitor steps during day-to-day living activities, performed naturally within real life environments [8-10]. It can potentially improve predictive performance at low cost.

No prior research, to the best of my knowledge, has combined off-the-shelf wearable sensor-derived data with the interRAI assessment system[5] to examine the characteristics of different faller groups in older adults living in community, and to build classification models for fall risk assessment.

By definition, a fall refers to "an event which results in a person coming to rest inadvertently on the ground or floor or other lower level" [82]. The number of previous falls (falls frequency) was targeted as a proxy for fall risk throughout this thesis project.

1.2 Overview

This thesis contains the following main sections. Section 2 summarizes the existing literature related to this research topic. Section 3 outlines the objectives and hypotheses. Sections 4 and 5 describe the methods and results of the two parallel studies conducted within this thesis. Finally, Sections 6 and 7 provide a discussion and conclusions.

[5] A suite of standardized clinical instruments assessing function, health, social support, and service, with each instrument targeting on a particular population [43-44].

2. Literature Review

2.1 Seniors and Falls

Various studies and reviews have estimated that 30% of community-dwellers aged ≥ 65, and 50% of older people aged ≥ 85 experience at least one fall every year [8, 11-13, 16]. An accidental fall can cause chronic pain, reduced mobility, long-term disability, loss of independence and even death to the individuals affected [11-15]. Approximately 4-15% of falls lead to significant injuries, and falls cause 23-40% of injury-related deaths in the aging population [12, 13, 15]. As an emerging public health dilemma, the long-term impact resulting from falls include higher mortality, morbidity, hospitalization, and increased cost-burden to the health care system [11, 12, 15, 16]. In Canada, $6.2 billion are spent for falls annually, which represents 31.3% of the total economic burden of injury [16]. Among the total cost, the direct cost arising from health care expenditures associated with injurious falls was $4.5 billion annually [16]. Expenditures spent on caring for seniors with injurious falls (per capita) are 3.7 times higher than those caring for younger adults aged 25-64 [16].

Along with the physiological changes associated with aging, physical fatigue such as diminished muscle mass, impaired vision, as well as reduced reaction and reflex time affects gait characteristics in older people, who tend to have slow gait and decreased stride [17, 18]. Some older adults suffer from pain due to chronic disease, with a decline in balance control, having difficulty in walking, all of which makes them more vulnerable to falls than other populations [17-19].

Fear of falling results in two important dimensions of negative health consequences, i.e. poor physical and mental health [64-69]. Physical harm includes lower mobility and activity levels, functional decline and loss of independence [64-69]. Psychological impact involves a higher level of depression, social embarrassment and indignity, as well as damage to confidence and identity [64-69]. Several studies have revealed an association between falls and fear of falling. Friedman et al. examined the temporal association between these two factors in one prospective observational study [69]. The results demonstrated at baseline, the two factors shared predictors, i.e. people who exposed to one condition are at a high risk of developing the other [69].

As a multi-factorial problem, falls are often caused by more than one risk factor. Several studies have identified multiple factors that directly influence or mediate the risk of falling in the aging population. Among a wide range of intrinsic and extrinsic factors [11-13, 15, 22, 27], an extensive evidence base demonstrates that low levels of PA affect postural control [11-13, 22, 27], insufficient sleep contributes to the loss of balance [29, 31-34], which may cause falls.

2.2 Physical Activity (PA), Exercise, and Falls

Participation in PA is a healthy behavior that can prevent the occurrence of chronic diseases and foster health and wellness among older adults [20-22]. The health benefits include dropped mortality rates, lower disease onset, controlled chronic conditions, reduced fall risk, lessen of functional decline, as well as the improvement in mental health in the aging population [20-22].

For the purposes of increasing or preserving physical function, and maintaining an independent living, regular PA is recommended [20-22, 26]. Considerable evidence indicates that half an hour of moderate PA everyday can keep muscles toned and prevent a decline in muscle strength, balance, flexibility, mobility and endurance in older people [17, 18, 20-22, 26]. Although some declines are inevitable due to normal aging process, older adults who are physically active maintain longer healthy functioning than sedentary individuals, who have demonstrated an increased risk and incidence of falls [11-13, 20-23, 26, 27].

Due to the negative physiological effects caused by chronic conditions or fear of falling, many older people reduce their daily activities. However, the decline of PA has negative impact on the response mechanisms of the human body's balance control [1, 4, 19, 24, 25]. Muscle function is strongly associated with PA [18, 23, 25-27]. Evidence suggests that sedentary behavior can cause muscular atrophy, specifically around joints, which cause an increase in the risk of falling [18, 19, 22, 23]. Recurrent fallers are less active, and their muscles will atrophy. This cohort would expose to higher risk for falls comparing to their peers who are moderately or vigorously active [18, 23, 24].

Engaging in activities or targeted exercise programs can improve obstacle avoidance [20-23, 25, 26]. Long-term exercise and remaining active has shown to be an effective way to prevent falls in the aging population [23-27]. Sherrington et al. conducted one meta-analysis consisting of 44 studies, and the results determined that the minimum exercise intervention to mitigate the risk for falls is 50 hours during 3 months, 6 months, or a longer period, depending on the trial [26]. Evidence suggested that 50 hours of exercise spreading over 6 months or less achieved a slightly greater effectiveness comparing to extending over a longer period [26]. Exercise interventions focusing on the improvement of balance and gait as well as the strength of lower extremities can decrease the risk for falls [23-27]. In addition to improving the balance and muscle strength, exercise interventions also aim to enhance the flexibility and endurance for the aging population [23-27].

2.3 Sleep Problems and Falls

Sleep is essential and beneficial for physical and mental restoration. Sleep problems are common among older people [28-35]. Although moderate change in sleep quality is normal in the aging process, disturbed sleep patterns can result in serious health consequences [28-30]. Existing studies have suggested that sleep problems are associated with falls, accidents, and chronic fatigue in the aging population [29-34]. Several possible explanations exist for this association. For example, individuals with disturbed sleep patterns may be more active at night to relieve distress from poor sleep. This increased activity at night may increase the incidence of falls [31, 32]. Another possibility is that morning drowsiness and deficient concentration due to inadequate night sleep may result in more falls [31, 32].

Numerous factors may interfere with sleep-wake patterns in the aging population. Many cases of sleep disturbance in this cohort can be attributed to physical and psychiatric illnesses and the medications taken to treat the diseases (tranquillizers, diuretics, other antihypertensive agents, anti-parkinsonism drugs and antidepressants) [28-30]. Poor sleep habits, circadian rhythm shifts and primary sleep disorders are other processes that can interfere with sleep [29, 30]. McEvoy et al. identified six types of sleep disorders that affect older adults [30]. Insomnia is the most common type and presents as difficulty falling asleep or staying asleep, or as problems with the sleep-wake cycle, such as early morning awakening [29, 30, 32]. It has been reported that 44% of older adults have one or more symptoms of insomnia at least a few nights per week [30].

Various studies have shown that loss of sleep implicates a decline in the sense of balance, associating with a number of cognitive impairments, such as poor concentration, memory loss, low reaction, and impaired problem solving and cognition [31, 32]. It has suggested that insufficient sleep may result in risk for falls [29, 31-34]. Short sleep duration, which accounts for habitual night sleep difficulties, is significantly associated with falls [45, 47, 50, 52, 53]. Utilizing the Study of Osteoporotic Fractures (SOF) data from older women, Stone et al. investigated the correlation between sleep problems and the increased risk for falls in this cohort [33]. It has verified that women who slept 5-7 hours every day had a higher risk of recurrent falls than their peers who slept 7-8 hours (OR = 1.36, 95% CI: 1.07−1.74) [33]. Likewise, women whose sleep duration was greater than 10 hours every day also had a higher risk of recurrent falls comparing with those who slept 7-8 hours, but the difference was not statistically significant [33]. In addition, poor sleep quality and extended awake time would cause fragmented sleep, which was also correlated with higher risk of recurrent falls [31-34].

Several studies have demonstrated that a decline of PA was associated with poor sleep and risk of falling [33, 35]. It has found the general tendency towards lower physical functioning in a group of fallers [33, 35]. People with a history of falls were characterized by shorter sleep duration, lower PA level, and consequently by worse basic functional status [33, 35]. Studies have shown that daily activity and exercise may promote better sleep, reduce the risk of insomnia or sleep disturbances, hence mitigate the risk for falls [33, 35].

2.4 Heart Rate (HR), Heart Rate Variability (HRV), Frailty, and Falls

Vital signs, including HR, body temperature, and blood pressure are objective measurements of physiologic function. These data compose an essential component of the clinical assessment, reflecting aging and pathological changes in older people [36]. The consequence of molecular changes due to aging results in altered sensitivity, reliability, and normative ranges of these vital signs [36]. For example, HR reflects both sympathetic and parasympathetic control of the heart function [36]. With the increasing age, the maximal HR decreases and the resting HR increases [36, 37].

Heart rate variability (HRV) is a widely known indicator of overall health and fitness. It is regulated by the autonomic nervous system. Parasympathetic activities decrease HR and increase HRV, whereas sympathetic activities increase HR and decrease HRV [36, 38, 39]. Nevertheless, the normal range of HRV measurements in the healthy cohort has not been identified, which makes it difficult to classify abnormal HRV [71-73]. Studies show that older people had lower HRV than younger adults, with the most decline at age group of 65-69, less at 70-74, and least at age ≥ 75 [73].

HR and HRV are hypothesized biomarkers of frailty, which implies a growing susceptibility to stressors and functional decline [38, 39]. These two parameters mirror the adaptability of the heart to stressors. In one recent study, Ogliari et al. examined whether HR and HRV are correlated with functional status in the aging population [38]. Participants with the highest resting HR had increased risk of decline in performing basic activities on the ADL scale and IADL tasks, with a nearly 80% and a 35% increased risk, respectively [38]. Participants with the lowest HRV had approximately a 25% increased risk of decline in performing the ADL and IADL tasks [38]. The results have shown that a higher resting HR and lower HRV in the target population was associated with poorer functional performance in daily life, as well as higher risk of functional decline [38].

Frail older people expose to great risk for serious health problems, including falls, disability, hospitalization and mortality [40]. A functional decline and a higher level of frailty caused by the muscular atrophy would escalate the risk for falls in older population [37, 39, 41]. The occurrence of falls increases with frailty level [41, 42]. Frailty and HRV are not only indicators of the decline in health condition [37-39], but also served as independent predictors for incident falls in several studies [37, 41, 63]. For example, De Vries et al. investigated the association of frailty and its components with falls in a large sample of older community-dwellers [41]. The results demonstrated a significant correlation between frailty and recurrent falls, with a hazard ratio of 1.53 (95% CI, 1.07-2.18), and an odds ratio (OR) of 1.74 (95% CI, 1.19-2.55) in participants aged 75 and over, suggesting frailty could be an independent predictor for falls [41]. Melillo et al. investigated the correlation between HRV and the risk for falls in a retrospective study, analyzing 24-hour electrocardiograms (ECGs) recording from hypertensive clinical inpatients [62]. The preliminary results demonstrated a significant correlation between a low HRV and the risk for falls (OR = 5.12, 95% CI, 1.42-18.41), suggesting that a low HRV could be an independent predictor to assess fall risks [62].

2.5 The interRAI Assessment System

A variety of clinical and support services across various care settings are beneficial to vulnerable populations with different care needs. As a comprehensive health information system, the introduction of interRAI instruments dated back in the 1990s has realized its potential [43, 44]. The interRAI assessment system was designed to standardize data collection and assessment using a modularized approach to increase the reliability of data, guiding routine care and service planning in a wide range of settings, from independent residences through assisted living [43, 45]. It has been used to link the major providers of health services in North America, Australia, and other European and Asian countries [43].

The Resident Assessment Instrument for Home Care (RAI-HC), in specific, is a baseline geriatric assessment to evaluate older adults who utilize home care services by assessing their needs and ability levels [45, 73]. With a variety of assessment information, the RAI-HC system is composed of two key components, the Minimum Data Set-Home Care (MDS-HC), which is the basal portion of the RAI-HC, and the Clinical Assessment Protocols (CAPs) [73]. In addition, various clinical scales and indices within each interRAI instrument can also be used to evaluate each client's current health conditions [77]. For instance, the measurement of ADL, cognition, communication, pain, behavior and mood utilizes standardized scoring schema to generate summary indicators [45]. Table 1 lists key domains assessed in the MDS-HC, CAPs triggered by the MDS-HC, and some of the widely used Scales [73, 77].

Table 1: Key Domains Assessed in the MDS-HC, CAPs triggered by the MDS-HC, and Scales associated with the MDS-HC [73, 77]

MDS-HC	**CAPs/Scales**
Name & Identification Information Personal Items Referral Items Assessment Information Communication/Hearing Patterns Vision Patterns Mood & Behaviour Patterns Social Functioning Informal Support Services Physical Functioning ❖ IADL Performance ❖ ADL Performance Continence Disease Diagnoses Health Conditions & Preventive Health Measures Nutrition/Hydration Status Dental Status (Oral Health) Skin Condition Environmental Assessment Service Utilization Medications	**CAPs** ❖ Clinical issues ❖ Sensory Performance ❖ Health Problems/Syndromes ❖ Continence ❖ Service Oversight **Scales** ❖ Activities of Daily Living (ADL) Hierarchy ❖ CHESS (The Changes in Health, End-Stage Disease, Signs, and Symptoms Scale) ❖ CPS (Cognitive Performance Scale) ❖ DIVERT (The Detection of Indicators and Vulnerabilities for Emergency Room Trips Scale) ❖ DRS (Depression Rating Scale) ❖ DSI (Depressive Severity Index) ❖ IADL Summary Scale ❖ MAPLe (The Method of Assigning Priority Levels) ❖ Pain Scale ❖ SCI (Self-Care Index)

The interRAI assessment system in general is not only a suite of comprehensive and standardized assessment tools that are used in different care settings, but has been utilized in several fall-related studies [66-69, 73-76]. For example, Muir et al. conducted one prospective cohort study, using the Berg Balance Scale to examine the predictive effectiveness for any fall (≥ 1 fall), recurrent falls (≥ 2 falls), and injury-related falls based on the interRAI Community Health Assessment (RAI-CHA) [74]. The RAI-CHA and RAI-HC assessments have been widely used in studies investigating the risk factors for falls [73-76], fear of falling [66-69], and the comparative analyses of non-fallers vs. fallers, non-fallers/one-time fallers vs. recurrent fallers [73-76]. In particular, the MDS-HC is a comprehensive assessment instrument across various key domains, including function/health/social support/services [68, 73]. Fletcher & Hirdes, In-Young, and Poss et al. conducted independent studies utilizing the MDS-HC to assess the risk factors for falls in various care settings [68, 73, 76, 79].

2.6 Wearable Sensor Devices and Objective Measures of PA

Thanks to the recent technological advances, the number and type of wearable sensors that attach to the human body and monitor bio-signals have increased. Currently available sensors can measure total PA and components of PA that play important roles in human health [46-48, 51, 52]. BUTTE et al. examined the current technology that has been used to measure PA using wearable monitors, and elaborated the main categories of wearable monitors for assessing PA [46].

2.6.1 Accelerometers and Gyroscopes

Accelerometers are sensory devices, which have been used to measure linear acceleration along a particular axis [46, 52]. Current uniaxial and triaxial sensors can record PA during extended periods [46, 52]. Triaxial accelerometers measure accelerations/decelerations, velocity, and displacement of a body segment in the X, Y, and Z axes [46, 52]. Gyroscopes have the capacity of measuring angular velocity and the rate of rotation around a particular axis [46, 52], which helps determine orientation.

The combination of accelerometers and gyroscopes has been widely used in many devices, for example, smart wearable devices that track fitness and other measurements in the body movement [47, 48, 51, 52]. It provides objective and reliable measurements of mobility and PA, including the amount, duration, frequency, and intensity of PA [47, 48, 51, 52]. In addition to measuring the components of PA, further development of analytic techniques enables classification of PA modes by partitioning awake time into multiple categories, for example, sedentary, light, moderate, and vigorous [47, 48, 51, 52]. The amount of time spent in different PA modes can also be quantified [47, 48, 51, 52]. Furthermore, these sensors are capable of automating the detection of night sleep and awake time, and have been used in studies addressing sleep disorders [47, 52].

2.6.2 Heart Rate (HR) Monitors

Lightweight HR monitors have been used to measure human's HR in real time [46]. Electrocardiography (ECG) and photoplethysmography (PPG) are two principal technologies to facilitate HR measurements [53, 54]. ECG biosensors use electrodes attached to the human body and record the electrical signals produced by heart activity over a period of time [53, 54]. A light-based technology has been employed by PPG sensors to detect the rate of blood flow and blood volume variation in the skin with the pressure pulse of each cardiac cycle [53, 54]. Composed of infrared LEDs (light-emitting diodes) and photodetectors, PPG sensor devices provide a simple, reliable, noninvasive monitoring of the pulse rate with low-cost [54]. Using high-intensity green LEDs for PPG with advanced optical technology has increased the adoption of the PPG technique [54]. To achieve a better accuracy and precision in analyzing sleep quality, combination of accelerometers and HR monitors outperforms either method alone [46].

2.6.3 Physical Placement of Monitors and Duration of Measurements

In one study, Garatachea et al. evaluated the objective measurements of PA and energy expenditure using accelerometers in older people, and investigated placements of monitors and number of days worn [47]. Due to the small and compact size, current accelerometers can be worn and calibrated on different body locations and positions [52]. The ideal position was attached to body's center of mass as close as possible, with the most common placement on the trunk location, such as hip or lower back [46, 52]. It has shown that wrist-worn sensors can monitor fine, upper body movements during day-to-day living activities while sitting or standing [47, 48, 51]. For example, sewing or playing cards while sitting, or washing dishes while standing, which are part of common day-to-day living activities in the aging population. To date, little evidence proposed one position is better than another [48, 51].

Furthermore, Garatachea et al. examined the number of days people need to wear the sensor device [47]. Depending on the study setting, resource, and research questions, it is suggested a typical sampling period between 3 and 7 days for PA measurements using accelerometers in older people [47]. Similarly, Hart et al. conducted a study to estimate the number of days needed to wear accelerometer sensors for predicting habitual PA and sedentary behavior in older adults [49]. It has concluded that 3-4 days of measurement can assess habitual PA, while 5 days of monitoring can estimate sedentary behavior reliably [49]. A systematic review by De Bruin, Eling D. et al. validated the current recommendations of the duration of measurements using wearable sensors to monitor mobility-related activities in the aging population [48].

2.7 The Current Practices in Fall Risk Assessment

To accurately predict falls and mitigate physical and psychological damages caused by falls has become prominent with great research value and scientific implications. Intervention programs targeting at people who are at high risk for falls can reduce the incidence of future falls drastically [10]. However, a major challenge of fall prevention is to accurately identify high-risk individuals so as to design and deploy customized intervention plans effectively.

Evidence-based fall risk assessments determine proper interventions for people who are at risk for falls. To categorize subjects into faller (high risk) and non-faller (low risk) groups, previous history of falls, future falls, and clinical assessments are three main methods identified in the literature [8]. Several studies have incorporated a variety of independent predictors into prediction models based on clinical tests [34, 37, 41, 55-59]. For example, the Berg Balance Test [55], clinical and impairment based tests [56], neuromuscular or cognitive tests [57], the blood pressure change on upright tilting [58], depressive symptoms [59], sleep problems or urinary incontinence [34], and frailty [37, 41] have been utilized to predict falls in the aging population. These clinical assessments often use assessment scores to categorize older adults with binary outcome, i.e. fallers (high risk) or non-fallers (low risk) [8, 9]. However, this type of assessment oversimplifies the risk of falling in older people, which is more accurately classified by continuous fuzzy boundaries between multiple risk categories, rather than a binary outcome [8].

The recent technological advances have incorporated wearable sensor-based systems into fall risk assessment protocols [8-10]. A wearable sensor system can continuously monitor PA during day-to-day activities, carried out naturally in real life environments [8-10]. In a review of fall risk assessment in older adults with sensor-based systems, Howcroft et al. evaluated inertial sensors, sensor location, assessed activity, variables, and prediction models of fall risk assessment [8]. Accelerometers and gyroscopes are inertial sensors to measure activities, via attachment to a body part [8-10]. All gait and distinct variables, for example, speed, position and angle, angular velocity, and linear acceleration had significant outcomes, together with sensor locations [8-10]. Various activities, such as level ground walking, Sit-to-Stand Test (STS), standing postural sway, Timed Up and Go (TUG), Alternating Step Test (AST), and uneven-ground walking were used to assess the fall risk with inertial sensor systems [8-10]. A combination of activities has been applied in many studies [1-3, 7]. As evidenced by the prospective study, variables measured by sensors have the potential to not only predict individuals who are at risk of falling but forecast the time-to-incident as well [8].

Marschollek et al. conducted a research to compare the predictive performance between the conventional fall risk assessment and sensor-based assessment in older adults [9]. The results demonstrated that accelerometer-based fall risk model has almost the same performance as a conventional assessment model [9]. Due to the multi-factorial risk factors for falls, sensor-based prediction models may provide important information to conventional assessments and are possible to perform within real life environments at low cost [8-10].

3. Objectives and Hypotheses

3.1 Objectives

The overall objectives of this project are to:

1) Investigate the similarities and differences in PA, HR and SP patterns among three independent older adult faller groups, i.e. *non-fallers*, *single fallers*, and *recurrent fallers* in community-based settings, with continuous measurements using a smart wrist-worn device;

2) Examine the risk factors for falls in the target population, create fall risk classification models, and assess the classification performance based on: i) wearable data, ii) the RAI-HC system, and iii) the combination of wearable data and the RAI-HC system. Hence evaluate whether wearable data can complement the RAI-HC system in better classifying an older people into one of the three faller groups, i.e., are the differences among three faller groups most pronounced when wearable and the RAI-HC system are combined.

3.2 Hypotheses

Several hypotheses were formulated prior to conducting this project. It was hypothesized that there were differences in the participants' PA, HR and SP among three faller groups. Specifically, since the decline of PA and sleep duration are known to be correlated with the increased occurrence of falls [18, 19, 22-24, 29, 31-34, 45, 47, 50, 52, 53], it was hypothesized that recurrent fallers would have the least daily activities (distance/steps) and the shortest sleep duration at night in comparison with the single faller and non-faller group. Similarly, it was hypothesized that the recurrent faller group would have the highest resting HR compared to the other two groups, since a higher resting HR in the aging population has been determined to be correlated with poorer functional performance in daily life, as well as a higher risk of future functional decline and serious health problems, such as falls [38, 40].

In terms of fall risk classification modeling, it was hypothesized that wearable data can complement the RAI-HC assessment system in better classifying older adults into three faller groups with higher classification accuracy.

4. Methods

4.1 Study Design

To examine the risk factors for falls and the unique characteristics of different faller groups, as well as to build and assess fall risk classification models, two parallel studies were conducted.

Study I was a community-based cross-sectional study, utilizing the existing RAI-HC data (secondary data analysis) to assess the risk factors for falls in the aging population. It was intended to build a comprehensive knowledge base for a deeper investigation in Study II, a prospective experimental study utilizing data derived from smart wearables to achieve the overall objectives described above.

Study II, a prospective, observational study was designed to investigate the similarities and differences among three independent faller groups in a sample of older community-dwellers, with continuous measurements of PA, HR and SP, which are risk factors associated with falls, using a smart wearable device. The wearable and RAI-HC data were further analyzed and utilized to create fall risk classification models and evaluate the classification performances.

4.2 Study I: Risk Factors for Falls: A Secondary Analysis of the RAI-HC System

The risk factors for falls in older adults were investigated utilizing the RAI-HC data collected from Ontario home care clients who were assessed between May 2002 and March 2015. In the RAI-HC data set available for this study, there were 852 variables in total, consisting of two independent home care assessments at different time points for each individual. The assessment at later time point (t2) was used to examine the risk factors of falling. Only older adults aged ≥ 65 were included in this study.

The dependent variable of interest was the number of previous falls a home care client experienced in last 90 days prior to the assessment. Individuals were categorized into three groups based on their fall frequencies: non-faller (zero falls), single faller (1 fall), and recurrent faller (≥ 2 falls).

The independent variables of interest were initially screened using two different approaches: i) based on evidence in the literature (human selection) from the MDS-HC items; ii) feature selection algorithm (computer selection) based on the MDS-HC items, CAPs and various clinical scales and algorithms ("CAPs/Scales" hereinafter) separately, and all available items on the RAI-HC data set. The algorithm was performed by rank-ordering the predictive power of all variables based on their Information Value (IV) and Weight of Evidence (WOE). Given the great number of features in the data set, there was a good chance that many of them are collinear or redundant. Prior to the model-building process, the RAI-HC data set was screened, and only variables with IV ≥ .1 (medium predictive power) [78] was selected for further analyses. This approach was applied to computer feature selection on the MDS-HC items, CAPs/Scales, and all available items on the RAI-HC data set.

An extensive univariate analysis was conducted, and only statistically significant variables at the bivariate level ($p < .05$) were selected for multivariate analysis. Furthermore, the multicollinearity test was conducted to examine if two or more predictors in the same model were highly correlated. The collinear variables with a high variance inflation factor (VIF ≥ 5)

[91] were omitted for further analyses, only one predictor per sub-section of each key domain was kept in the final models. Backward elimination of shortlisted independent variables was performed to select the best subset of features in logistic regression model.

For model-building, the ordinal attribute of falls within last 90 days was used as the outcome variable in the primary analysis, representing the three faller groups, i.e. G_0 (zero falls), G_1 (1 fall), and G_2 (≥ 2 falls). After a subset of features has been identified, proportional odds models were built. Each of the final models was evaluated using a 10-fold cross-validation procedure. A confusion matrix with the classification accuracy was calculated for each of the final models. See Figure 1 for Study I Protocols.

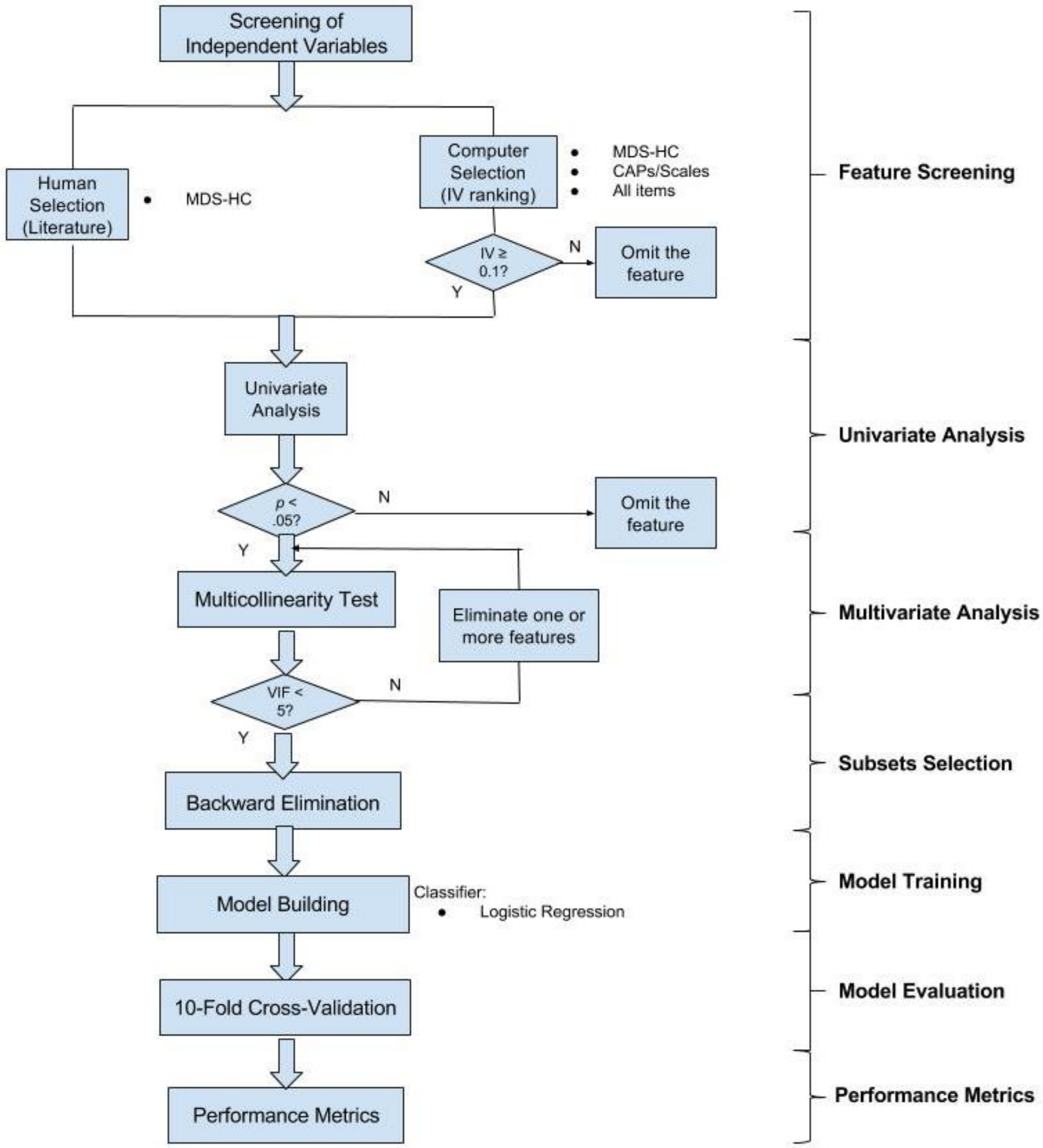


Figure 1: Study I Protocols

In the secondary analysis, the binary attribute of falls (yes/no) was used, discriminating fallers (≥ 1 fall) and non-fallers (zero falls). To evaluate the classification performance, the calculation of a set of performance metrics was performed, including the classification accuracy (ACC), sensitivity (SEN), specificity (SPE), positive and negative predictive values (PPV, NPV), area under the curve (AUC) and the Brier score, which is a measure of calibration to evaluate the difference between the predicted probability and the actual outcome [83] for each final model. The RAI-HC data were statistically analyzed using SAS version 9.4 (SAS Institute Inc.) in Study I.

4.3 Study II: Data-Driven Characterization of Groups with Varying Fall Histories: A Prospective, Observational Study

4.3.1 General Approach

A sample of community-dwelling older people, who were active clients of the Waterloo Wellington Community Care Access Centre (WW CCAC) and were assessed with the RAI-HC instrument within one-year time window was sought out and recruited. For participant recruitment, 440 random phone calls were made and 500 posters were printed and distributed during home visits in the KWCG communities between August 2016 and December 2016.

4.3.2 Participant Recruitment

The inclusion criteria were that the subjects were aged ≥ 65, living independently with or without family members at-home or community-based settings (retirement home), able to walk with no assistive device or on cane/walker/crutch (not confined to a wheelchair), and were assessed by the RAI-HC instrument within one-year. Assignment to one of the three fall-risk groups was determined by a self-reported number of falls within last 90 days. To prevent selection bias, individuals who have been diagnosed with end-stage disease or have been on medications of benzodiazepines, antidepressants, cardiac medications, narcotics and anticonvulsants were excluded from participating in this study.

Informed and written consent was obtained from all participants. This study was granted ethics clearance (ORE # 21455) through a University of Waterloo Research Ethics Committee, and was conducted as stated in the standard ethical protocols. The study was also approved by the institutional review board at WW CCAC. See Figure 2 for Study II Protocols.

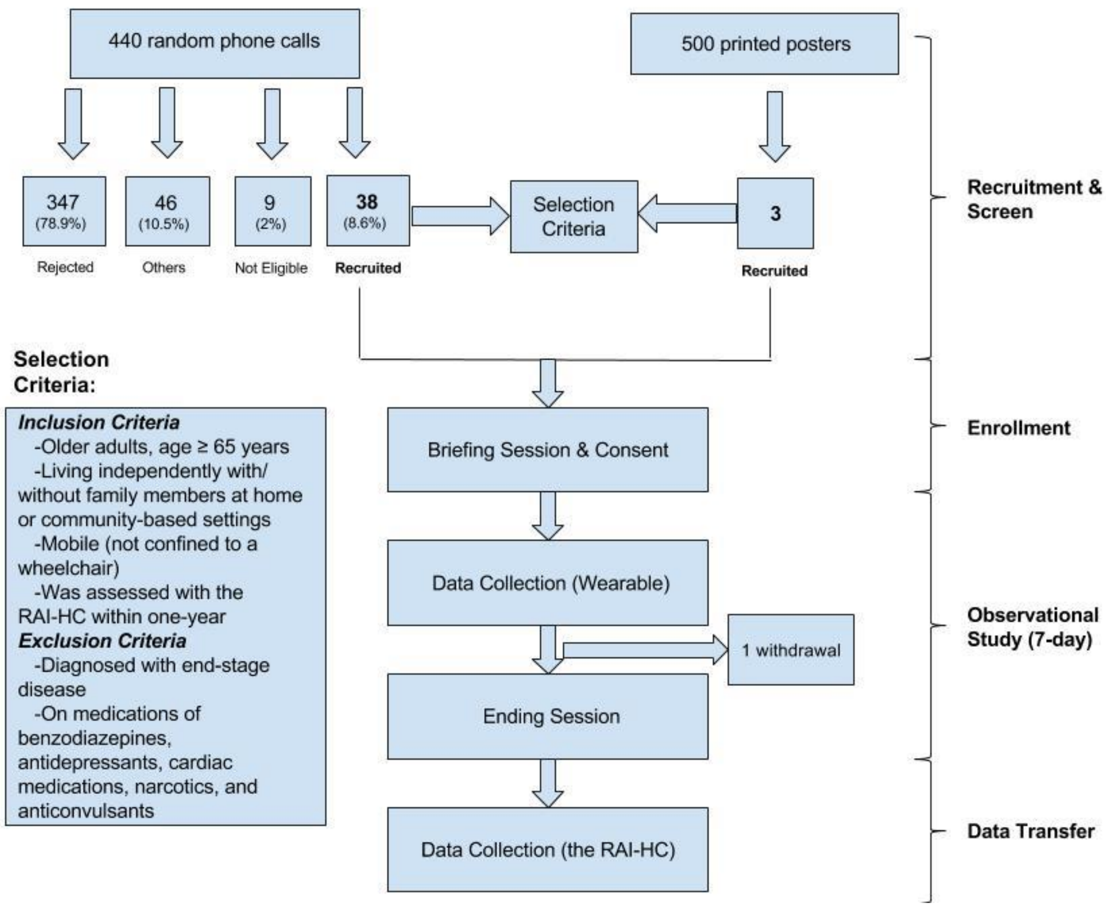


Figure 2: Study II Protocols

4.3.3 Instruments Used

During the wearable data collection phase of this study, each participant was instructed and requested to wear the Xiaomi Mi Band Pulse 1S (the "Mi Band" hereinafter) on their wrist for 7 consecutive days while carrying out day-to-day activities in their normal lives. In order to have access to the wearable data, each participant was provided with a Moto E smartphone paired with their Mi Band wirelessly via Bluetooth. The smartphone was used to collect data from the Mi Band, synchronize, and provide health metrics to each individual.

Participants were also advised about the two companion apps, i.e. Mi Fit app and Mi Band Tools, and their abilities to present health metrics about PA and SP, as well as the measurements of real-time HR.

4.3.4 Measurements

4.3.4.1 Falls

To assess the falls frequency, participants responded to the following questions upon enrollment and at the end of the wearable data collection phase: (1) "Have you fallen in last 90 days?" (2) "How many times have you fallen in last 90 days?" Participants were categorized based on their self-reported number of falls at the end of the wearable data collection phase, G_0 (non-faller, zero falls), G_1 (single faller, 1 fall), and G_2 (recurrent faller, ≥ 2 falls).

Ideally, all participants would have started the study at the standardized time and day upon immediately assessed with the RAI-HC. However, there was a time gap between the RAI-HC assessment and wearable data collection (mean_{gap} (*M*) = 107.6 days, standard deviation (*SD*) = 18.1, range = -67.5-431 days). Some participants have had new falls since their last RAI-HC assessments, which resulted in discrepancies between the self-reported falls frequency at wearable data collection and the corresponding assessment on the RAI-HC system. To be consistent, self-reported falls frequency at the end of the wearable data collection phase was used when analyzing wearable data only. The falls frequency on the RAI-HC assessment was used for model-building based on the RAI-HC data only as well as the combination of wearable and the RAI-HC data set.

4.3.4.2 Wearable Data

Raw data collected from the Mi Band included continuous monitoring of PA, SP and HR measurements. PA and SP were collected every minute, while HR was monitored every 2 minutes. Table 2 describes raw data extracted from the Mi Band.

Table 2: Raw Data Extracted from the Xiaomi Mi Band

Category	Variable	Unit
Activities	Time	Date and Time
	Description	Sleep/Idle/Walk/Run
	Steps	Numeric
	Walk Distance	Meter
	Run Distance	Meter
	Walk Calories	Calories
	Run Calories	Calories
	Raw Activity	Numeric
HR	Rate	BPM
	Measurement Time	Date and Time

By default, the Mi Band and Mi Fit apps present no build-in function to extract data. A third-party script allowed data extraction via Android backup [90]. After the wearable data collection, data were extracted from the Mi Band database on the paired smartphone to the student researcher's laboratory computer, converting the raw data to CSV format. Various summary reports were also generated based on the raw data. Raw data were aggregated as daily averages for the analyses in this study.

4.3.4.3 The RAI-HC Data Set

All participants with informed and written consent contributed one assessment each. If more than one RAI-HC assessment was available, the latest one was selected. At the end of the wearable data collection phase, the WW CCAC transferred the RAI-HC data set containing all participants' assessments via the secure Sendit platform available to all UW students.

4.3.5 Data Analytics Approach

Data analyses were performed using IBM SPSS Statistics 22.0 in Study II. Prior to the primary analyses, missing values were imputed using the maximum likelihood estimates with the expectation-maximization (EM) algorithm. Relying on available complete data, each iteration of the expectation step computes the expected log-likelihood ratio, and the subsequent maximization step calculates the estimates which maximize the expected log-likelihood ratio on the expectation step [92]. Descriptive statistics and simple statistical analyses were conducted to examine the similarities and differences in wearable data collected from the Mi Band from all participants. All wearable parameters (continuous variables) extracted from the Mi Band were tested for normality by using the Shapiro-Wilk test and a visual inspection of their histograms. In the primary analyses, a one-way analysis of variance (ANOVA) and Kruskal-Wallis H test were conducted to compare the means of three independent groups (G_0, G_1, and G_2) for normally distributed and skewed data, respectively. A two-way repeated measures ANOVA test was performed to examine the differences between groups with repeated measurements of PA, HR and SP, and hence evaluate if there was an interaction between 7-day of measurement and groups. Mean (M) ± SD was used to report normally distributed variables, median ± interquartile ranges (IQR) was used to present skewed data; and numbers and percentages were used to report categorical data in this study.

In order to build the classification models and evaluate classification performances of several fall risk classification models, a two-fold approach was employed, utilizing two supervised machine learning algorithms: logistic regression (LR) and decision tree (DT). To identify discriminative independent variables contributing to falls frequency and to create accurate classification models, the same computerized feature selection algorithm was performed by rank-ordering the predictive power of all variables based on their IVs and WOE (the same approach as Study I). Since both wearable and the RAI-HC data set have many variables and relatively few samples, the objective of this feature selection process in Study II was to get a total number of best subset features no more than 10% of the sample size for the final classification models.

For model building, the ordinal attribute of falls within last 90 days was used as the target variable, representing three faller groups (G_0, G_1, and G_2). Classification models were trained based on: i) wearable data exclusively; ii) the RAI-HC data set exclusively; and iii) the combination of both data sets. The growing method for DT models was Classification and Regression Trees (CART) algorithm, with pruning to avoid overfitting. Key parameters included minimum parent size = 5, minimum child size = 3, pruned, and gini was applied as the impurity measure. Due to the small size of training data in Study II, each final model was evaluated using a leave-one-out cross-validation (LOOCV) procedure to estimate the generalization performance. It makes use of almost the entire training set (N-1 data points) in each iteration, getting estimates of test error with low bias but high variance [95]. A confusion matrix with the classification accuracy was calculated for each of the final models.

5. Results

5.1 Study I: Risk Factors for Falls: A Secondary Analysis of the RAI-HC Data

5.1.1 Primary Analysis

Of 167,077 individuals aged 65 or older, 113,529 (68.0%) had no history of falls, 27,320 (16.4%) had one fall, and 26,226 (15.7%) experienced multiple (≥ 2) falls in last 90 days prior to the assessment, with 58,968 (35.3%) males and 108,103 (64.7%) females (age: M = 82.4 years, SD = 7.5, range = 65-123 years).

5.1.1.1 Human Feature Selection on the MDS-HC

The human screening of independent variables based on evidence in the literature included 72 variables from the MDS-HC. These independent variables incorporated key items from most of the assessment sections, except for name & identification information, referral information, informal support services, nutrition/hydration status, dental status, and skin condition, which were irrelevant to the risk factors for falls in the literature. Table 3 lists the human screened variables from the MDS-HC [45], and Table 4 shows selected characteristics based on the MDS-HC assessment by group.

Table 3: Human Selected Variables from the MDS-HC [45]

SECTION BB. PERSONAL ITEMS	HEART/CIRCULATION: Irregularly Irregular pulse (J1e)
Gender (bb1)	HEART/CIRCULATION: Peripheral vascular disease (J1f)
Age Group	NEUROLOGICAL: Alzheimer’s (J1g)
SECTION CC. REFERRAL ITEMS	NEUROLOGICAL: Dementia other than Alzheimer's disease (J1h)
WHO LIVED WITH AT REFERRAL (CC6)	NEUROLOGICAL: Hemiplegia/hemiparesis (J1j)
SECTION B. COGNITIVE PATTERNS	NEUROLOGICAL: Multiple sclerosis (J1k)
MEMORY RECALL ABILITY: Short-term memory OK—seems/appears to recall after 5 minutes (B1a)	SENSES: Cataract (J1q)
MEMORY RECALL ABILITY: Procedural memory OK—can perform all or almost all steps in a multitask sequence without cues for initiation (B1b)	SENSES: Glaucoma (J1r)
INDICATORS OF DELIRIUM: Sudden or new onset/change in mental function over LAST 7 DAY (B3a)	OTHER DISEASES: Diabetes (J1y)
SECTION C. COMMUNICATION/HEARING PATTERNS	OTHER DISEASES: Parkinsonism (J1l)
HEARING (C1)	MUSCULO-SKELETAL: Arthritis (J1m)
SECTION D. VISION PATTERNS	MUSCULO-SKELETAL: Hip fracture (J1n)
VISION (D1)	MUSCULO-SKELETAL: Other fractures (J1o)
VISUAL LIMITATION/DIFFICULTIES (D2)	MUSCULO-SKELETAL: Osteoporosis (J1p)

VISION DECLINE (D3)	**SECTION K. HEALTH CONDITIONS AND PREVENTIVE HEALTH MEASURES**
SECTION E. MOOD AND BEHAVIOUR PATTERNS	PROBLEM CONDITIONS PRESENT ON 2 OR MORE DAYS: Difficulty urinating or urinating 3 or more times at night (K2b)
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: A FEELING OF SADNESS OR BEING DEPRESSE (E1a)	PROBLEM CONDITIONS: Chest pain/pressure at rest or on exertion (K3a)
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: WITHDRAWAL FROM ACTIVITIES OF INTEREST (E1h)	PROBLEM CONDITIONS: Dizziness or lightheadedness (K3c)
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: REDUCED SOCIAL INTERACTION (E1i)	PROBLEM CONDITIONS: Shortness of breath (K3e)
MOOD DECLINE (E2)	PAIN: Frequency with which client complains or shows evidence of pain (K4a)
CHANGES IN BEHAVIOUR SYMPTOMS (E4)	PAIN: Intensity of pain (K4b)
SECTION F. SOCIAL FUNCTIONING	PAIN: From client's point of view, pain intensity disrupts usual activities (K4c)
CHANGE IN SOCIAL ACTIVITIES (F2)	DANGER OF FALL: Unsteady gait (K6a)
SECTION H. PHYSICAL FUNCTIONING	DANGER OF FALL: Client limits going outdoors due to fear of falling (K6b)
ADL SELF-PERFORMANCE: MOBILITY IN BED (H2a)	LIFESTYLE (Drinking/Smoking): In the LAST 90 DAYS, client felt the need or was told by others to cut down on drinking, or others were concerned with client's drinking (K7a)
ADL SELF-PERFORMANCE: TRANSFER (H2b)	LIFESTYLE (Drinking/Smoking): In the LAST 90 DAYS, client had to have a drink first thing in the morning to steady nerves or has been in trouble because of drinking (K7b)

ADL SELF-PERFORMANCE: LOCOMOTION IN HOME (H2c)	HEALTH STATUS INDICATORS: Has conditions or diseases that make cognition, ADL, mood, or behaviour patterns unstable (K8b)
ADL SELF-PERFORMANCE: LOCOMOTION OUTSIDE OF HOME (H2d)	HEALTH STATUS INDICATORS: Experiencing a flare up of a recurrent or chronic problem (K8c)
ADL DECLINE (H3)	OTHER STATUS INDICATORS: Physically restrained (K9e)
PRIMARY MODES OF LOCOMOTION- Indoors (H4a)	**SECTION 0. ENVIRONMENTAL ASSESSMENT**
PRIMARY MODES OF LOCOMOTION- Outdoors (H4b)	HOME ENVIRONMENT: Lighting in evening (O1a)
STAIR CLIMBING (H5)	HOME ENVIRONMENT: Flooring and carpeting (O1b)
STAMINA: In a typical week, during the LAST 30 DAYS (or since last assessment), code the number of days client usually went out of the house or building in which client lives (H6a)	HOME ENVIRONMENT: Bathroom and toilet room (O1c)
STAMINA: Hours of physical activities in the last 3 days (H6b)	HOME ENVIRONMENT: Kitchen (O1d)
SECTION I. CONTINENCE IN LAST 7 DAYS	HOME ENVIRONMENT: Access to home (O1g)
BLADDER CONTINENCE: In LAST 7 DAYS control of urinary bladder function (I1a)	HOME ENVIRONMENT- Access to rooms in house (O1h)
BLADDER CONTINENCE: Worsening of bladder incontinence as compared to status 90 days ago (I1b)	LIVING ARRANGEMENT: As compared to 90 DAYS AGO, client now lives with other persons (O2a)
SECTION J. DISEASE DIAGNOSES	**SECTION Q. MEDICATIONS**
HEART/CIRCULATION: Cerebrovascular accident (stroke) (J1a)	NUMBER OF MEDICATIONS (Q1)

HEART/CIRCULATION: Congestive heart failure (J1b)	RECEIPT OF PSYCHOTROPIC MEDICATION: Antipsychotic/neuroleptic (Q2a)
HEART/CIRCULATION: Coronary artery disease (J1c)	RECEIPT OF PSYCHOTROPIC MEDICATION: Anxiolytic (Q2b)
HEART/CIRCULATION: Hypertension (J1d)	RECEIPT OF PSYCHOTROPIC MEDICATION: Antidepressant (Q2c)
	RECEIPT OF PSYCHOTROPIC MEDICATION: Hypnotic (Q2d)

Table 4: The Selected Characteristics of Participants in Study I

Characteristics	**Non-Faller (no., %)**	**Single Faller (no., %)**	**Recurrent Faller (no., %)**	**Total (no., %)**
SECTOIN: PERSONAL ITEMS				
Gender *(bb1)*				
Male	37842, 22.7%	9624, 5.8%	11502, 6.9%	58968, 35.3%
Female	75682, 45.3%	17695, 10.6%	14724, 8.8%	108101, 64.7%
Age (M ± SD, years)	82.2 ± 7.4	83.1 ± 7.4	82.5 ± 7.7	82.4 ± 7.5
Male (*M ± SD*, years)	81.4 ± 7.5	82.4 ± 7.3	81.8 ± 7.5	81.6 ± 7.5
Female (*M ± SD*, years)	82.7 ± 7.4	83.5 ± 7.4	83.1 ± 7.7	82.9 ± 7.4
Age Group				
65-74 years	21343, 12.8%	4253, 2.6%	4825, 2.9%	30421, 18.2%
75-84 years	50762, 30.4%	11853, 7.1%	11269, 6.8%	73884, 44.2%
85-94 years	37873, 22.7%	10168, 6.1%	9102, 5.5%	57143, 34.2%
≥95 years	2865, 1.7%	910, 0.5%	884, 0.5%	4659, 2.8%
SECTION: HEALTH CONDITIONS AND PREVENTIVE HEALTH MEASURES				
DANGER OF FALL: Unsteady Gait *(K6a)*				
No	45670, 27.3%	5835, 3.5%	2377, 1.4%	53882, 32.3%
Yes	67859, 40.6%	21485, 12.9%	23849, 14.3%	113193, 67.8%
DANGER OF FALL: Limit going outdoors due to fear of falling *(K6b)*				
No	63751, 38.2%	11813, 7.1%	8593, 5.1%	84157, 50.4%
Yes	49777, 29.8%	15507, 9.3%	17633, 10.6%	82917, 49.6%

Characteristics	Non-Faller (no., %)	Single Faller (no., %)	Recurrent Faller (no., %)	Total (no., %)
<u>SECTION: PHYSICAL FUNCTIONING</u>				
IADL SELF-PERFORMANCE				
MEAL PREPARATION / Difficulty *(H1ab)*				
No difficulty	15644, 9.4%	2879, 1.7%	1808, 1.1%	20331, 12.2%
Some difficulty	36330, 21.8%	8433, 5.1%	7094, 4.3%	51857, 31.0%
Great difficulty	61552, 36.8%	16008, 9.6%	17323, 10.4%	94883, 56.8%
ADL SELF-PERFORMANCE				
ADL DECLINE *(H3)*				
No	74849, 44.8%	13664, 8.2%	9378, 5.6%	97891, 58.6%
Yes	38680, 23.2%	13656, 8.2%	16848, 10.1%	69184, 41.4%
TRANSFER *(H2b)*				
Independent	87168, 52.2%	18412, 11.0%	13758, 8.2%	119338, 71.4%
Setup help only	6662, 4.0%	2058, 1.2%	2047, 1.2%	10767, 6.4%
Supervision	5875, 3.5%	2179, 1.3%	2949, 1.8%	11003, 6.6%
Limited assistance	6173, 3.7%	2437, 1.5%	3953, 2.4%	12563, 7.5%
Extensive assistance	3378, 2.0%	1312, 0.8%	2207, 1.3%	6897, 4.1%
Maximal assistance	1911, 1.1%	575, 0.3%	873, 0.5%	3359, 2.0%
Total dependence	2004, 1.2%	306, 0.2%	396, 0.2%	2706, 1.6%
Activity did not occur	357, 0.2%	41, 0.02%	43, 0.03%	441, 0.3%
LOCOMOTION IN HOME *(H2c)*				
Independent	85295, 51.1%	19471, 11.7%	16696, 10.0%	121462, 72.7%
Setup help only	7514, 4.5%	2054, 1.2%	2127, 1.3%	11695, 7.0%
Supervision	9951, 6.0%	3116, 1.9%	4094, 2.5%	17161, 10.3%
Limited assistance	4745, 2.8%	1490, 0.9%	1986, 1.2%	8221, 4.9%
Extensive assistance	2257, 1.4%	573, 0.3%	718, 0.4%	3548, 2.1%
Maximal assistance	1143, 0.7%	246, 0.2%	307, 0.2%	1696, 1.0%
Total dependence	1745, 1.0%	268, 0.2%	235, 0.1%	2248, 1.4%
Activity did not occur	877, 0.5%	99, 0.1%	62, 0.04%	1038, 0.6%
PRIMARY MODES OF LOCOMOTION: Indoors *(H4a)*				
No assistive device	47122, 28.2%	8233, 4.9%	5393, 3.2%	60748, 36.4%
Cane	17975, 10.8%	4544, 2.7%	3802, 2.3%	26321, 15.8%
Walker/crutch	38784, 23.2%	12203, 7.3%	13859, 8.3%	64846, 38.8%
Scooter	334, 0.2%	88, 0.1%	125, 0.1%	547, 0.3%
Wheelchair	8251, 4.9%	2063, 1.2%	2849, 1.7%	13163, 7.9%
Activity did not occur	1059, 0.6%	188, 0.1%	198, 0.1%	1445, 0.9%

Characteristics	Non-Faller (no., %)	Single Faller (no., %)	Recurrent Faller (no., %)	Total (no., %)
SECTION: CONTINENCE				
BLADDER CONTINENCE *(I1a)*				
Continent	60721, 36.3%	11953, 7.2%	8615, 5.2%	81289, 48.7%
Continent with catheter	3541, 2.1%	746, 0.5%	786, 0.5%	5073, 3.0%
Usually continent	15148, 9.1%	4311, 2.6%	4038, 2.4%	23497, 14.1%
Occasionally incontinent	12836, 7.7%	3830, 2.3%	4151, 2.5%	20817, 12.5%
Frequently incontinent	13988, 8.4%	4423, 2.7%	5803, 3.5%	24214, 14.5%
Incontinent	7067, 4.2%	1998, 1.2%	2774, 1.7%	11839, 7.1%
Did not occur	228, 0.1%	59, 0.04%	59, 0.04%	346, 0.2%
SECTION: SERVICE UTILIZATION				
VISITS IN LAST 90 DAYS OR SINCE LAST ASSESSMENT: Number of times visited emergency room without an overnight stay *(P4b)*				
0	90476, 54.2%	20712, 12.4%	19093, 11.4%	130281, 78.0%
1	17740, 10.6%	5184, 3.1%	5196, 3.1%	28120, 16.8%
2	3590, 2.2%	940, 0.6%	1320, 0.8%	5850, 3.5%
≥3	1721, 1.0%	482, 0.3%	617, 0.4%	2820, 1.7%
OVERALL CHANGE IN CARE NEEDS *(P6)*				
No change	46880, 28.1%	9857, 5.9%	8235, 4.9%	64972, 38.9%
Improved-receives fewer support	6816, 4.1%	1423, 0.9%	997, 0.6%	9236, 5.5%
Deteriorated-receives more support	59830, 35.8%	16040, 9.6%	16994, 10.2%	92864, 55.6%

In the proportional odds model (POM_Human_MDSHC) derived from the MDS-HC items based on human screening of independent variables, the following variables were identified as strong predictors: unsteady gait (K6a) (G_2: OR = 3.27; 95% CI, 3.11-3.45; G_1: OR = 1.79; 95% CI, 1.72-1.87), felt the need or was told by others to cut down on drinking (K7a) (G_2: OR = 2.30; 95% CI, 1.99-2.66; G_1: OR = 1.47; 95% CI, 1.26-1.72), ADL decline as compared to status 90 days ago (H3) (G_2: OR = 2.07; 95% CI, 2.00-2.14; G_1: OR = 1.53; 95% CI, 1.48-1.58), had to have a drink first thing in the morning to steady nerves (K7b) (G_2: OR = 1.61; 95% CI, 1.25-2.07; G_1: OR = 1.31; 95% CI, 1.00-1.73), dizziness or lightheadedness (K3c) (G_2: OR = 1.51; 95% CI, 1.46-1.57; G_1: OR = 1.23; 95% CI, 1.18-1.28), gender being male (bb1) (G_2: OR = 1.51; 95% CI, 1.46-1.56; G_1: OR = 1.12; 95% CI, 1.08-1.16), home environment hazardous or uninhabitable in bathroom and toilet room (O1c) (G_2: OR = 1.47; 95% CI, 1.31-1.65; G_1: OR = 1.23; 95% CI, 1.10-1.38), Parkinsonism (J1l) (G_2: OR = 1.45; 95% CI, 1.40-1.51; G_1: OR = 1.12; 95% CI, 1.07-1.17), and short-term memory problem (B1a) (G_2: OR = 1.41; 95% CI, 1.36-1.47; G_1: OR = 1.22; 95% CI, 1.18-1.27). Individuals who presented any of the above conditions were at higher risk for falls. Table 5 lists the results of model POM_Human_MDSHC, and Figure 3 shows the plot of odds ratios.

Table 5: The Relationship between Risk Factors and Falls (Model: POM_Human_MDSHC)

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
Gender (bb1) [ref: female]	2	1.51	1.46	1.56	<.0001
	1	1.12	1.08	1.16	<.0001
Age Group [ref: ≥95 years] 65-74 years	2	1.00	0.91	1.10	0.008
	1	0.76	0.69	0.83	<.0001
Age Group [ref: ≥95 years] 75-84 years	2	0.91	0.84	1.00	0.009
	1	0.83	0.76	0.90	0.005
Age Group [ref: ≥95 years] 85-94 years	2	0.90	0.82	0.98	<.0001
	1	0.88	0.82	0.96	0.10

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
REFERRAL ITEMS: WHO LIVED WITH AT REFERRAL (CC6)	2	0.99	0.98	1.00	0.01
	1	0.97	0.96	0.98	<.0001
MEMORY RECALL ABILITY: Short-term memory (B1a)	2	1.41	1.36	1.47	<.0001
	1	1.22	1.18	1.27	<.0001
MEMORY RECALL ABILITY: Procedural memory (B1b)	2	0.98	0.94	1.02	0.30
	1	0.93	0.89	0.97	0.0005
INDICATORS OF DELIRIUM: Sudden or new onset/change in mental function over LAST 7 DAYS (B3a)	2	1.31	1.21	1.42	<.0001
	1	1.22	1.12	1.33	<.0001
HEARING (C1) [ref: 3- HIGHLY IMPAIRED] 0- HEARS ADEQUATELY	2	0.91	0.79	1.05	0.0007
	1	0.90	0.79	1.04	0.002
HEARING (C1) [ref: 3- HIGHLY IMPAIRED] 1- MINIMAL DIFFICULTY	2	0.98	0.84	1.13	0.90
	1	0.97	0.84	1.11	0.89
HEARING (C1) [ref: 3- HIGHLY IMPAIRED] 2- HEARS IN SPECIAL SITUATIONS ONLY	2	1.04	0.90	1.20	0.02
	1	0.99	0.86	1.14	0.30
VISION (D1) [ref: 4- SEVERELY IMPAIRED] 0- ADEQUATE	2	1.13	0.98	1.31	0.04
	1	1.15	1.00	1.32	0.25

Risk Factors	Group	OR	95% CI		p Value
VISION (D1) [ref: 4- SEVERELY IMPAIRED] 1- IMPAIRED	2	1.16	1.00	1.34	0.004
	1	1.20	1.04	1.39	0.001
VISION (D1) [ref: 4- SEVERELY IMPAIRED] 2- MODERATELY IMPAIRED	2	1.12	0.96	1.31	0.25
	1	1.17	1.01	1.36	0.12
VISION (D1) [ref: 4- SEVERELY IMPAIRED] 3- HIGHLY IMPAIRED	2	1.02	0.86	1.20	0.11
	1	1.09	0.93	1.29	0.52
VISION DECLINE (D3)	2	1.09	1.03	1.16	0.002
	1	1.07	1.01	1.13	0.02
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: A FEELING OF SADNESS OR BEING DEPRESSED (E1a) [ref: 2- Exhibited on each of last 3 days] 0- not exhibited in last 3 days	2	0.82	0.78	0.87	<.0001
	1	0.95	0.89	1.00	0.03
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: A FEELING OF SADNESS OR BEING DEPRESSED (E1a) [ref: 2- Exhibited on each of last 3 days] 1- Exhibited 1–2 of last 3 days	2	0.92	0.86	0.98	0.62
	1	0.98	0.92	1.04	0.81
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: WITHDRAWAL FROM ACTIVITIES OF INTEREST (E1h) [ref: 2- Exhibited on each of last 3 days] 0- not exhibited in last 3 days	2	1.13	1.06	1.21	<.0001

Risk Factors	Group	OR	95% CI		p Value
	1	1.04	0.97	1.11	0.07
INDICATORS OF DEPRESSION, ANXIETY, SAD MOOD: WITHDRAWAL FROM ACTIVITIES OF INTEREST (E1h) [ref: 2- Exhibited on each of last 3 days] 1- Exhibited 1–2 of last 3 days	2	0.98	0.90	1.06	0.01
	1	0.99	0.91	1.08	0.35
MOOD DECLINE (E2)	2	1.08	1.03	1.14	0.001
	1	1.04	0.99	1.09	0.12
CHANGES IN BEHAVIOUR SYMPTOMS (E4)	2	1.16	1.09	1.23	<.0001
	1	0.99	0.93	1.05	0.71
CHANGE IN SOCIAL ACTIVITIES (F2) [ref: 2- Decline, distressed] 0- No decline	2	0.89	0.85	0.94	<.0001
	1	0.89	0.84	0.93	<.0001
CHANGE IN SOCIAL ACTIVITIES (F2) [ref: 2- Decline, distressed] 1- Decline, not distressed	2	0.97	0.92	1.02	0.18
	1	0.97	0.92	1.02	0.11
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	0.88	0.73	1.05	<.0001
	1	0.88	0.73	1.06	0.33

Risk Factors	Group	OR	95% CI		p Value
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	0.82	0.68	1.00	0.16
	1	0.86	0.70	1.04	0.96
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	0.82	0.67	1.00	0.27
	1	0.85	0.70	1.05	1.00
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	0.83	0.69	1.01	0.07
	1	0.91	0.74	1.11	0.13
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	0.77	0.63	0.94	0.77
	1	0.87	0.70	1.08	0.68
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	0.75	0.60	0.95	0.60
	1	0.84	0.66	1.08	0.84
ADL SELF-PERFORMANCE (H2a) MOBILITY IN BED [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	0.47	0.36	0.62	<.0001

Risk Factors	Group	OR	95% CI		p Value
	1	0.66	0.50	0.88	0.007
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	1.17	0.78	1.74	<.0001
	1	1.86	1.22	2.84	0.21
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	1.25	0.83	1.87	0.003
	1	1.93	1.26	2.95	0.06
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	1.72	1.15	2.57	<.0001
	1	2.23	1.46	3.40	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	1.95	1.30	2.91	<.0001
	1	2.20	1.45	3.35	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	1.95	1.31	2.91	<.0001
	1	2.18	1.43	3.32	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	1.50	1.01	2.24	0.28

Risk Factors	Group	OR	95% CI		p Value
	1	1.88	1.24	2.85	0.31
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	1.15	0.77	1.72	0.004
	1	1.34	0.88	2.04	0.0005
ADL DECLINE (H3)	2	2.07	2.00	2.14	<.0001
	1	1.53	1.48	1.58	<.0001
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 0- No assistive device	2	0.99	0.81	1.23	<.0001
	1	1.04	0.85	1.29	0.04
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 1- Cane	2	1.29	1.04	1.59	0.26
	1	1.19	0.96	1.47	0.08
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 2- Walker/crutch	2	1.79	1.45	2.20	<.0001
	1	1.30	1.06	1.60	<.0001
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 3- Scooter	2	1.74	1.28	2.38	0.009
	1	1.15	0.83	1.59	0.80

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 4- Wheelchair	2	1.43	1.17	1.75	0.05
	1	1.06	0.86	1.30	0.12
STAIR CLIMBING (H5) [ref: 2- Not go up and down stairs] 0- Up and down stairs without help	2	0.91	0.87	0.95	<.0001
	1	0.94	0.90	0.98	0.006
STAIR CLIMBING (H5) [ref: 2- Not go up and down stairs] 1- Up and down stairs with help	2	1.01	0.94	1.05	0.003
	1	0.99	0.95	1.02	0.42
STAMINA: The number of days usually went out of the house or building (H6a) [ref: 3- No days] 0- Every day	2	1.20	1.12	1.28	<.0001
	1	1.13	1.07	1.21	0.02
STAMINA: The number of days usually went out of the house or building (H6a) [ref: 3- No days] 1- 2-6 days a week	2	1.13	1.08	1.18	0.02
	1	1.11	1.06	1.17	0.03
STAMINA: The number of days usually went out of the house or building (H6a) [ref: 3- No days] 2- 1 day a week	2	1.06	1.01	1.10	0.01
	1	1.09	1.05	1.14	0.57

Risk Factors	Group	OR	95% CI		*p* Value
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 0- CONTINENT	2	0.82	0.60	1.13	<.0001
	1	0.89	0.65	1.21	0.001
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 1- CONTINENT WITH CATHETER	2	0.76	0.55	1.06	<.0001
	1	0.84	0.61	1.15	0.001
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 2- USUALLY CONTINENT	2	1.05	0.76	1.45	0.08
	1	1.04	0.77	1.42	0.009
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 3- OCCASIONALLY INCONTINENT	2	1.12	0.81	1.54	0.0002
	1	1.03	0.76	1.41	0.03
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 4- FREQUENTLY INCONTINENT	2	1.23	0.89	1.70	<.0001
	1	1.03	0.76	1.40	0.03
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 5- INCONTINENT	2	1.10	0.79	1.52	0.007

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
	1	0.96	0.70	1.31	0.83
BLADDER CONTINENCE: Worsening of bladder incontinence as compared to status 90 days ago (I1b)	2	1.19	1.14	1.24	<.0001
	1	1.08	1.03	1.13	0.001
DISEASES: Cerebrovascular accident (stroke) (J1a)	2	1.06	1.03	1.09	0.0001
	1	1.05	1.02	1.08	0.0002
DISEASES: Congestive heart failure (J1b)	2	0.91	0.88	0.94	<.0001
	1	0.98	0.95	1.01	0.22
DISEASES: Peripheral vascular disease (J1f)	2	0.95	0.91	0.99	0.01
	1	0.95	0.92	0.99	0.02
DISEASES: Alzheimer's (J1g)	2	0.95	0.91	0.99	0.009
	1	0.99	0.95	1.02	0.44
DISEASES: Dementia other than Alzheimer's disease (J1h)	2	1.04	1.01	1.07	0.01
	1	1.03	1.00	1.06	0.03
DISEASES: Multiple sclerosis (J1k)	2	1.24	1.08	1.42	0.003
	1	1.08	0.93	1.26	0.29
DISEASES: Diabetes (J1y)	2	1.07	1.04	1.09	<.0001
	1	1.05	1.02	1.08	0.0001
DISEASES: Parkinsonism (J1l)	2	1.45	1.40	1.51	<.0001
	1	1.12	1.07	1.17	<.0001
DISEASES: Arthritis (J1m)	2	0.96	0.94	0.98	0.0004

Risk Factors	Group	OR	95% CI		*p* Value
	1	0.97	0.95	0.99	0.005
DISEASES: Hip fracture (J1n)	2	0.87	0.82	0.92	<.0001
	1	1.10	1.05	1.15	<.0001
DISEASES: Other fractures (J1o)	2	1.24	1.20	1.29	<.0001
	1	1.37	1.33	1.42	<.0001
PROBLEM CONDITIONS PRESENT ON 2 OR MORE DAYS: Difficulty urinating or urinating 3 or more times at night (K2b)	2	1.10	1.05	1.15	0.0001
	1	1.00	0.95	1.05	0.92
PROBLEM CONDITIONS: Dizziness or lightheadedness (K3c)	2	1.51	1.46	1.57	<.0001
	1	1.23	1.18	1.28	<.0001
PROBLEM CONDITIONS: Shortness of breath (K3e)	2	0.92	0.88	0.95	<.0001
	1	0.96	0.93	0.99	0.01
PAIN: Frequency of pain (K4a) [ref: 0- No pain] 1- Less than daily	2	1.02	0.97	1.08	0.43
	1	1.15	1.09	1.20	<.0001
PAIN: Frequency of pain (K4a) [ref: 0- No pain] 2- Daily-one period	2	1.18	1.10	1.26	<.0001
	1	1.24	1.17	1.32	<.0001
PAIN: Frequency of pain (K4a) [ref: 0- No pain] 3- Daily—multiple periods	2	1.22	1.16	1.28	<.0001

Risk Factors	Group	OR	95% CI		p Value
	1	1.21	1.16	1.26	<.0001
PAIN: Pain intensity disrupts usual activities (K4c)	2	0.91	0.87	0.95	<.0001
	1	0.95	0.92	0.99	0.01
DANGER OF FALL: Unsteady gait (K6a)	2	3.27	3.11	3.45	<.0001
	1	1.79	1.72	1.87	<.0001
DANGER OF FALL: Limit going outdoors due to fear of falling (K6b)	2	1.15	1.11	1.19	<.0001
	1	1.04	1.01	1.08	0.02
LIFESTYLE (Drinking/Smoking): Felt the need or was told by others to cut down on drinking (K7a)	2	2.30	1.99	2.66	<.0001
	1	1.47	1.26	1.72	<.0001
LIFESTYLE (Drinking/Smoking): Had to have a drink first thing in the morning to steady nerves (K7b)	2	1.61	1.25	2.07	0.0002
	1	1.31	1.00	1.73	0.05
HEALTH STATUS INDICATORS: Has conditions or diseases that make cognition, ADL, mood, or behaviour patterns unstable (K8b)	2	1.16	1.12	1.20	<.0001
	1	1.05	1.02	1.09	0.002
HOME ENVIRONMENT: Hazardous or uninhabitable flooring and carpeting (O1b)	2	1.41	1.29	1.54	<.0001
	1	1.25	1.15	1.37	<.0001

Risk Factors	Group	OR	95% CI		*p* Value
HOME ENVIRONMENT: Hazardous or uninhabitable bathroom and toilet room (O1c)	2	1.47	1.31	1.65	<.0001
	1	1.23	1.10	1.38	0.0004
HOME ENVIRONMENT: Hazardous or uninhabitable access to home (O1g)	2	1.08	1.03	1.14	0.002
	1	1.03	0.98	1.09	0.26
LIVING ARRANGEMENT: Now lives with other persons (O2a)	2	1.15	1.08	1.22	<.0001
	1	1.18	1.11	1.25	<.0001
RECEIPT OF PSYCHOTROPIC MEDICATION: Anxiolytic (Q2b)	2	1.10	1.05	1.14	<.0001
	1	1.04	1.00	1.08	0.07
RECEIPT OF PSYCHOTROPIC MEDICATION: Antidepressant (Q2c)	2	1.41	1.36	1.46	<.0001
	1	1.18	1.14	1.22	<.0001
RECEIPT OF PSYCHOTROPIC MEDICATION: Hypnotic (Q2d)	2	1.08	1.04	1.12	<.0001
	1	1.00	0.97	1.04	0.89

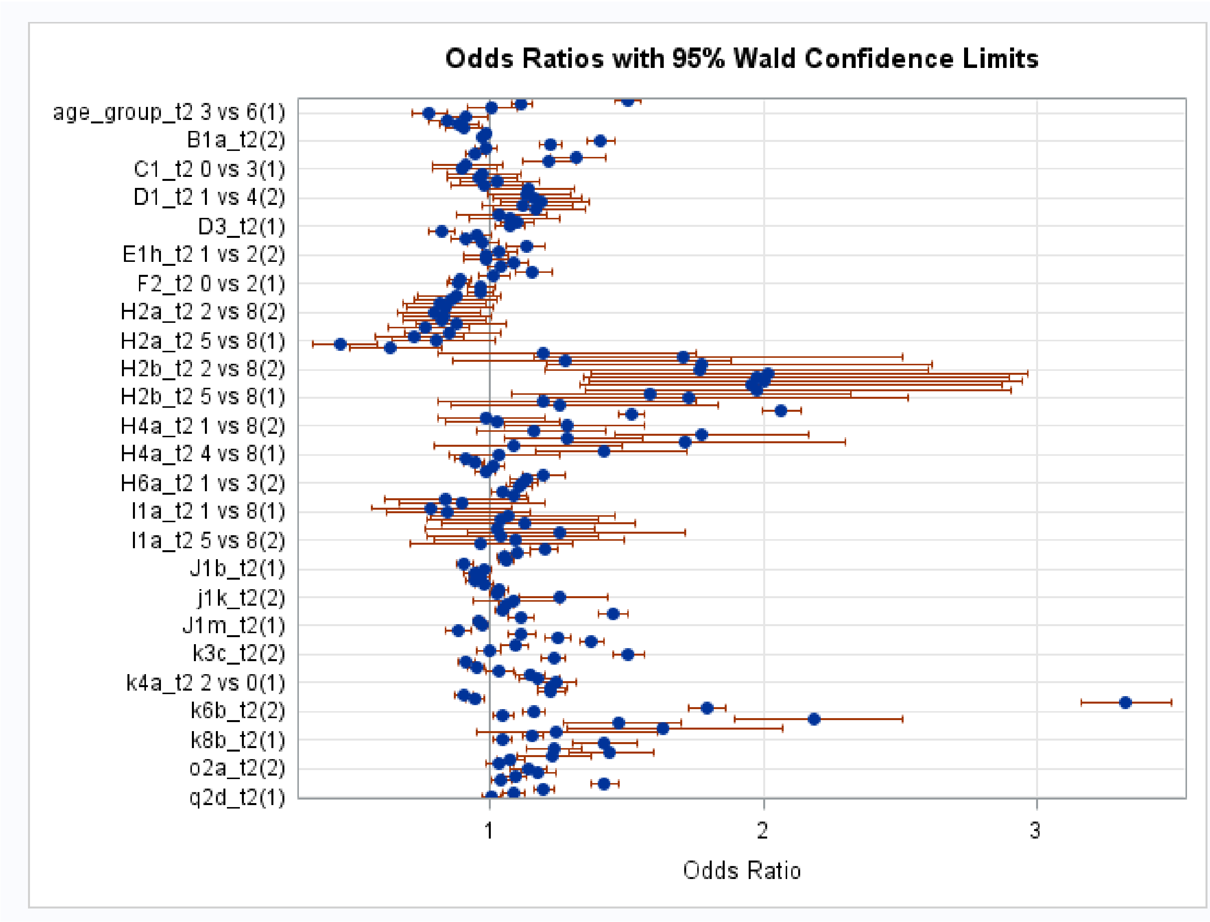


Figure 3: The Plot of Odds Ratios (Model: POM_Human_MDSHC)

The overall accuracy of model POM_Human_MDSHC was 68.2%, with accuracies of 95.6%, 0.1%, and 20.4% in classifying G_0, G_1 and G_2, respectively. Table 6 shows the confusion matrix for model POM_Human_MDSHC.

Table 6: The Confusion Matrix (Model: POM_Human_MDSHC)

Confusion Matrix (POM_Human_MDSHC)				
	Predicted Group			
Group	0	1	2	Total
0	108583	22	3703	112308
1	24570	29	2333	26932
2	20427	36	5361	25824
Total	153580	87	11397	165064
Frequency Missing = 2013				

5.1.1.2 Computer Feature Selection on the MDS-HC

The computer feature selection on the MDS-HC items incorporated 28 shortlisted independent variables into the proportional odds model (POM_Computer_MDSHC). They were short-term memory problem (B1a), how well client made decisions about organizing the day (B2a), IADL self-performance on meal preparation performance (H1aa), IADL self-performance on meal preparation difficulty (H1ab), IADL self-performance on ordinary housework performance (H1ba), IADL self-performance on ordinary housework difficulty (H1bb), IADL self-performance on managing medications performance (H1da), IADL self-performance on managing medications difficulty (H1db), IADL self-performance on shopping performance (H1fa), IADL self-performance on shopping difficulty (H1fb), IADL self-performance on transportation performance (H1ga), IADL self-performance on transportation difficulty (H1gb), ADL self-performance on mobility in bed (H2a), ADL self-performance on transfer (H2b), ADL self-performance on eating (H2g), ADL self-performance on toilet use (H2h), ADL self-performance on personal hygiene (H2i), ADL self-performance on bathing (H2j), ADL decline (H3), primary modes of locomotion - indoors (H4a), stair climbing (H5), bladder continence (I1a), worsening of bladder incontinence as compared to status 90 days ago (I1b), unsteady gait (K6a), limit going outdoors due to fear of falling (K6b), client would be better off in another living environment (O2b), the number of times visited emergency room without an overnight stay (P4b), and the overall change in care needs (P6).

Table 7 lists the results of model POM_Computer_MDSHC derived from the MDS-HC items based on computer feature selection, and Figure 4 shows the corresponding plot of odds ratios.

Table 7: The Relationship between Risk Factors and Falls (Model: POM_Computer_MDSHC)

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
MEMORY RECALL ABILITY (B1a) Short-term memory	2	1.24	1.19	1.29	<.0001
	1	1.17	1.12	1.22	<.0001
COGNITIVE SKILLS FOR DAILY DECISIONMAKING (B2a) How well client made decisions about organizing the day [ref: 4- SEVERELY IMPAIRED] 0- INDEPENDENT	2	0.94	0.86	1.03	<.0001
	1	1.09	1.00	1.19	0.76

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
COGNITIVE SKILLS FOR DAILY DECISIONMAKING (B2a) How well client made decisions about organizing the day [ref: 4- SEVERELY IMPAIRED] 1- MODIFIED INDEPENDENCE	2	1.10	1.01	1.19	0.05
	1	1.15	1.06	1.25	0.005
COGNITIVE SKILLS FOR DAILY DECISIONMAKING (B2a) How well client made decisions about organizing the day [ref: 4- SEVERELY IMPAIRED] 2- MINIMALLY IMPAIRED	2	1.22	1.13	1.32	<.0001
	1	1.14	1.05	1.24	0.02
COGNITIVE SKILLS FOR DAILY DECISIONMAKING (B2a) How well client made decisions about organizing the day [ref: 4- SEVERELY IMPAIRED] 3- MODERATELY IMPAIRED	2	1.07	0.99	1.16	0.73
	1	1.11	1.03	1.21	0.55
IADL SELF-PERFORMANCE (H1aa) MEAL PREPARATION - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	1.32	0.99	1.75	0.72
	1	1.20	0.93	1.56	0.34
IADL SELF-PERFORMANCE (H1aa) MEAL PREPARATION - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 1- SOME HELP	2	1.42	1.07	1.87	0.09

Risk Factors	Group	OR	95% CI		p Value
	1	1.24	0.96	1.60	0.05
IADL SELF-PERFORMANCE (H1aa) MEAL PREPARATION - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 2- FULL HELP	2	1.51	1.14	2.00	0.0003
	1	1.20	0.92	1.55	0.34
IADL SELF-PERFORMANCE (H1aa) MEAL PREPARATION - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 3- BY OTHERS	2	1.51	1.15	1.99	0.0002
	1	1.20	0.93	1.56	0.28
IADL SELF-PERFORMANCE (H1ba) ORDINARY HOUSEWORK - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	0.80	0.65	0.99	0.50
	1	0.81	0.67	0.98	0.15
IADL SELF-PERFORMANCE (H1ba) ORDINARY HOUSEWORK - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 1- SOME HELP	2	0.75	0.62	0.90	0.002
	1	0.84	0.71	0.99	0.26
IADL SELF-PERFORMANCE (H1ba) ORDINARY HOUSEWORK - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 2- FULL HELP	2	0.80	0.67	0.95	0.17
	1	0.83	0.70	0.98	0.07
IADL SELF-PERFORMANCE (H1ba) ORDINARY HOUSEWORK - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 3- BY OTHERS	2	0.82	0.69	0.98	0.81

Risk Factors	Group	OR	95% CI		p Value
	1	0.86	0.73	1.01	0.70
IADL SELF-PERFORMANCE (H1da) MANAGING MEDICATIONS - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	1.32	1.11	1.56	0.03
	1	1.08	0.93	1.25	0.79
IADL SELF-PERFORMANCE (H1da) MANAGING MEDICATIONS - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 1- SOME HELP	2	1.30	1.10	1.54	0.03
	1	1.07	0.93	1.24	0.90
IADL SELF-PERFORMANCE (H1da) MANAGING MEDICATIONS - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 2- FULL HELP	2	1.33	1.13	1.57	0.001
	1	1.10	0.95	1.27	0.24
IADL SELF-PERFORMANCE (H1da) MANAGING MEDICATIONS - Performance [ref: 8- ACTIVITY DID NOT OCCUR] 3- BY OTHERS	2	1.24	1.05	1.46	0.86
	1	1.11	0.96	1.28	0.17
IADL SELF-PERFORMANCE (H1db) MANAGING MEDICATIONS - Difficulty [ref: 2- GREAT DIFFICULTY] 0- NO DIFFICULTY	2	0.92	0.85	1.00	0.001
	1	0.99	0.92	1.07	0.13

Risk Factors	Group	OR	95% CI		*p* Value
IADL SELF-PERFORMANCE (H1db) MANAGING MEDICATIONS - Difficulty [ref: 2- GREAT DIFFICULTY] 1- SOME DIFFICULTY	2	1.07	1.02	1.13	<.0001
	1	1.09	1.04	1.13	<.0001
IADL SELF-PERFORMANCE (H1fb) SHOPPING - Difficulty [ref: 2- GREAT DIFFICULTY] 0- NO DIFFICULTY	2	1.13	1.02	1.25	0.25
	1	1.06	0.98	1.14	0.43
IADL SELF-PERFORMANCE (H1fb) SHOPPING - Difficulty [ref: 2- GREAT DIFFICULTY] 1- SOME DIFFICULTY	2	1.13	1.08	1.19	0.03
	1	1.05	1.01	1.10	0.31
IADL SELF-PERFORMANCE (H1gb) TRANSPORTATION - Difficulty [ref: 2- GREAT DIFFICULTY] 0- NO DIFFICULTY	2	1.08	1.02	1.15	0.11
	1	1.04	0.99	1.09	0.65
IADL SELF-PERFORMANCE (H1gb) TRANSPORTATION - Difficulty [ref: 2- GREAT DIFFICULTY] 1- SOME DIFFICULTY	2	1.07	1.03	1.11	0.18
	1	1.05	1.01	1.09	0.05
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	1.11	0.74	1.65	<.0001
	1	1.83	1.20	2.77	0.61

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	1.22	0.82	1.82	0.002
	1	1.94	1.27	2.95	0.07
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	1.71	1.15	2.56	<.0001
	1	2.23	1.47	3.40	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	1.95	1.31	2.90	<.0001
	1	2.24	1.48	3.41	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	1.96	1.31	2.91	<.0001
	1	2.27	1.49	3.44	<.0001
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	1.53	1.03	2.28	0.05
	1	1.98	1.30	3.00	0.07
ADL SELF-PERFORMANCE (H2b) TRANSFER [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	1.04	0.70	1.55	<.0001
	1	1.34	0.88	2.02	<.0001

Risk Factors	Group	OR	95% CI		p Value
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	0.41	0.19	0.90	0.07
	1	0.69	0.28	1.69	0.98
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	0.43	0.20	0.95	0.33
	1	0.68	0.28	1.66	0.84
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	0.45	0.21	0.98	0.72
	1	0.70	0.29	1.71	0.81
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	0.47	0.21	1.02	0.76
	1	0.72	0.29	1.71	0.81
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	0.44	0.20	0.97	0.63
	1	0.74	0.30	1.82	0.42
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	0.40	0.18	0.89	0.14
	1	0.60	0.24	1.49	0.19

Risk Factors	Group	OR	95% CI		p Value
ADL SELF-PERFORMANCE (H2g) EATING [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	0.30	0.13	0.66	<.0001
	1	0.50	0.20	1.23	0.001
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	0.77	0.56	1.05	0.46
	1	1.33	0.93	1.92	0.01
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	0.69	0.50	0.94	0.005
	1	1.26	0.88	1.82	0.44
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	0.74	0.54	1.00	0.46
	1	1.24	0.86	1.78	0.86
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	0.75	0.55	1.02	0.73
	1	1.28	0.89	1.84	0.19
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	0.69	0.50	0.94	0.008

Risk Factors	Group	OR	95% CI		p Value
	1	1.21	0.84	1.74	0.65
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	0.69	0.50	0.95	0.07
	1	1.26	0.86	1.84	0.64
ADL SELF-PERFORMANCE (H2i) PERSONAL HYGIENE [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	0.75	0.54	1.06	1.00
	1	1.28	0.87	1.90	0.55
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 0- INDEPENDENT	2	1.04	0.89	1.21	0.003
	1	1.00	0.86	1.16	0.47
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 1- SETUP HELP ONLY	2	0.91	0.75	1.09	0.47
	1	0.97	0.81	1.15	0.28
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 2- SUPERVISION	2	0.98	0.84	1.13	0.26
	1	1.07	0.92	1.24	0.06
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 3- LIMITED ASSISTANCE	2	0.96	0.83	1.11	0.36

Risk Factors	Group	OR	95% CI		p Value
	1	1.06	0.92	1.22	0.02
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 4- EXTENSIVE ASSISTANCE	2	0.95	0.82	1.09	0.90
	1	1.05	0.92	1.21	0.06
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 5- MAXIMAL ASSISTANCE	2	0.91	0.78	1.05	0.17
	1	1.00	0.86	1.17	0.67
ADL SELF-PERFORMANCE (H2j) BATHING [ref: 8- ACTIVITY DID NOT OCCUR] 6- TOTAL DEPENDENCE	2	0.83	0.70	0.98	0.002
	1	0.99	0.83	1.16	0.48
ADL DECLINE (H3)	2	1.54	1.48	1.60	<.0001
	1	1.32	1.28	1.37	<.0001
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 0- No assistive device	2	1.09	0.88	1.34	<.0001
	1	1.02	0.82	1.25	0.004
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 1- Cane	2	1.47	1.20	1.82	0.57
	1	1.21	0.98	1.49	0.02

Risk Factors	Group	OR	95% CI		p Value
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 2- Walker/crutch	2	1.87	1.52	2.29	<.0001
	1	1.29	1.05	1.59	<.0001
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 3- Scooter (e.g. Amigo)	2	1.96	1.44	2.67	0.003
	1	1.14	0.83	1.58	0.83
PRIMARY MODES OF LOCOMOTION - Indoors (H4a) [ref: 8- ACTIVITY DID NOT OCCUR] 4- Wheelchair	2	1.56	1.27	1.91	0.03
	1	1.07	0.87	1.31	0.22
STAIR CLIMBING (H5) [ref: 2- Not go up and down stairs] 0- Up and down stairs without help	2	1.00	0.96	1.05	0.13
	1	0.96	0.92	1.00	0.03
STAIR CLIMBING (H5) [ref: 2- Not go up and down stairs] 1- Up and down stairs with help	2	1.08	1.04	1.12	0.0002
	1	1.00	0.96	1.04	0.33
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 0- CONTINENT	2	0.78	0.57	1.08	<.0001
	1	0.89	0.66	1.21	0.004

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 1- CONTINENT WITH CATHETER	2	0.70	0.50	0.97	<.0001
	1	0.79	0.58	1.08	<.0001
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 2- USUALLY CONTINENT	2	0.96	0.70	1.33	0.31
	1	1.05	0.78	1.43	0.001
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 3- OCCASIONALLY INCONTINENT	2	1.03	0.75	1.42	0.002
	1	1.04	0.76	1.41	0.008
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 4- FREQUENTLY INCONTINENT	2	1.13	0.82	1.56	<.0001
	1	1.03	0.76	1.40	0.02
BLADDER CONTINENCE: Control of urinary bladder function (I1a) [ref: 8- DID NOT OCCUR] 5- INCONTINENT	2	1.02	0.74	1.41	0.01
	1	0.96	0.70	1.30	0.89
BLADDER CONTINENCE: Worsening of bladder incontinence as compared to status 90 days ago (I1b)	2	1.18	1.13	1.23	<.0001
	1	1.06	1.02	1.11	0.009

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
DANGER OF FALL: Unsteady gait (K6a)	2	3.63	3.44	3.82	<.0001
	1	1.87	1.80	1.95	<.0001
DANGER OF FALL: Limit going outdoors due to fear of falling (K6b)	2	1.12	1.08	1.16	<.0001
	1	1.05	1.02	1.09	0.003
LIVING ARRANGEMENT (O2b) Client or primary caregiver feels that client would be better off in another living environment	2	1.17	1.16	1.19	<.0001
	1	1.06	1.04	1.07	<.0001
VISITS IN LAST 90 DAYS OR SINCE LAST ASSESSMENT: Number of times VISITED EMERGENCY ROOM without an overnight stay (P4b)	2	1.57	1.53	1.60	<.0001
	1	1.37	1.34	1.40	<.0001
OVERALL CHANGE IN CARE NEEDS (P6) [ref: 0- No change] 1- Improved	2	0.83	0.78	0.88	<.0001
	1	0.92	0.88	0.97	0.002
OVERALL CHANGE IN CARE NEEDS (P6) [ref: 0- No change] 2- Deteriorated	2	1.64	1.57	1.70	<.0001
	1	1.34	1.29	1.39	<.0001

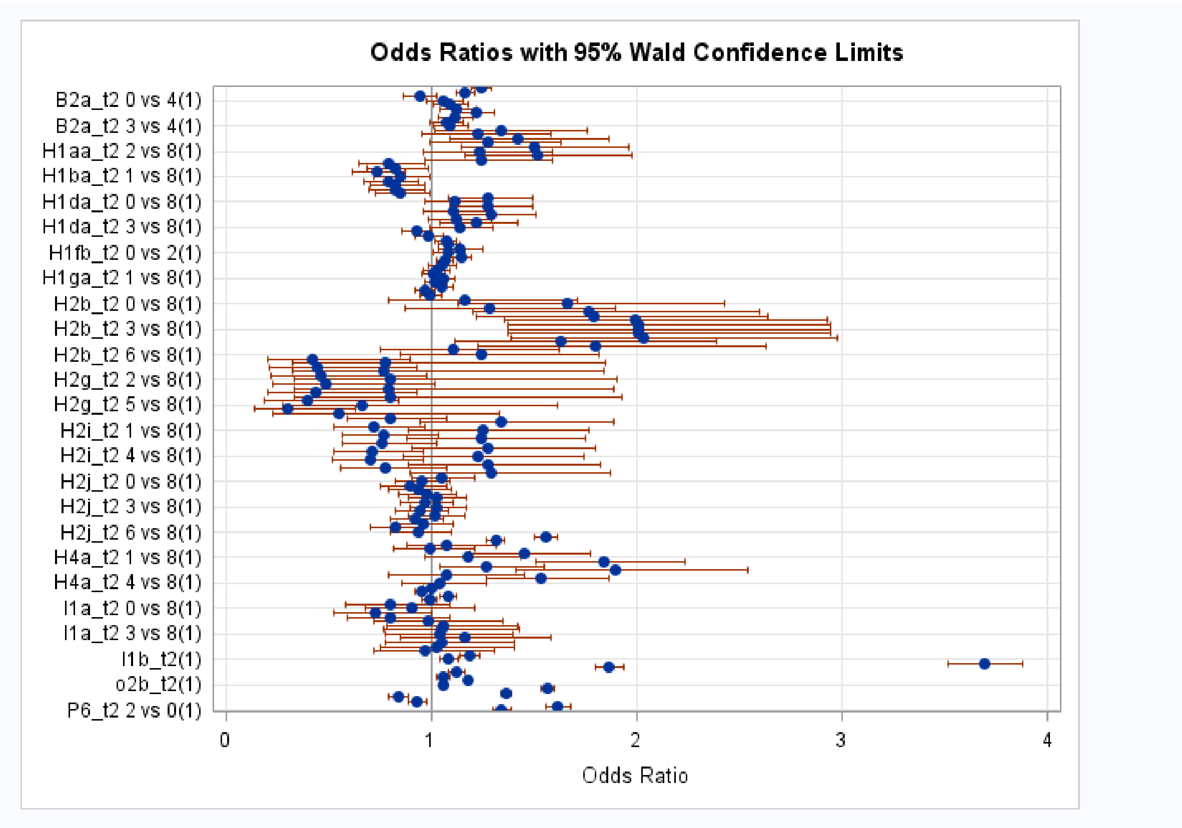


Figure 4: The Plot of Odds Ratios (Model: POM_Computer_MDSHC)

The overall accuracy of model POM_Computer_MDSHC was 69.2%, with accuracies of 96.6%, 0.01%, and 22.4% in classifying G_0, G_1 and G_2, respectively. Table 8 shows the confusion matrix for model POM_Computer_MDSHC.

Table 8: The Confusion Matrix (Model: POM_Computer_MDSHC)

Confusion Matrix (POM_Computer_MDSHC)				
	Predicted Group			
Group	0	1	2	Total
0	109681	7	3792	113480
1	24624	4	2683	27311
2	20355	1	5865	26221
Total	154660	12	12340	167012
Frequency Missing = 65				

5.1.1.3 Computer Feature Selection on the CAPs/Scales

Likewise, the independent variables selected based on the CAPs/Scales using the same computerized feature selection algorithm included CHESS (The Changes in Health, End-Stage Disease, Signs, and Symptoms), MAPLe (The Method of Assigning Priority Levels), IADL Summary Scale (IADLsum), ADL CAP (cADL), Cognitive CAP (cCOGNIT), Risk CAP (cRISK), and Urinary Incontinence CAP (cURIN). The results revealed that MAPLe (1 vs. 5: OR = 0.20; 95% CI, 0.18-0.22), CHESS (0 vs. 5: OR = 0.27; 95% CI, 0.21-0.36), as well as cADL (0 vs. 2: OR = 0.21; 95% CI, 0.20-0.22), cCOGNIT (0 vs. 2: OR = 0.33; 95% CI, 0.31-0.35), and cURIN (3 vs. 0: OR = 1.77; 95% CI, 1.62-1.94) were strong predictors in classifying older adults with different falls frequency. Table 9 lists the results of model POM_Computer_CAPScales, and Figure 5 shows the corresponding plot of odds ratios.

Table 9: The Relationship between Risk Factors and Falls (Model: POM_Computer_CAPScales)

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
CHESS [ref: 5-Highly unstable] 0- Not at all unstable	2	0.27	0.21	0.36	<.0001
	1	0.73	0.55	0.96	<.0001
CHESS [ref: 5-Highly unstable] 1	2	0.33	0.25	0.43	<.0001
	1	0.74	0.56	0.98	0.0007
CHESS [ref: 5-Highly unstable] 2	2	0.38	0.28	0.50	<.0001
	1	0.75	0.57	1.00	0.006
CHESS [ref: 5-Highly unstable] 3	2	0.43	0.33	0.57	0.29
	1	0.79	0.59	1.05	0.26
CHESS [ref: 5-Highly unstable] 4	2	0.55	0.41	0.74	<.0001
	1	0.92	0.69	1.23	0.004
IADL Summary Scale (IADLsum)	2	1.00	0.99	1.00	0.23
	1	0.98	0.98	0.99	<.0001
MAPLe [ref: 5- Very High Need] 1- Low Need	2	0.20	0.18	0.22	<.0001
	1	1.15	1.06	1.24	0.0001
MAPLe [ref: 5- Very High Need] 2- Mild Need	2	0.28	0.25	0.30	0.03
	1	1.48	1.37	1.60	<.0001

Risk Factors	Group	OR	95% CI		*p* Value
MAPLe [ref: 5- Very High Need] 3- Moderate Need	2	0.06	0.05	0.06	<.0001
	1	1.67	1.57	1.78	<.0001
MAPLe [ref: 5- Very High Need] 4- High Need	2	0.71	0.68	0.74	<.0001
	1	1.08	1.02	1.13	<.0001
ADL CAP (cADL) [ref: 2- Triggered- Facilitate Improvement] 0- Not Triggered	2	0.21	0.20	0.22	<.0001
	1	0.78	0.69	0.75	<.0001
ADL CAP (cADL) [ref: 2- Triggered- Facilitate Improvement] 1- Triggered- Prevent Decline	2	0.20	0.18	0.21	<.0001
	1	0.19	0.18	0.20	<.0001
Cognitive CAP (cCOGNIT) [ref: 2- Triggered- Prevent Decline] 0- Not Triggered	2	0.33	0.31	0.35	<.0001
	1	1.07	1.01	1.14	0.002
Cognitive CAP (cCOGNIT) [ref: 2- Triggered- Prevent Decline] 1- Triggered- Monitor	2	1.78	1.69	1.87	<.0001
	1	1.37	1.31	1.44	<.0001
Risk CAP (cRISK) [ref: 1- Triggered] 0- Not Triggered	2	0.56	0.53	0.59	<.0001
	1	0.29	0.28	0.30	<.0001

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
Urinary Incontinence CAP (cURIN) [ref: 0- Not Triggered: Continent at Baseline] 1- Not Triggered: Poor Decision Making at Baseline	2	0.96	0.89	1.05	0.37
	1	1.12	1.03	1.21	0.009
Urinary Incontinence CAP (cURIN) [ref: 0- Not Triggered: Continent at Baseline] 2- Triggered: Prevent Decline	2	1.31	1.21	1.41	<.0001
	1	1.26	1.17	1.37	<.0001
Urinary Incontinence CAP (cURIN) [ref: 0- Not Triggered: Continent at Baseline] 3- Triggered: Facilitate Improvement	2	1.77	1.62	1.94	<.0001
	1	1.32	1.20	1.44	<.0001

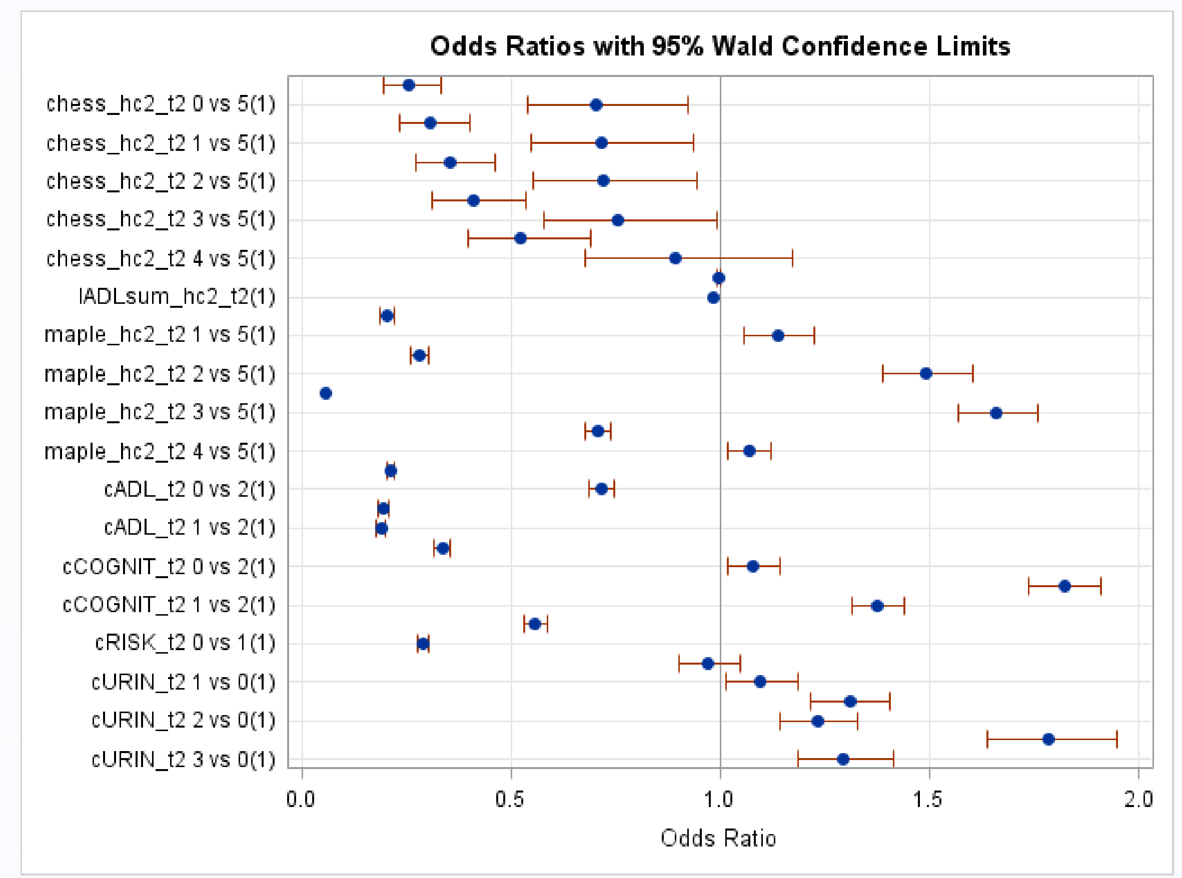


Figure 5: The Plot of Odds Ratios (Model: POM_Computer_CAPScales)

The overall accuracy of model POM_Computer_CAPScales was 70.8%, with accuracies of 94.7%, 2.1%, and 38.7% in classifying G_0, G_1 and G_2, respectively. Table 10 shows the confusion matrix for model POM_Computer_CAPScales.

Table 10: The Confusion Matrix (Model: POM_Computer_CAPScales)

Confusion Matrix (POM_Computer_CAPScales)				
	Predicted Group			
Group	0	1	2	Total
0	107527	561	3131	111219
1	24554	564	1449	26567
2	15176	0	10146	25322
Total	147257	1125	14726	163108
Frequency Missing = 3969				

5.1.1.4 Computer Feature Selection on All Items

The same feature selection technique was finally applied on all available items on the RAI-HC data set, and the final proportional odds model (POM_Computer_All) incorporated 12 independent variables, including CHESS, MAPLe, IADL Summary Scale (IADLsum), ADL CAP (cADL), Cognitive CAP (cCOGNIT), Risk CAP (cRISK), and Urinary Incontinence CAP (cURIN) derived from the CAPs/Scales, as well as stair climbing (H5), unsteady gait (K6a), limit going outdoors due to fear of falling (K6b), client would be better off in another living environment (O2b), and the number of times visited emergency room without an overnight stay (P4b) from the MDS-HC. Table 11 lists the results of model POM_Computer_All, and Figure 6 shows the corresponding plot of odds ratios.

Table 11: The Relationship between Risk Factors and Falls (Model: POM_Computer_All)

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
CHESS [ref: 5-Highly unstable] 0- Not at all unstable	2	0.54	0.41	0.71	<.0001
	1	1.04	0.79	1.37	0.008
CHESS [ref: 5-Highly unstable] 1	2	0.55	0.42	0.73	<.0001
	1	0.98	0.74	1.28	0.69
CHESS [ref: 5-Highly unstable] 2	2	0.58	0.44	0.76	0.004
	1	0.93	0.71	1.22	0.15
CHESS [ref: 5-Highly unstable] 3	2	0.56	0.43	0.74	0.0005
	1	0.89	0.68	1.17	0.006
CHESS [ref: 5-Highly unstable] 4	2	0.62	0.47	0.82	0.88
	1	0.96	0.73	1.27	0.97
IADL Summary Scale (IADLsum)	2	0.98	0.98	0.99	<.0001
	1	0.98	0.97	0.98	<.0001
MAPLe [ref: 5- Very High Need] 1- Low Need	2	0.24	0.22	0.26	<.0001
	1	1.28	1.19	1.38	0.38
MAPLe [ref: 5- Very High Need] 2- Mild Need	2	0.25	0.23	0.27	<.0001
	1	1.47	1.36	1.58	<.0001

Risk Factors	Group	OR	95% CI		*p* Value
MAPLe [ref: 5- Very High Need] 3- Moderate Need	2	0.05	0.05	0.06	<.0001
	1	1.58	1.49	1.67	<.0001
MAPLe [ref: 5- Very High Need] 4- High Need	2	0.67	0.64	0.70	<.0001
	1	1.06	1.01	1.11	<.0001
ADL CAP (cADL) [ref: 2- Triggered- Facilitate Improvement] 0- Not Triggered	2	0.26	0.25	0.27	<.0001
	1	0.77	0.74	0.80	<.0001
ADL CAP (cADL) [ref: 2- Triggered- Facilitate Improvement] 1- Triggered- Prevent Decline	2	0.21	0.20	0.22	<.0001
	1	0.20	0.19	0.21	<.0001
Cognitive CAP (cCOGNIT) [ref: 2- Triggered- Prevent Decline] 0- Not Triggered	2	0.39	0.37	0.41	<.0001
	1	1.15	1.08	1.22	0.72
Cognitive CAP (cCOGNIT) [ref: 2- Triggered- Prevent Decline] 1- Triggered- Monitor	2	1.62	1.55	1.71	<.0001
	1	1.29	1.23	1.35	<.0001
Risk CAP (cRISK) [ref: 1- Triggered] 0- Not Triggered	2	0.57	0.54	0.60	<.0001
	1	0.29	0.28	0.30	<.0001

Risk Factors	**Group**	**OR**	**95% CI**		***p* Value**
Urinary Incontinence CAP (cURIN) [ref: 3- Triggered: Facilitate Improvement] 0- Not Triggered: Continent at Baseline	2	0.66	0.61	0.73	<.0001
	1	0.83	0.76	0.91	0.0002
Urinary Incontinence CAP (cURIN) [ref: 3- Triggered: Facilitate Improvement] 1- Not Triggered: Poor Decision Making at Baseline	2	0.66	0.63	0.69	<.0001
	1	0.93	0.89	0.97	0.84
Urinary Incontinence CAP (cURIN) [ref: 3- Triggered: Facilitate Improvement] 2- Triggered: Prevent Decline	2	0.77	0.73	0.81	0.49
	1	0.97	0.93	1.02	0.002
STAIR CLIMBING (H5) [ref: 0- Up and down stairs without help] 1- Up and down stairs with help	2	1.45	1.38	1.53	<.0001
	1	1.18	1.13	1.23	<.0001
STAIR CLIMBING (H5) [ref: 0- Up and down stairs without help] 2- Not go up and down stairs	2	1.35	1.29	1.41	<.0001
	1	1.08	1.04	1.12	<.0001
DANGER OF FALL: Unsteady gait (K6a)	2	4.19	3.98	4.41	<.0001
	1	2.00	1.93	2.08	<.0001

Risk Factors	Group	OR	95% CI		*p* Value
DANGER OF FALL: Limit going outdoors due to fear of falling (K6b)	2	1.27	1.23	1.32	<.0001
	1	1.07	1.04	1.11	<.0001
LIVING ARRANGEMENT (O2b) Client or primary caregiver feels that client would be better off in another living environment	2	1.10	1.08	1.11	<.0001
	1	1.04	1.02	1.05	<.0001
VISITS IN LAST 90 DAYS OR SINCE LAST ASSESSMENT: Number of times VISITED EMERGENCY ROOM without an overnight stay (P4b)	2	1.57	1.54	1.61	<.0001
	1	1.36	1.33	1.39	<.0001

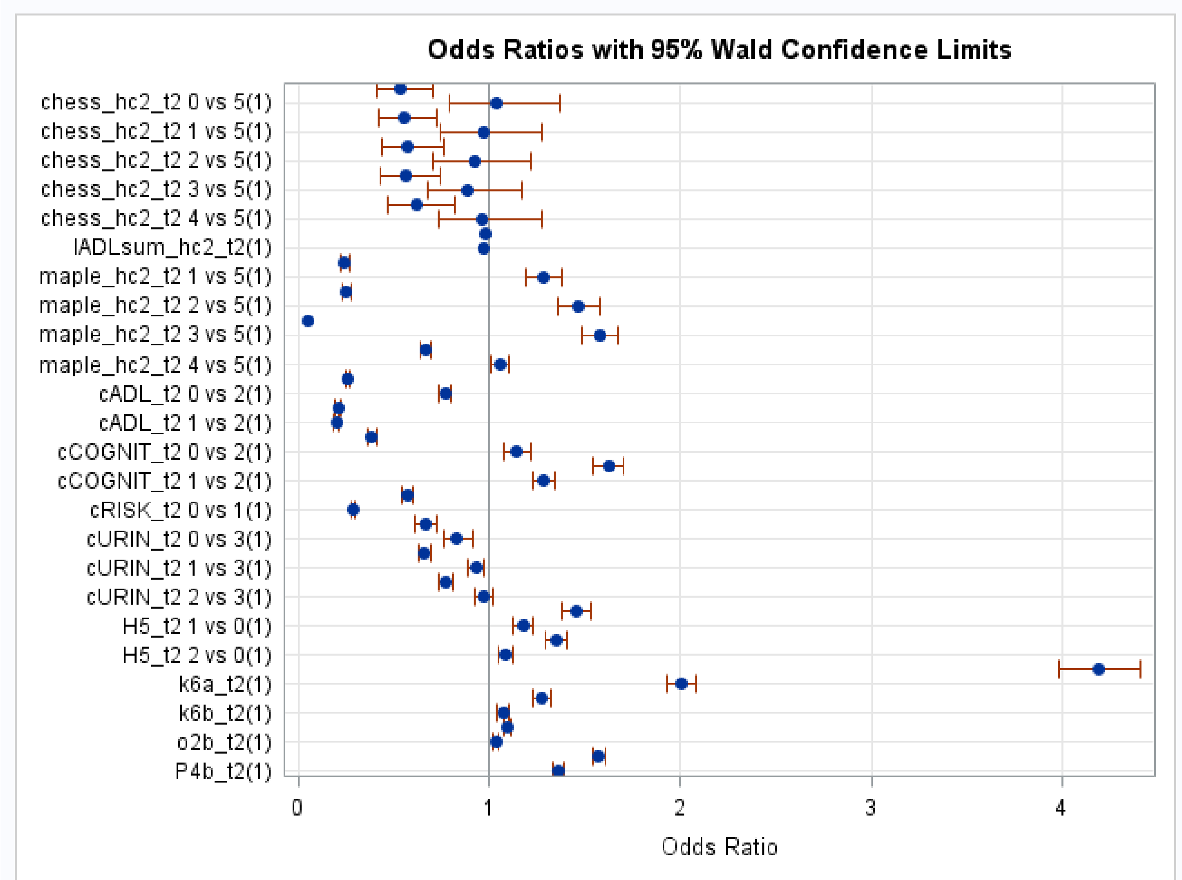


Figure 6: The Plot of Odds Ratios (Model: POM_Computer_All)

The overall accuracy of model POM_Computer_All was 71.5%, with accuracies of 93.3%, 5.5%, and 46.0% in classifying G_0, G_1 and G_2, respectively. Table 12 shows the confusion matrix for model POM_Computer_All.

Table 12: The Confusion Matrix (Model: POM_Computer_All)

Confusion Matrix (POM_Computer_All)				
	Predicted Group			
Group	0	1	2	Total
0	105955	1386	3871	111212
1	22729	1510	2327	26566
2	13109	135	12075	25319
Total	141793	3031	18273	163097
Frequency Missing = 3980				

5.1.2 Secondary Analysis

As a secondary analysis within Study I, the final logistic regression models from Section 5.1.1 were tested to evaluate the classification performance in distinguishing fallers and non-fallers (i.e., binary classification as opposed to three-group classification). To compare the classification performances, Table 13 lists the ACC, SEN, SPE, PPV, NPV, AUC, and the Brier score of each model. In addition, the overlay of the ROC curves for four logistic regression models was plotted (see Figure 7).

Table 13: Classification Results and Model Evaluation

Logistic Regression Model	Classification Accuracy (ACC) (%)			SEN (%) (95% CI)	SPE (%) (95% CI)	PPV (%)	NPV (%)	AUC (95% CI)	Brier Score
	Overall (95% CI)	Non-Faller	Faller						
LR_Human_ MDSHC	71.5 (71.5 71.6)	88.8	32.1	32.6 (32.5 32.8)	89.8 (89.7 89.9)	60.0	73.9	0.726 (0.724 0.729)	0.187
LR_Computer _MDSHC	72.0 (72.0 72.1)	89.9	34.0	34.0 (33.8 34.2)	90.0 (89.9 90.0)	61.5	74.3	0.730 (0.728 0.733)	0.186
LR_Computer _CAPScales	73.2 (73.2 73.3)	87.1	38.5	39.6 (39.3 40.1)	88.9 (88.8 89.0)	62.5	75.9	0.730 (0.727 0.733)	0.181
LR_Computer _All	75.1 (75.0 75.1)	85.4	47.5	49.0 (48.9 49.2)	87.2 (87.1 87.2)	64.1	78.6	0.769 (0.766 0.771)	0.171

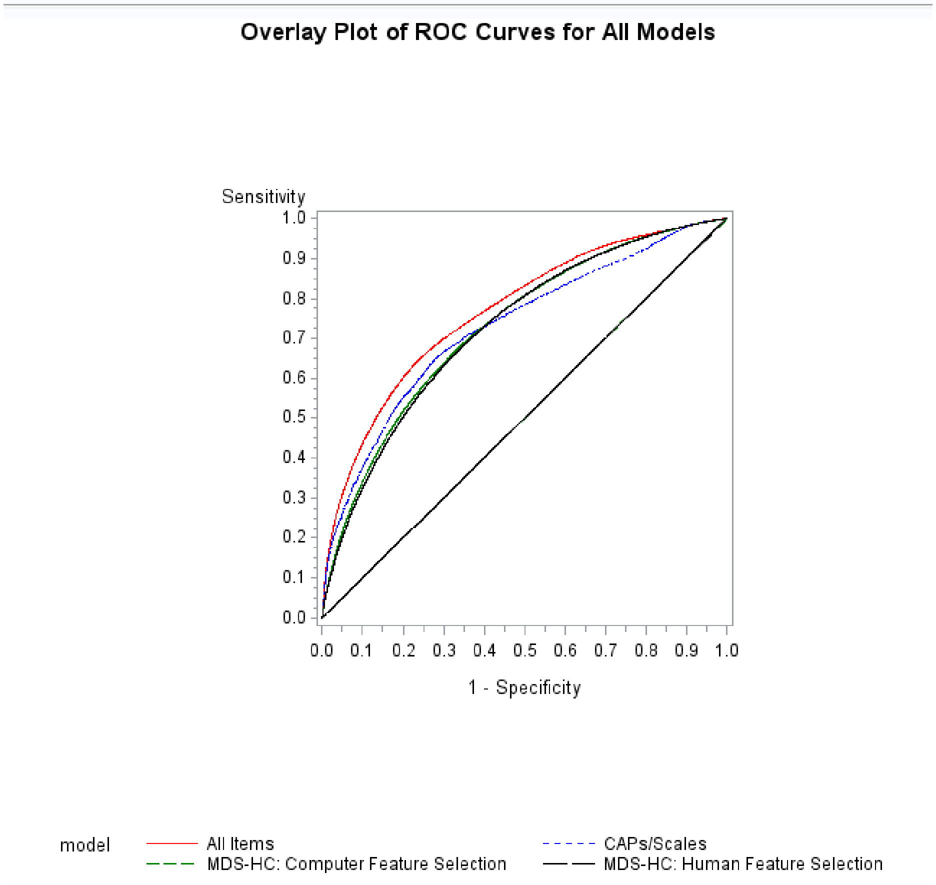


Figure 7: The Overlay Plot of the ROC Curves for All Models

5.2 Study II: Data-Driven Characterization of Groups with Varying Fall Histories: A Prospective, Observational Study

5.2.1 Descriptive Statistics and Simple Statistical Analyses

Of the total of 40 participants aged 65 to 93 years (M = 76.0, SD = 7.2) in study II, based on their self-reported falls frequency at the end of the wearable data collection phase, 15 older adults (37.5%) had no history of falls (age: M = 73.4, SD = 6.4, range = 65-88), 13 individuals (32.5%) had one fall (age: M = 77.9, SD = 7.7, range = 67-93), and 12 (30.0%) experienced multiple (≥ 2) falls (age: M = 76.3, SD = 5.8, range = 67-89). The study population included 22 (55%) males (age: M = 74.8, SD = 7.2, range = 65-89) and 18 (45%) females (age: M = 77.3, SD = 7.2, range = 69-93). Table 14 lists the baseline characteristics of the total of 40 participants in this study based on their latest RAI-HC assessments.

Table 14: Baseline Characteristics of Participants in Study II (as assessed by the RAI-HC)

Characteristics	**Non-Fallers (zero falls)**	**Single Fallers (1 fall)**	**Recurrent Fallers (≥ 2 falls)**	**Total**
Number of Participants (n, %)	16 (40.0%)	8 (20.0%)	16 (40.0%)	40 (100%)
Age (M ± SD, years)	*75.2 ± 7.5*	*74.0 ± 6.3*	*77.8 ± 7.4*	*76.0 ± 7.2*
Males (*M ± SD*, years)	73.8 ± 9.8	71.9 ± 2.1	76.1 ± 6.5	74.8 ± 7.2
Females (*M ± SD*, years)	76.2 ± 5.6	75.3 ± 7.9	82.9 ± 8.6	77.3 ± 7.2
Age Group				
65-74 years (n, %)	8 (20.0%)	7 (17.5%)	6 (15.0%)	21 (52.5%)
75-84 years (n, %)	6 (15.0%)	0	7 (17.5%)	13 (32.5%)
85-94 years (n, %)	2 (5.0%)	1 (2.5%)	3 (7.5%)	6 (15.0%)
Gender				
Males (n, %)	7 (17.5%)	3 (7.5%)	12 (30.0%)	22 (55.0%)
Females (n, %)	9 (22.5%)	5 (12.5%)	4 (10.0%)	18 (45.0%)

Characteristics	Non-Fallers (zero falls)	Single Fallers (1 fall)	Recurrent Fallers (≥ 2 falls)	Total
Who lived with at referral				
Alone (n, %)	3 (7.5%)	1 (2.5%)	3 (7.5%)	7 (17.5%)
Family members or others (n, %)	7 (17.5%)	3 (7.5%)	5 (12.5%)	15 (37.5%)
Group settings (n, %)	0	0	2 (5.0%)	2 (5.0%)
Unknown (n, %)	6 (15.0%)	4 (10.0%)	6 (15.0%)	16 (40.0%)
Primary Modes of Locomotion (Indoors)				
No assistive device (n, %)	9 (22.5%)	3 (7.5%)	7 (17.5%)	19 (47.5%)
Cane/Walker/Scooter (n, %)	6 (15.0%)	5 (12.5%)	7 (17.5%)	18 (45.0%)
Wheelchair (n, %)	1 (2.5%)	0	2 (5.0%)	3 (7.5%)
Primary Modes of Locomotion (Outdoors)				
No assistive device (n, %)	6 (15.0%)	2 (5.0%)	5 (12.5%)	13 (32.5%)
Cane/Walker/Scooter (n, %)	9 (22.5%)	6 (15.0%)	6 (15.0%)	21 (52.5%)
Wheelchair (n, %)	1 (2.5%)	0	4 (10.0%)	5 (12.5%)
Activity did not occur (n, %)	0	0	1 (2.5%)	1 (2.5%)
Short-term Memory				
Memory OK (n, %)	11 (27.5%)	6 (15.0%)	5 (12.5%)	22 (55.0%)
Memory problem (n, %)	5 (12.5%)	2 (5.0%)	11 (27.5%)	18 (45.0%)
IADL SELF-PERFORMANCE, Meal Preparation Difficulty				
No difficulty (n, %)	8 (15.0%)	1 (5.0%)	1 (2.5%)	10 (25.0%)
Some difficulty (n, %)	4 (10.0%)	0	3 (7.5%)	7 (17.5%)
Great difficulty (n, %)	4 (10.0%)	7 (17.5%)	12 (30.0%)	23 (57.5%)
Number of times visited emergency room without an overnight stay				
0 (n, %)	14 (35.0%)	7 (17.5%)	6 (15.0%)	27 (67.5%)
1 (n, %)	2 (5.0%)	1 (2.5%)	7 (17.5%)	10 (25.0%)
2 (n, %)	0	0	1 (2.5%)	1 (2.5%)
≥3 (n, %)	0	0	2 (5.0%)	2 (5.0%)

Characteristics	Non-Fallers (zero falls)	Single Fallers (1 fall)	Recurrent Fallers (≥ 2 falls)	Total
MAPLe				
1 (n, %)	8 (20.0%)	1 (2.5%)	1 (2.5%)	10 (25.0%)
2 (n, %)	2 (5.0%)	0	0	2 (5.0%)
3 (n, %)	2 (5.0%)	4 (10.0%)	1 (2.5%)	7 (17.5%)
4 (n, %)	2 (5.0%)	1 (2.5%)	9 (22.5%)	12 (30.0%)
5 (n, %)	2 (5.0%)	2 (5.0%)	5 (12.5%)	9 (22.5%)
CHESS				
0 (n, %)	6 (15.0%)	1 (2.5%)	2 (5.0%)	9 (22.5%)
1 (n, %)	6 (15.0%)	3 (7.5%)	4 (10.0%)	13 (32.5%)
2 (n, %)	2 (5.0%)	3 (7.5%)	6 (15.0%)	11 (27.5%)
3 (n, %)	2 (5.0%)	1 (2.5%)	4 (10.0%)	7 (17.5%)

Prior to the primary analyses, missing values in both wearable data and the corresponding RAI-HC data set, which contains the 40 participants' latest RAI-HC assessments were analyzed and imputed. Of the total of 38 variables, 40 cases and 1520 values in the wearable data, incomplete data with at least one missing value represented 55.3%, 65% and 6.4%, respectively; while incomplete data with at least one missing value in the RAI-HC data set was 19.8%, 100%, and 16.3% of the total of 106 variables, 40 cases and 4240 values, respectively. Figures 8-9 show the overall summary of missing values and the missing value patterns of both data sets. The missing values were imputed using the maximum likelihood estimates with the EM algorithm for analyses in this study.

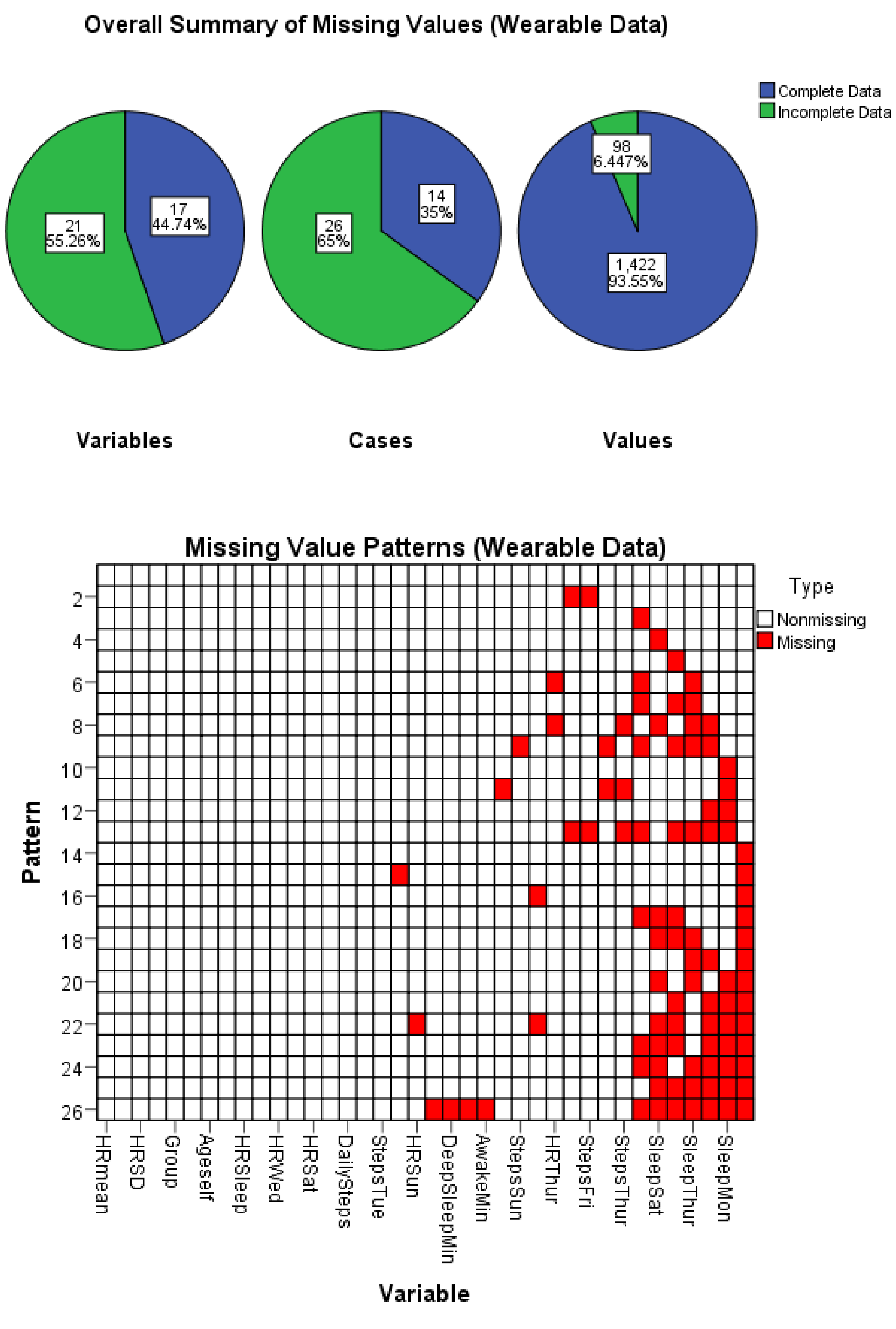
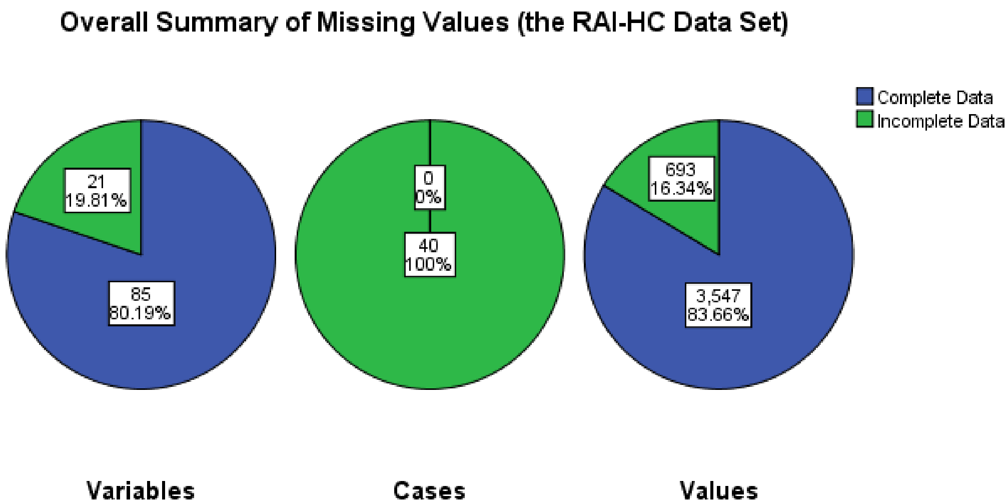


Figure 8: The Overall Summary of Missing Values and the Missing Value Patterns of Wearable Data (upper: the overall summary of missing values; lower: the missing value patterns)



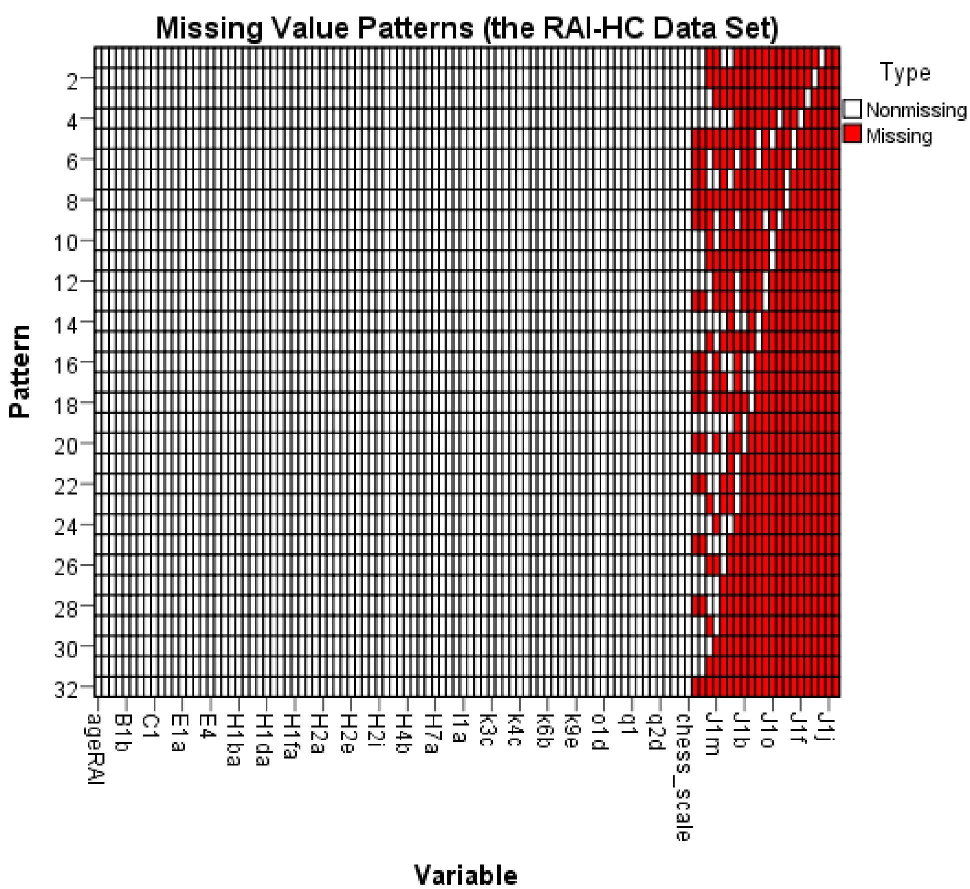


Figure 9: The Overall Summary of Missing Values and the Missing Value Patterns of the RAI-HC Data Set (upper: the overall summary of missing values; bottom: the missing value patterns)

Before conducting one-way ANOVA tests on wearable data, the assumption of normality was evaluated on all dependent (continuous) variables extracted from the Mi Band, including the daily resting HR (HR-Sleep), daily walking HR (HR-Walk), daily sleep duration (minutes), daily deep sleep time (minutes), daily light sleep time (minutes), daily awake time (minutes), daily distance (meters), daily steps and daily activity time (seconds), by using the Shapiro-Wilk test, and visual inspecting their histograms and normal Q-Q plots. The results of the tests of normality showed that only the daily activity time (G_0: $D(15) = .959$, $p = .668$; G_1: $D(13) = .926$, $p = .304$; G_2: $D(12) = .879$, $p = .086$) was normally distributed in all three groups.

The daily resting HR ($D(40) = .750$, $p < .001$), daily walking HR ($D(40) = .759$, $p < .001$), daily sleep duration ($D(40) = .948$, $p = .065$; the distribution between groups: G_0: $D(15) = .908$, $p = .126$; G_1: $D(13) = .938$, $p = .433$; G_2: $D(12) = .814$, $p = .014$), daily deep sleep time ($D(40) = .915$, $p = .005$), daily light sleep time ($D(40) = .961$, $p = .184$; the distribution between groups: G_0: $D(15) = .940$, $p = .379$; G_1: $D(13) = .941$, $p = .466$; G_2: $D(12) = .857$, $p = .045$), daily awake time ($D(40) = .892$, $p = .001$), daily distance ($D(40) = .827$, $p < .001$), and daily steps ($D(40) = .841$, $p < .001$) were shown to be significantly non-normal.

5.2.1.1 PA Measurements

Table 15 describes the PA measurements collected by the Mi Band across different faller groups.

Table 15: PA Measurements by Group

PA Measures	Non-Fallers (zero falls)	Single Fallers (1 fall)	Recurrent Fallers (≥ 2 falls)
Daily Distance (Meters)			
Median	2040.7	908.7	490.8
IQR	571.1-2643.2	163.4-1575.1	103.3-1551.2
Daily Steps			
Median	3094.1	1415.3	768.1
IQR	889.4-4029.5	238.1-2441.5	145.7-2408.6
Daily Activity Time (Seconds)			
Mean	3160.2	1921.4	1732.4
SD	1725.2	1264.1	1670.7
Range	100-7234	334-4123	75-5527

Figures 10-12 show the box plots of PA measurements (daily steps, daily distance, and daily activity time) by group.

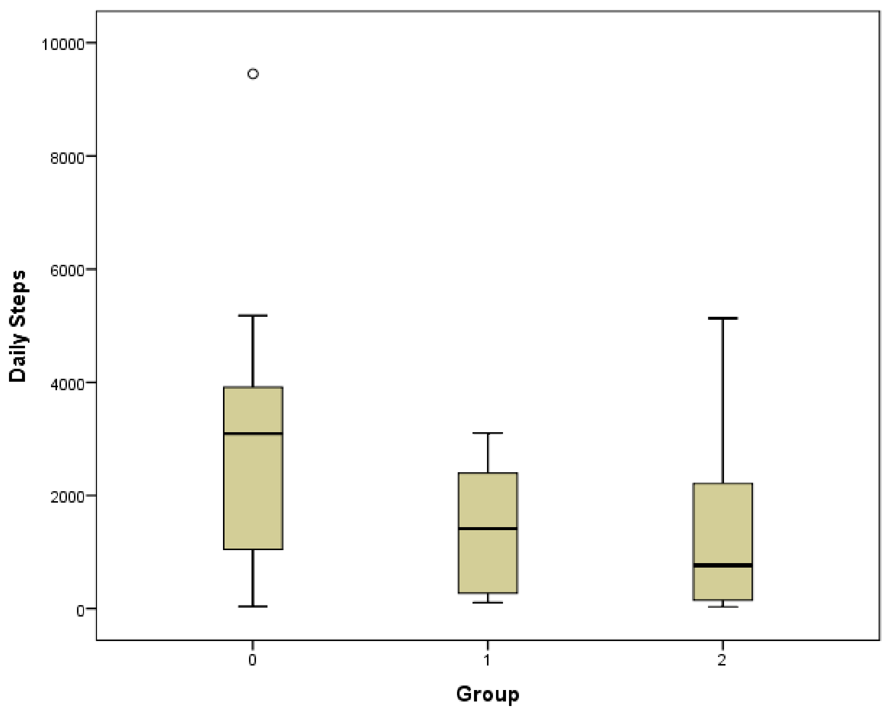


Figure 10: The Box Plot of Daily Steps

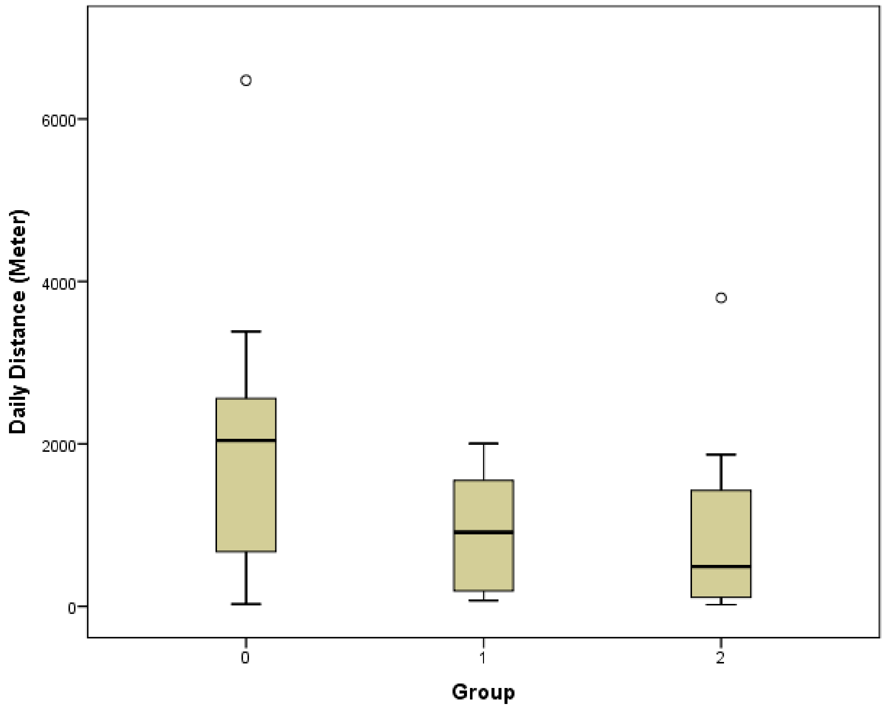


Figure 11: The Box Plot of Daily Distance

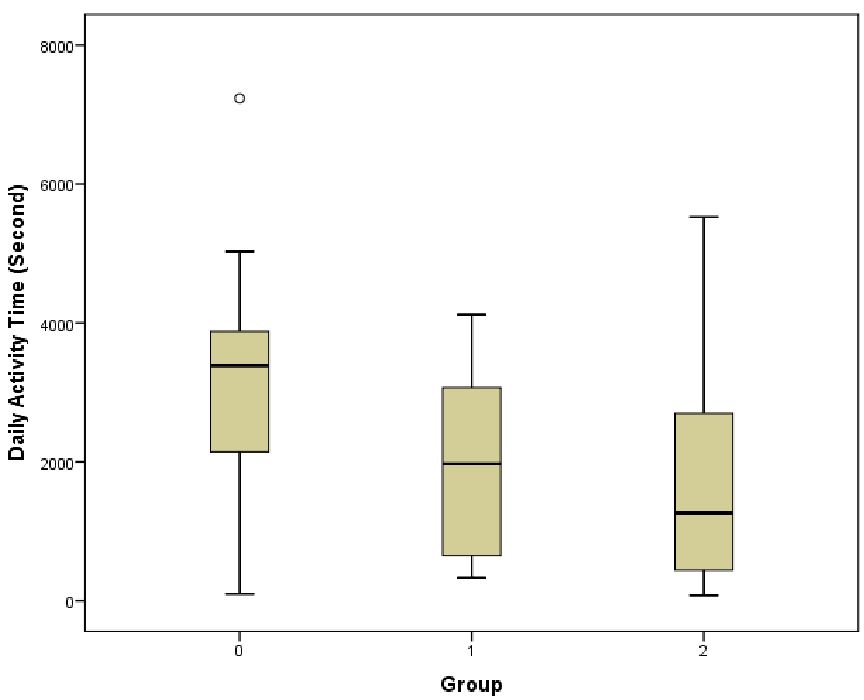


Figure 12: The Box Plot of Daily Activity Time

A one-way ANOVA was conducted to examine if there was a significant difference of participants' daily activity time based on their assigned group. The results indicated that there was a significant difference in daily activity time, $F(2, 37) = 3.394$, $p = .044$. However, follow-up comparisons with the Games-Howell test indicated that the actual pairwise differences were quite small ($p = .093$ between pairwise G_0 and G_1; $p = .096$ between pairwise G_0 and G_2; and $p = .946$ between pairwise G_1 and G_2), based on Cohen's (1988) conventions for interpreting effect size.

A Kruskal-Wallis H test, an alternative to one-way ANOVA was conducted, and the results revealed that there was a significant difference in daily steps among three faller groups, $H(2) = 6.641$, $p = .036$, with a mean rank daily steps of 26.53 for G_0, 18.00 for G_1, and 15.67 for G_2. The follow-up post hoc tests, Mann-Whitney tests on all possible pairwise comparisons, i.e. G_0 vs. G_1, G_1 vs. G_2, and G_0 vs. G_2, were conducted to determine where the differences lied between groups. A Bonferroni correction at a 0.05/3 = 0.0167 level of significance was applied on pairwise comparisons. The statistical test results show that daily steps were not significantly different between G_0 and G_1 ($U = 51$, $r = -.40$, $p = .032$), G_0 and G_2, ($U = 46$, $r = -.41$, $p = .032$) or G_1 and G_2 ($U = 64$, $r = -.15$, $p = .446$).

Similarly, a significant difference was found in daily distance among three faller groups, $H(2) = 6.608$, $p = .037$, with a mean rank daily distance of 26.53, 17.92, and 15.75 for G_0, G_1 and G_2, respectively. The follow-up post hoc tests on all possible group comparisons were conducted using the Mann-Whitney tests, with a Bonferroni correction at a 0.0167 level of significance. The results show that daily distance was not significantly different between G_0 and G_1 ($U = 50$, $r = -.41$, $p = .029$), G_0 and G_2 ($U = 47$, $r = -.40$, $p = .036$), or G_1 and G_2 ($U = 64$, $r = -.15$, $p = .446$).

Raw data of PA measurements were aggregated to examine the trend over the 7-day period. Figures 13-15 show the steps by days (Monday - Sunday), random-sampling within groups.

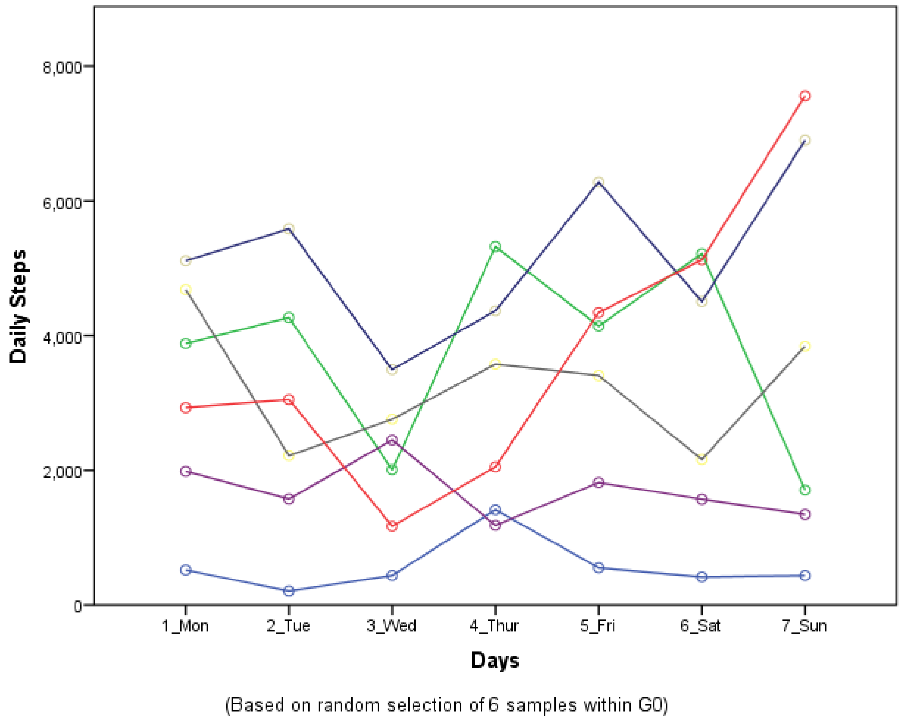


Figure 13: The Time Series Chart of Daily Steps within G_0 (random sampling within group)

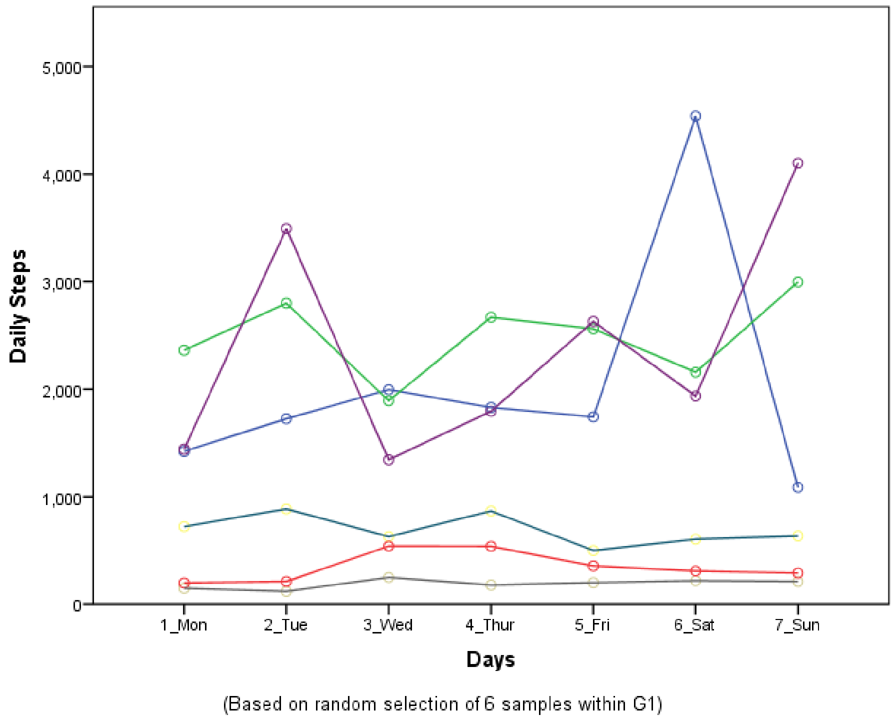


Figure 14: The Time Series Chart of Daily Steps within G_1 (random sampling within group)

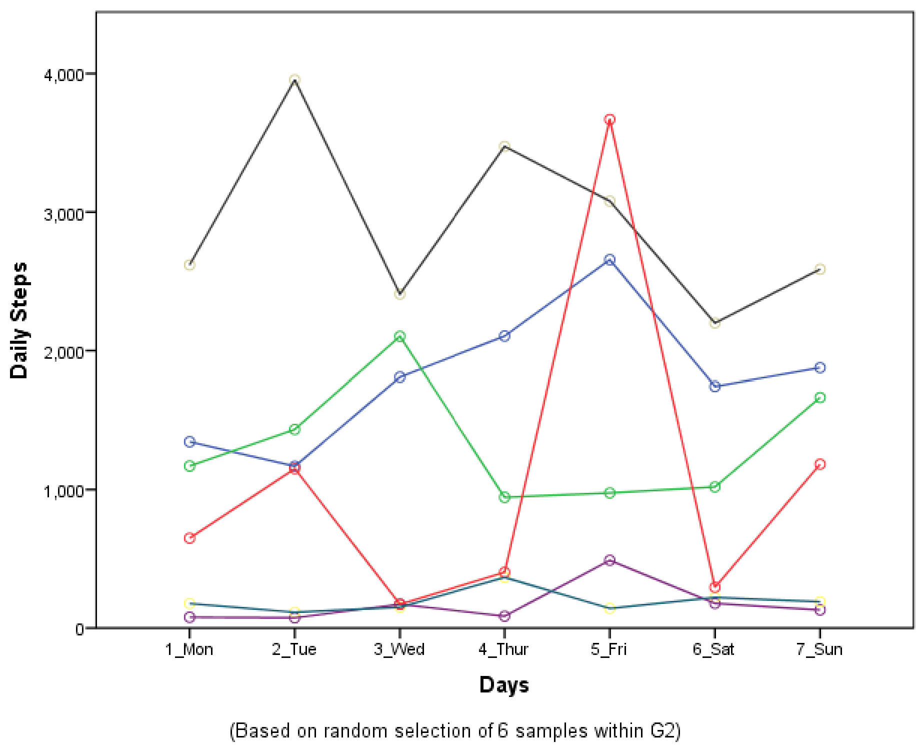


Figure 15: The Time Series Chart of Daily Steps within G_2 (random sampling within group)

A two-way repeated measures ANOVA test was conducted to examine the differences between groups with repeated PA measurements, and evaluate if there was an interaction between days of measurement and groups. Raw step counts were aggregated as daily averages in this analysis. The test results showed that there was a significant main effect of steps by days between groups ($F(2,37) = 4.379$, $p = .020$). The post hoc tests with Bonferroni correction showed no significant difference between groups ($p = .049$ between pairwise G_0 and G_1; $p = .092$ between pairwise G_0 and G_2; and $p = .991$ between pairwise G_1 and G_2). The main effect of the days being measured was non-significant ($F(4.243, 152.760) = 1.634$, $p = .165$), indicating that there was no consistent difference in step counts across different days, if the groups being measured were ignored. No significant interaction effect between daily steps and the three faller groups was detected ($F(8.487, 152.760) = 1.582$, $p = .130$). Figure 16 shows the split plot of mean daily steps by group.

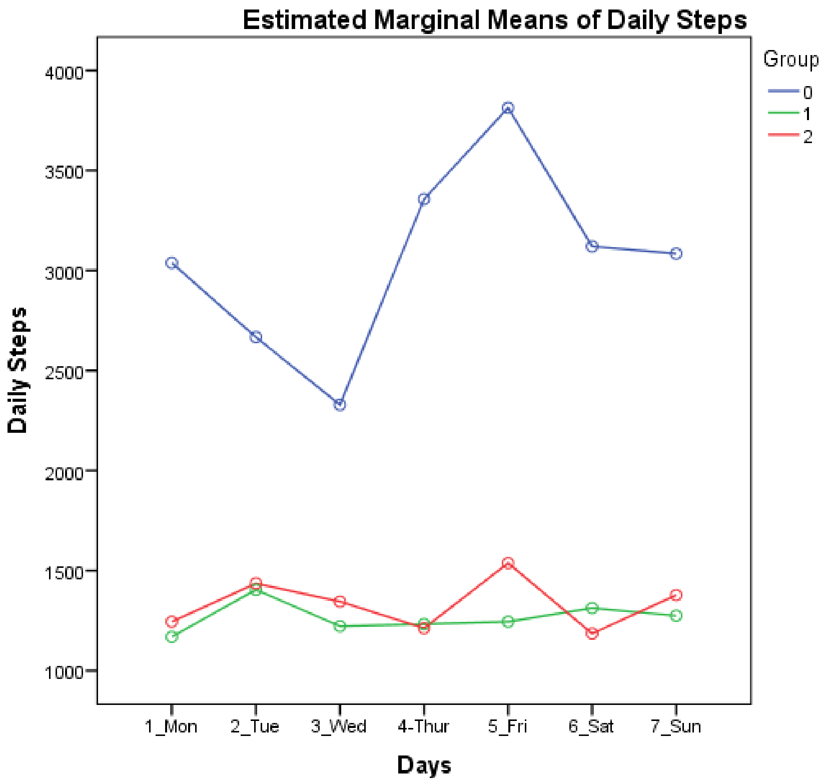


Figure 16: The Split Plot of Mean Daily Steps by Group

5.2.1.2 HR Measurements

Table 16 shows the HR measurements collected by the Mi Band by different faller groups.

Table 16: HR Measurements by Group

HR Measures	**Non-Fallers** (zero falls)	**Single Fallers** (1 fall)	**Recurrent Fallers** (≥ 2 falls)
Daily Resting HR			
Median	69.6	78.7	77.7
IQR	68.3-81.3	74.6-84.7	72.8-81.7
Daily Walking HR			
Median	96.4	94.6	103.5
IQR	93.4-101.1	91.6-105.3	92.2-130.0

Figures 17-18 show the box plots of HR measurements (daily resting HR and daily walking HR) by group.

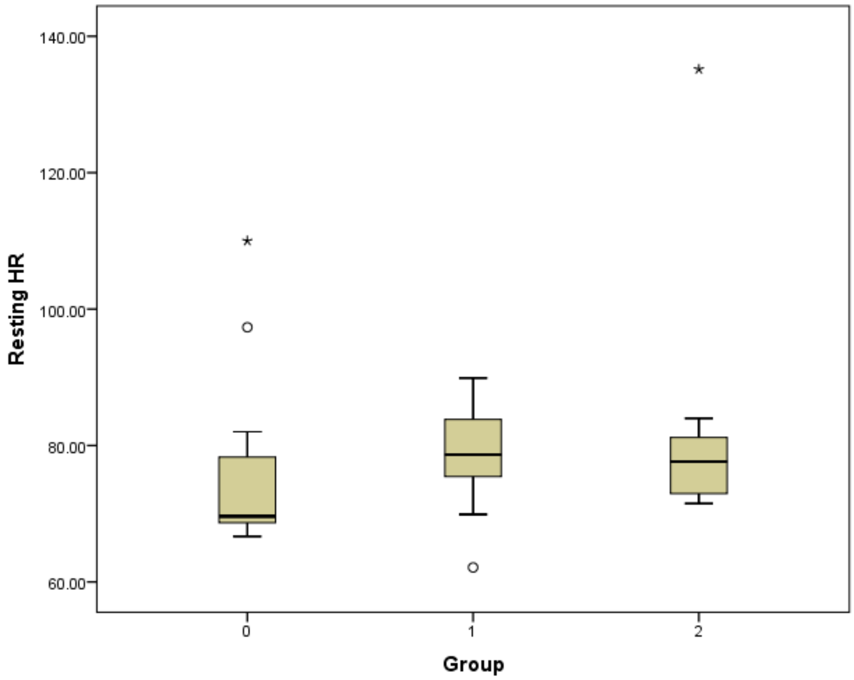


Figure 17: The Box Plot of Daily Resting HR

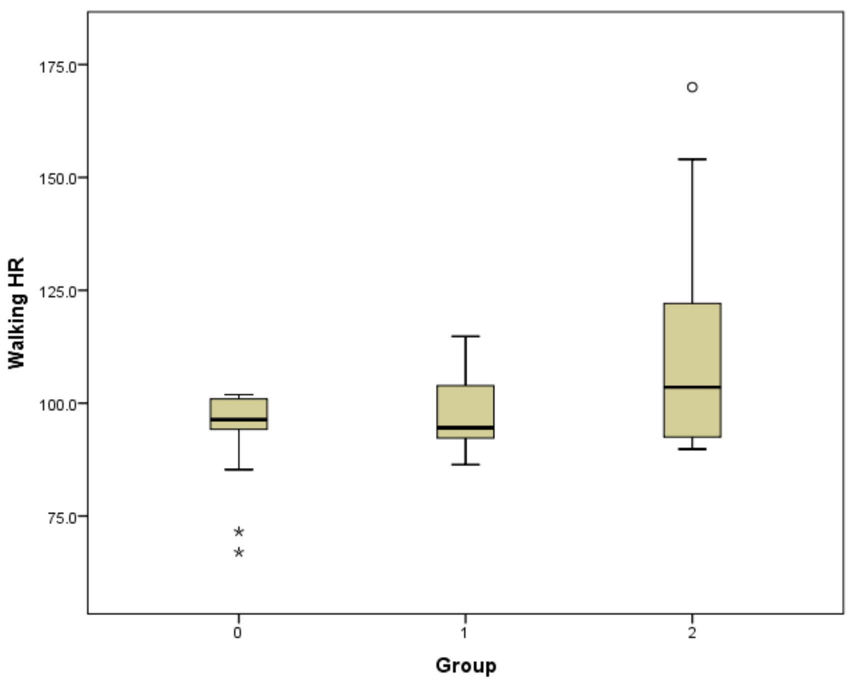


Figure 18: The Box Plot of Daily Walking HR

The Kruskal-Wallis H test results indicated no significant difference in the resting HR ($H(2) = 5.190$, $p = .075$), or the walking HR ($H(2) = 2.657$, $p = .265$) among three faller groups.

Given that persons' daily average HR has less variability as comparing to their PA or SP measurements, further analysis was conducted using the mean, median, SD, and IQR of each participant's daily average HR to examine if there was significant difference between groups. The results of the normality test revealed that the SD of daily average HR (HR_SD) (G_0: $D(15) = .911$, $p = .140$; G_1: $D(13) = .971$, $p = .906$; G_2: $D(12) = .955$, $p = .710$) were normally distributed across all three groups. The mean, median, and IQR of daily average HR (HR_Mean/HR_Median/HR_IQR) ($D(40) = .754$, $p < .001$; $D(40) = .697$, $p < .001$; $D(40) = .918$, $p = .007$) were shown to be significantly non-normal.

A one-way ANOVA was conducted and the test results indicated that there was no significant difference in the participants' SD of daily average HR, $F(2, 37) = 1.944$, $p = .158$. The Kruskal-Wallis H test results revealed no significant difference in the mean, median, or IQR of daily average HR ($H(2) = 2.596$, $p = .273$; $H(2) = 5.742$, $p = .057$; $H(2) = 3.988$, $p = .136$) between groups.

Figure 19 shows the comparison of HR measurements by group.

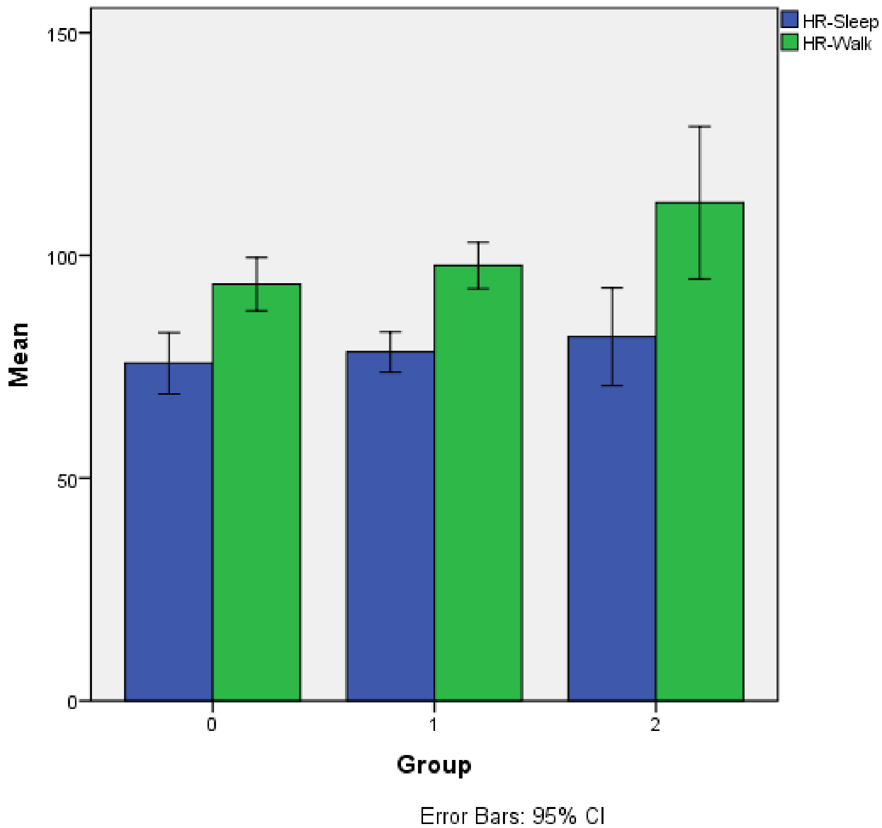


Figure 19: The Comparison of Daily HR by Group (the clustered bar chart comparing daily resting HR (HR-Sleep) and daily walking HR (HR-Walk))

Raw data of HR measurements were aggregated to examine the trend over the 7-day period. Figures 20-22 show the average HR by days (Monday - Sunday), random-sampling within groups.

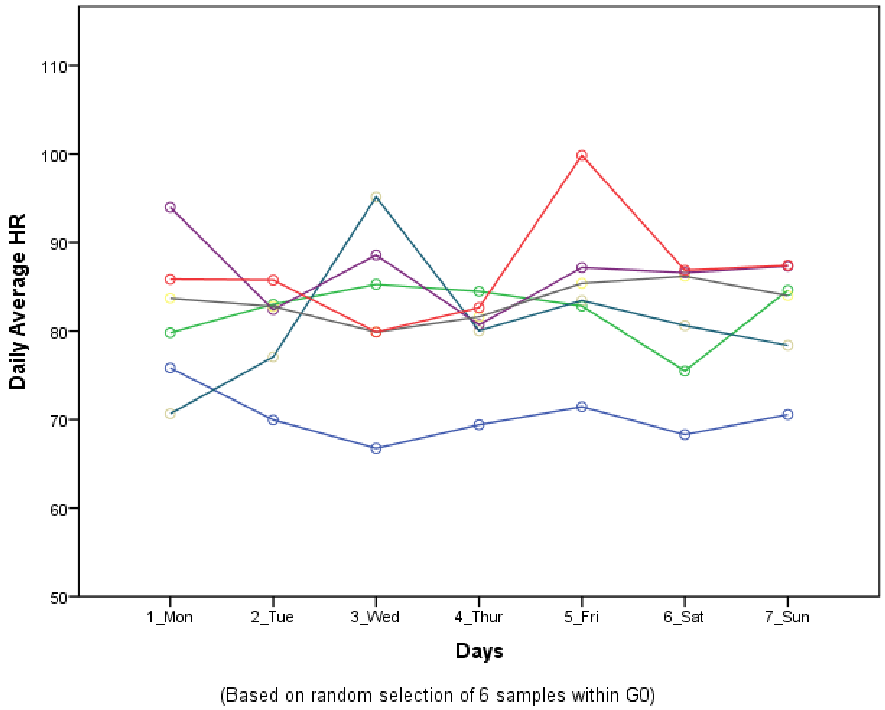


Figure 20: The Time Series Chart of Daily Average HR within G_0 (random sampling within group)

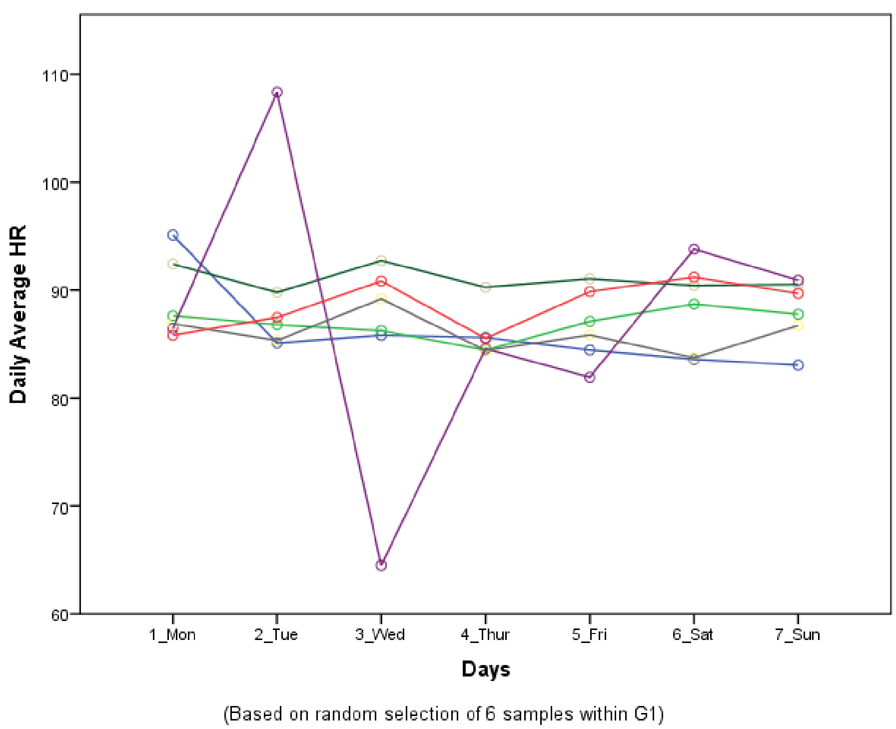


Figure 21: The Time Series Chart of Daily Average HR within G_1 (random sampling within group)

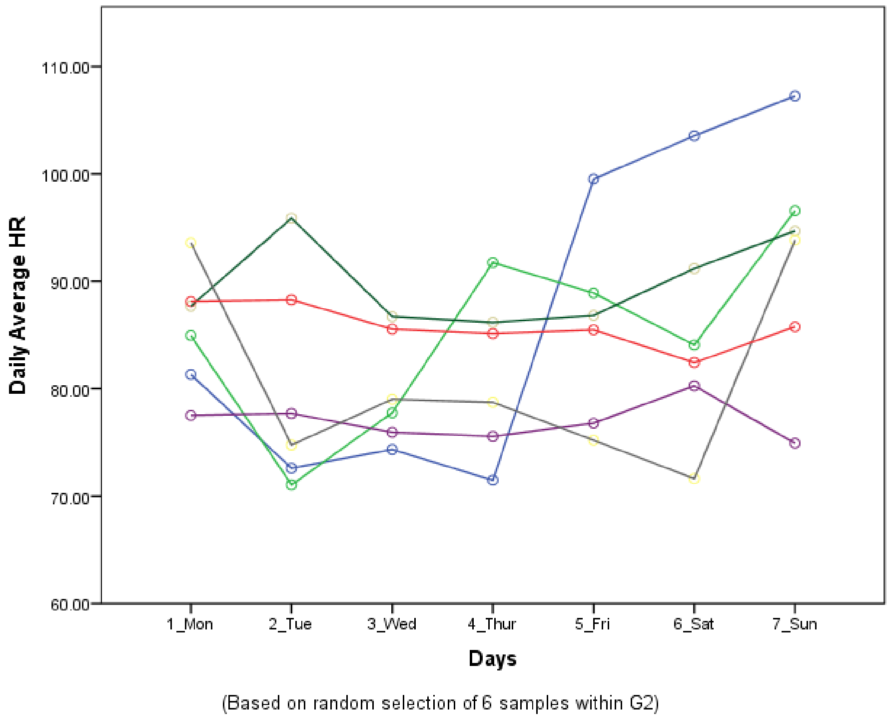


Figure 22: The Time Series Chart of Daily Average HR within G_2 (random sampling within group)

A two-way repeated measures ANOVA test was conducted to examine the differences between groups with repeated HR measurements, and evaluate if there was an interaction between days of measurement and groups. Raw HR data were aggregated as daily averages in this analysis. The test results revealed a non-significant main effect of HR by days between groups ($F(2,37) = 1.013$, $p = .373$). The main effect of the days being measured was non-significant ($F(4.089, 151.304) = 1.637$, $p = .167$), indicating that there was no consistent difference in HR across different days, if the groups being measured were ignored. No significant interaction effect between daily average HR and the three faller groups was detected ($F(8.179, 151.304) = 1.068$, $p = .389$). Figure 23 shows the split plot of mean daily average HR by group.

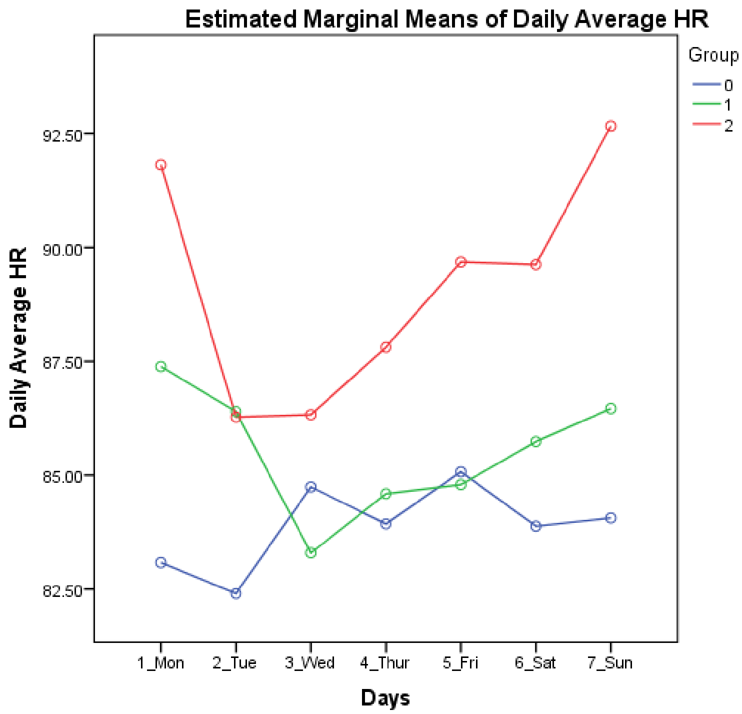


Figure 23: The Split Plot of Mean Daily Average HR by Group

5.2.1.3 SP Measurements

Table 17 shows the SP measurements collected by the Mi Band by different faller groups.

Table 17: SP Measurements by Group

SP Measures	**Non-Fallers** (zero falls)	**Single Fallers** (1 fall)	**Recurrent Fallers** (≥ 2 falls)
Daily Sleep Duration (Minutes)			
Median	282.7	287.9	134.3
IQR	247.8-368.3	144.8-428.0	112.8-234.8
Daily Deep Sleep Time (Minutes)			
Median	67.7	69.1	27.1
IQR	27.3-102.0	11.9-146.6	11.4-53.2
Daily Light Sleep Time (Minutes)			
Median	231.4	200.0	116.0
IQR	146.2-273.3	105.3-290.5	90.4-184.7
Daily Awake Time (Minutes)			
Median	21.0	11.9	6.1
IQR	11.6-40.8	2.9-39.1	1.0-38.1

Figures 24-27 show the box plots of SP measurements (daily sleep duration, daily deep sleep time, daily light sleep time, and daily awake time by group.

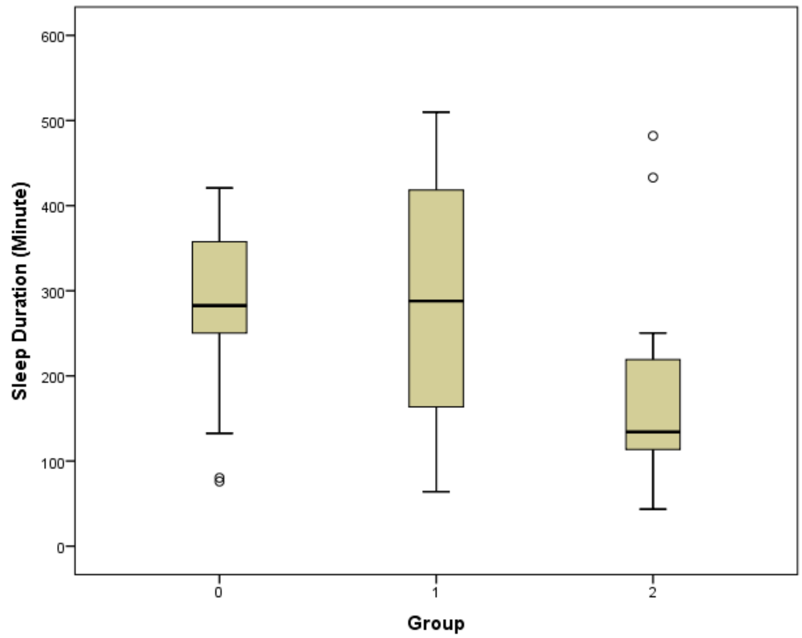


Figure 24: The Box Plot of Daily Sleep Duration

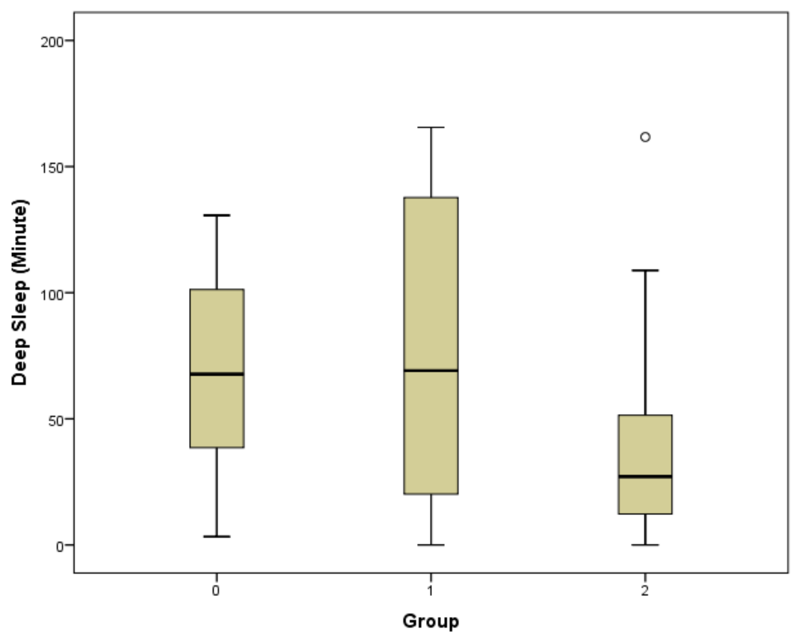


Figure 25: The Box Plot of Daily Deep Sleep Time

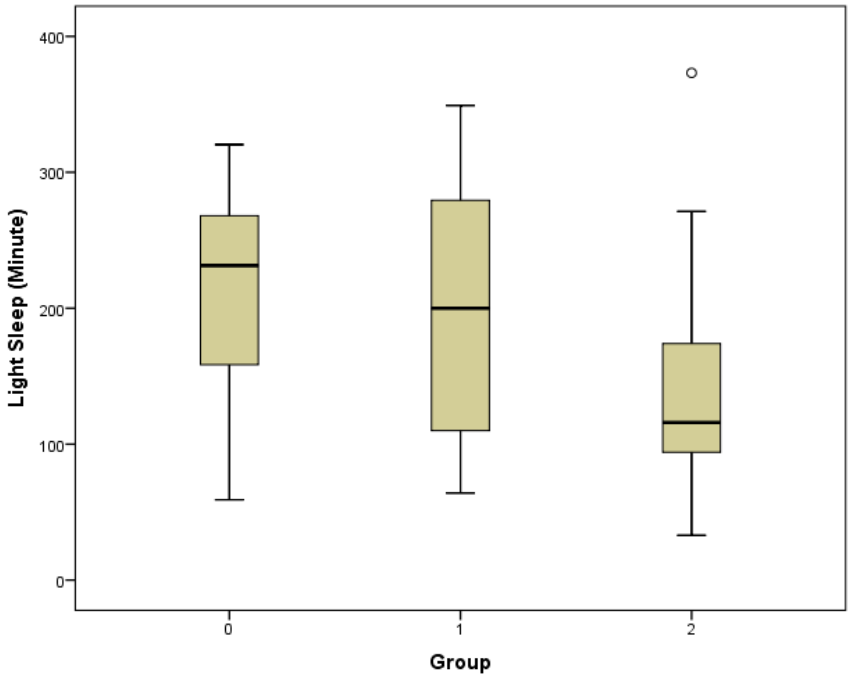


Figure 26: The Box Plot of Daily Light Sleep Time

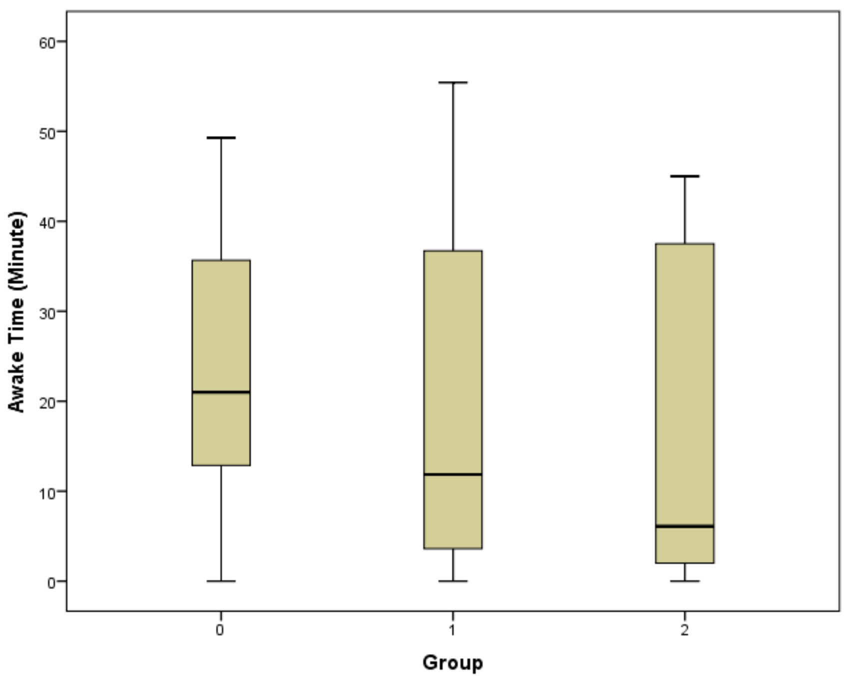


Figure 27: The Box Plot of Daily Awake Time

The Kruskal-Wallis H test results indicated that there was no statistically significant difference in daily sleep duration ($H(2) = 3.682$, $p = .159$), daily deep sleep time ($H(2) = 2.739$, $p = .254$), daily light sleep time ($H(2) = 3.699$, $p = .157$), or daily awake time ($H(2) = 1.114$, $p = .573$) among three faller groups. Figure 28 shows the comparison of night sleep patterns by group.

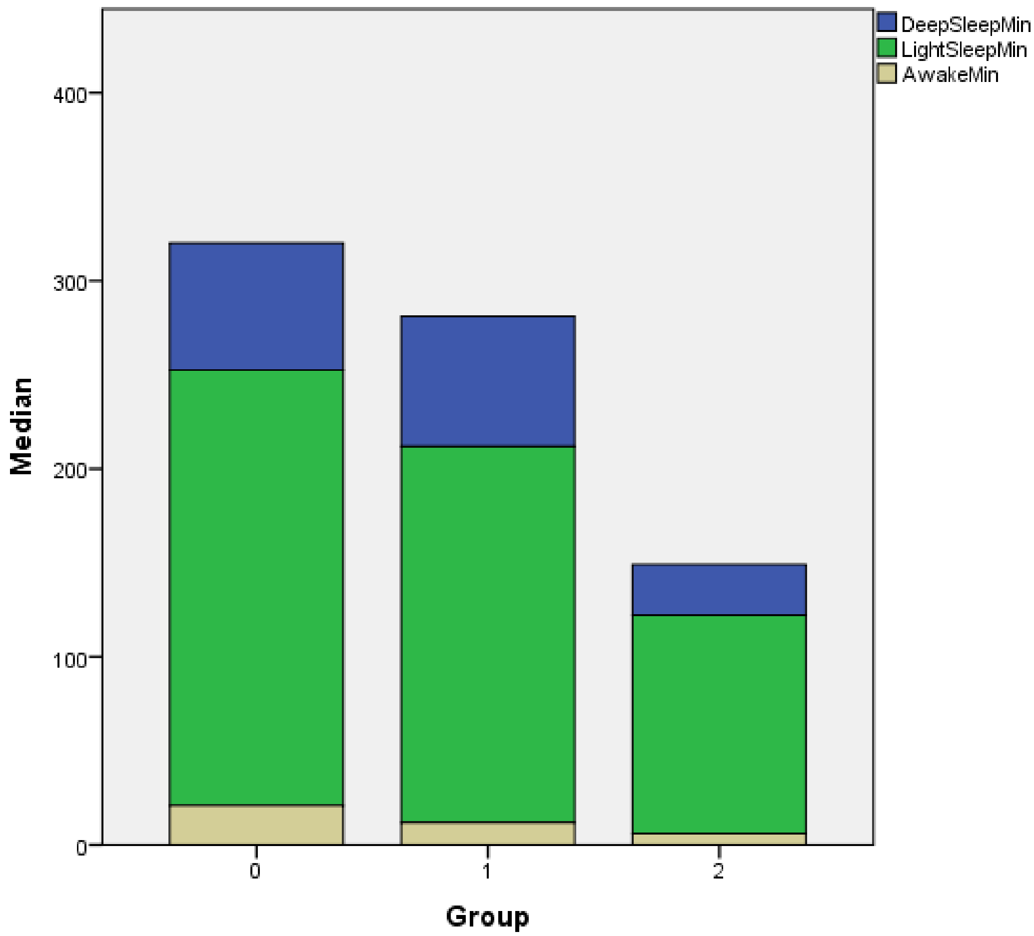


Figure 28: The Comparison of Night Sleep Patterns by Group (the stacked bar chart illustrating daily deep sleep time/daily light sleep time/daily awake time in minute)

Raw data of SP measurements were aggregated to examine the trend over the 7-day period. Figures 29-31 show the sleep duration by days (Monday - Sunday), random-sampling within groups.

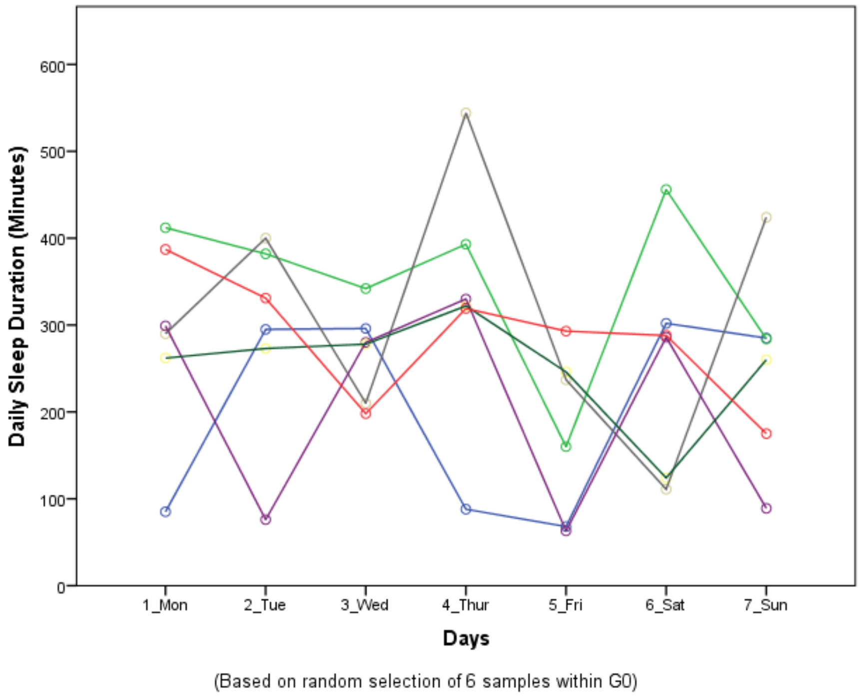


Figure 29: The Time Series Chart of Daily Sleep Duration within G_0 (random sampling within group)

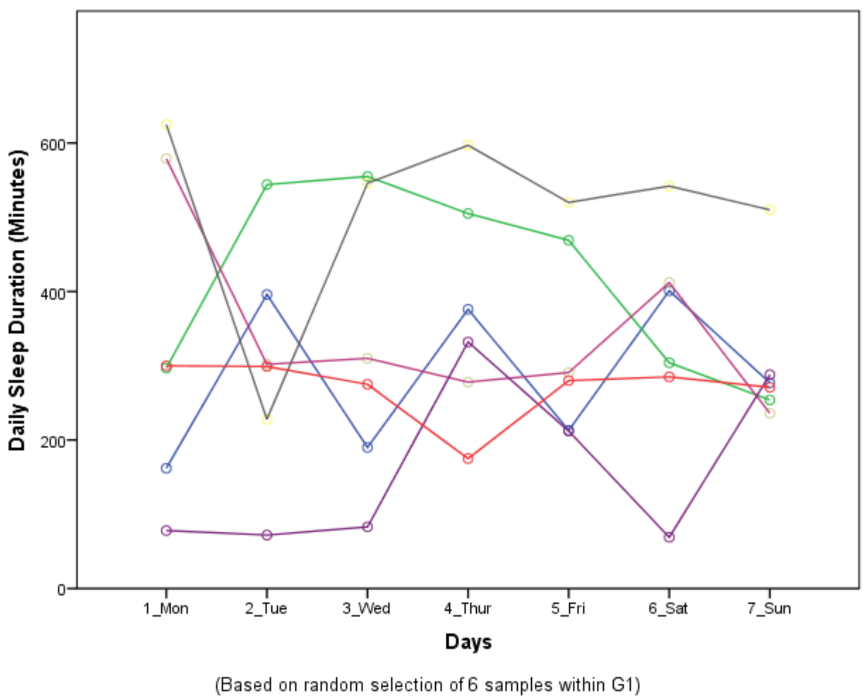


Figure 30: The Time Series Chart of Daily Sleep Duration within G_1 (random sampling within group)

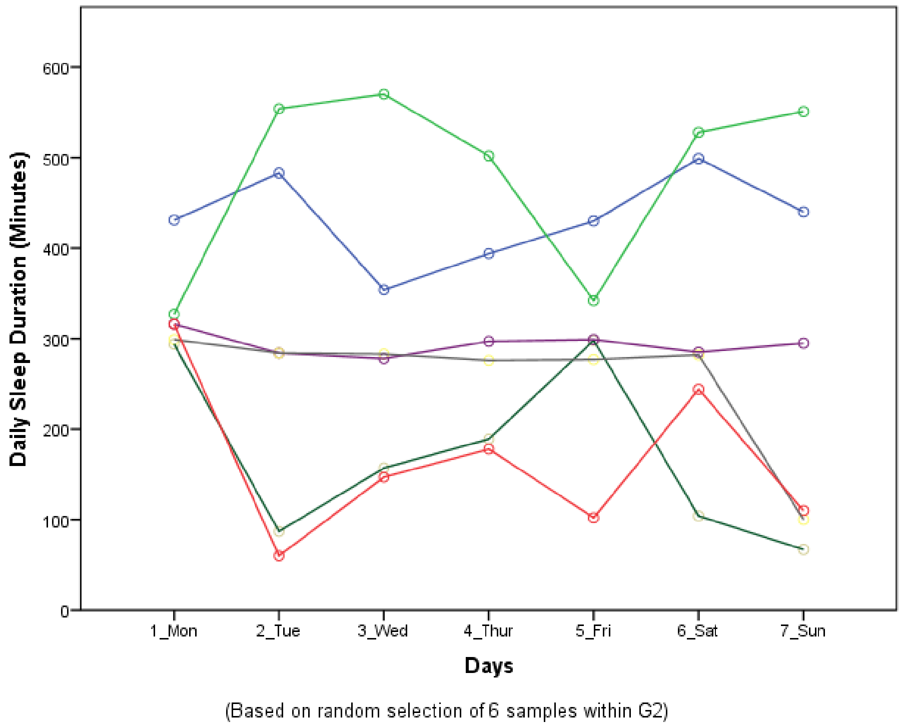


Figure 31: The Time Series Chart of Daily Sleep Duration within G_2 (random sampling within group)

A two-way repeated measures ANOVA test was conducted to examine the differences between groups with repeated SP measurements, and evaluate if there was an interaction between days of measurement and groups. Raw sleep duration was aggregated as daily averages in this analysis. The test results showed a non-significant main effect of sleep duration by days between groups ($F(2,37) = 1.298$, $p = .285$). The main effect of the days being measured was non-significant ($F(4.156, 153.764) = .231$, $p = .926$), indicating that there was no consistent difference in sleep duration across different days, if the groups being measured were ignored. No significant interaction effect between daily sleep duration and the three faller groups was detected ($F(8.312, 153.764) = 1.548$, $p = .142$). Figure 32 shows the split plot of mean daily sleep duration by group.

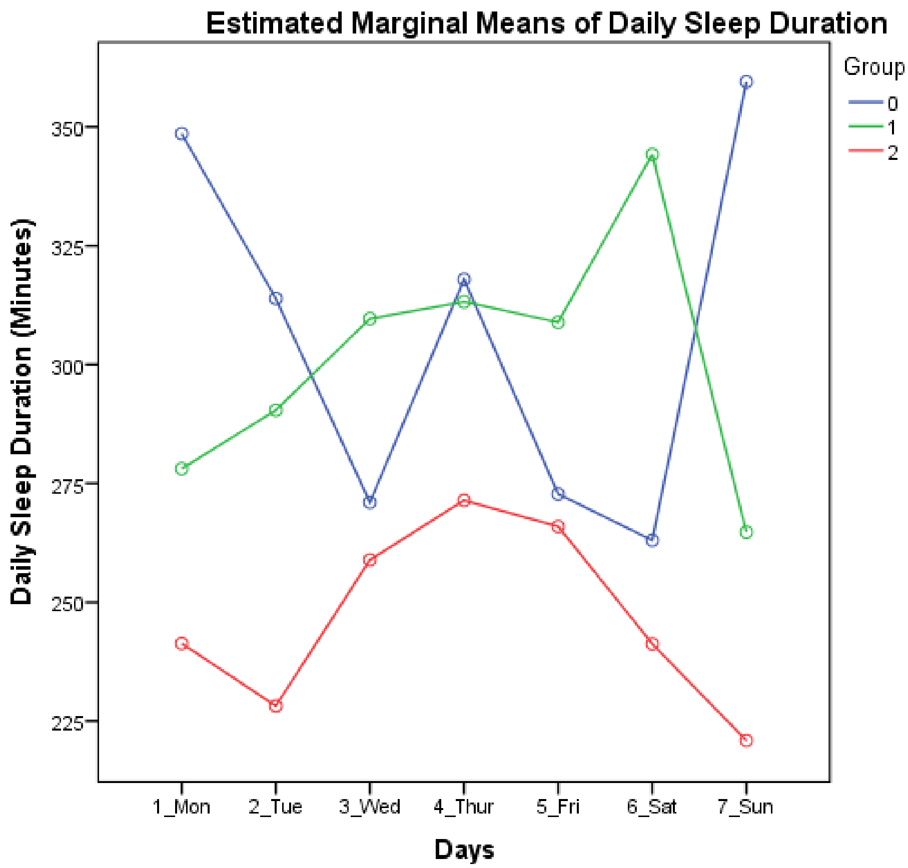


Figure 32: The Split Plot of Mean Daily Sleep Duration by Group

5.2.2 Classification Models and Assessment

To assess the discriminative power of i) wearable data exclusively, ii) the RAI-HC data set exclusively, and iii) the combination of both data sets, two supervised machine learning algorithms: logistic regression (LR) and decision tree (DT) were utilized in model-building and evaluation in Study II.

5.2.2.1 Wearable Data Exclusively

5.2.2.1.1 Proportional Odds Model (POM_Wearable)

The top two features with high IVs and were statistically significant ($p < .05$) at the univariate analysis included daily walking HR (HR-Walk) and daily activity time. These two features were incorporated into the proportional odds model on wearable data. The statistical test result indicated that there was no evidence to reject the assumption of proportional odds (equal slopes) ($p = .226$). The overall classification accuracy was 50.0% for this model, with accuracies of 80.0%, 38.5%, and 25.0% in classifying the non-faller, single faller and recurrent faller group, respectively. Table 18 shows the classification results with a confusion matrix for model POM_Wearable.

Table 18: The Confusion Matrix (Model: POM_Wearable)

Confusion Matrix (POM_Wearable)				
	Predicted Group			
Group	0	1	2	Total
0	12	3	0	15
1	4	5	4	13
2	3	6	3	12
Total	19	14	7	40

5.2.2.1.2 Decision Tree Model (DT_Wearable)

The independent variables used match those of the proportional odds model POM_Wearable (daily walking HR and daily activity time). The first split was performed on the daily walking HR, followed by the same feature and daily activity time on the second level. The final split was performed on the daily walking HR (see Figure 33). The overall classification accuracy was 77.5%, with accuracies of 93.3%, 92.3%, and 41.7% in classifying the non-faller, single faller and recurrent faller group, respectively (see Table 19).

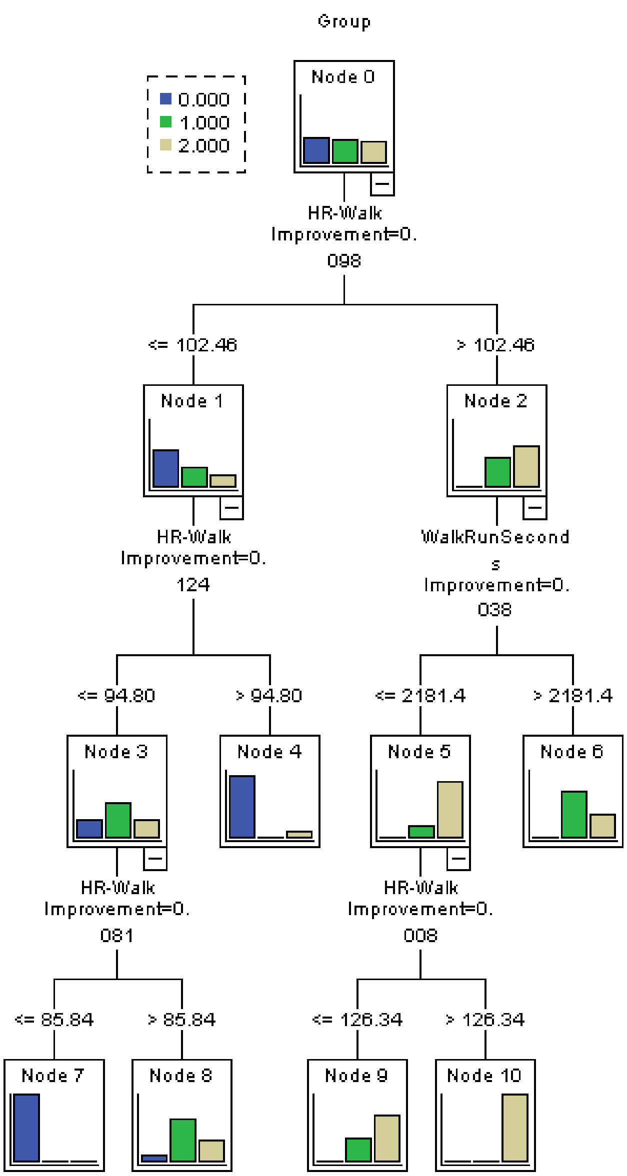


Figure 33: The Tree Diagram (Model: DT_Wearable)

Table 19: The Confusion Matrix (Model: DT_Wearable)

Classification

Observed	Predicted			
	0	1	2	Percent Correct
0	14	1	0	93.3%
1	0	12	1	92.3%
2	1	6	5	41.7%
Overall Percentage	37.5%	47.5%	15.0%	77.5%

Growing Method: CRT

Dependent Variable: Group

5.2.2.2 The RAI-HC Data Set Exclusively

5.2.2.2.1 Proportional Odds Model (POM_Computer_MDSHC)

The small RAI-HC data set containing the 40 participants' latest assessment information was first used as a test set to assess the classification performance of the proportional odds model built in Study I. This data set only consists of MDS-HC items and two scales (MAPLe and CHESS), the remaining CAPs and scales which were available in the large analytic data set in Study I were not available. Therefore, the small RAI-HC data set was used to assess model POM_Computer_MDSHC built on the MDS-HC items in Study I. The overall classification accuracy was 52.5%, with accuracies of 50.0%, 50.0%, and 56.3% in classifying the non-faller, single faller and recurrent faller group, respectively. Table 20 shows the classification results with confusion matrix for model POM_Computer_MDSHC being tested using the small RAI-HC data set.

Table 20: The Confusion Matrix (Model: POM_Computer_MDSHC)

Confusion Matrix (POM_Computer_MDSHC)				
Group	Predicted Group			
	0	1	2	Total
0	8	2	6	16
1	3	4	1	8
2	5	2	9	16
Total	16	8	16	40

5.2.2.2.2 Proportional Odds Model (POM_RAIHC)

The small RAI-HC data set was then used to build another proportional odds model, selecting the best subset of features with high IVs and statistically significant ($p < .05$) at the univariate analysis. MAPLe, the number of emergency room visits without an overnight stay (P4b), IADL self-performance on meal preparation difficulty (H1ab), and short-term memory problem (B1a) were incorporated into the proportional odds model as covariates on the RAI-HC data set. The proportional assumption was tested and the result led to not rejecting the null hypothesis ($p = .267$). The overall classification accuracy was 57.5% for this model, with accuracies of 62.5%, 37.5%, and 62.5% in classifying the non-faller, single faller and recurrent faller group, respectively. Table 21 shows the classification results with a confusion matrix for model POM_RAIHC.

Table 21: The Confusion Matrix (Model: POM_RAIHC)

Confusion Matrix (POM_RAIHC)				
	Predicted Group			
Group	0	1	2	Total
0	10	4	2	16
1	2	3	3	8
2	4	2	10	16
Total	16	9	15	40

5.2.2.2.3 Decision Tree Model (DT_RAIHC)

The features used on the tree model (MAPLe, the number of emergency room visits without an overnight stay (P4b), IADL self-performance on meal preparation difficulty (H1ab), and short-term memory problem (B1a)) match those of the proportional odds model POM_RAIHC. The first split was performed on MAPLe, and then on MAPLe and the number of emergency room visits without an overnight stay on the same level. The final split was performed on the IADL self-performance meal preparation difficulty (see Figure 34). The overall classification accuracy was 70.0% for the tree model on the RAI-HC data set, with accuracies of 62.5%, 50.0%, and 87.5% in classifying the non-faller, single faller and recurrent faller group, respectively (see Table 22).

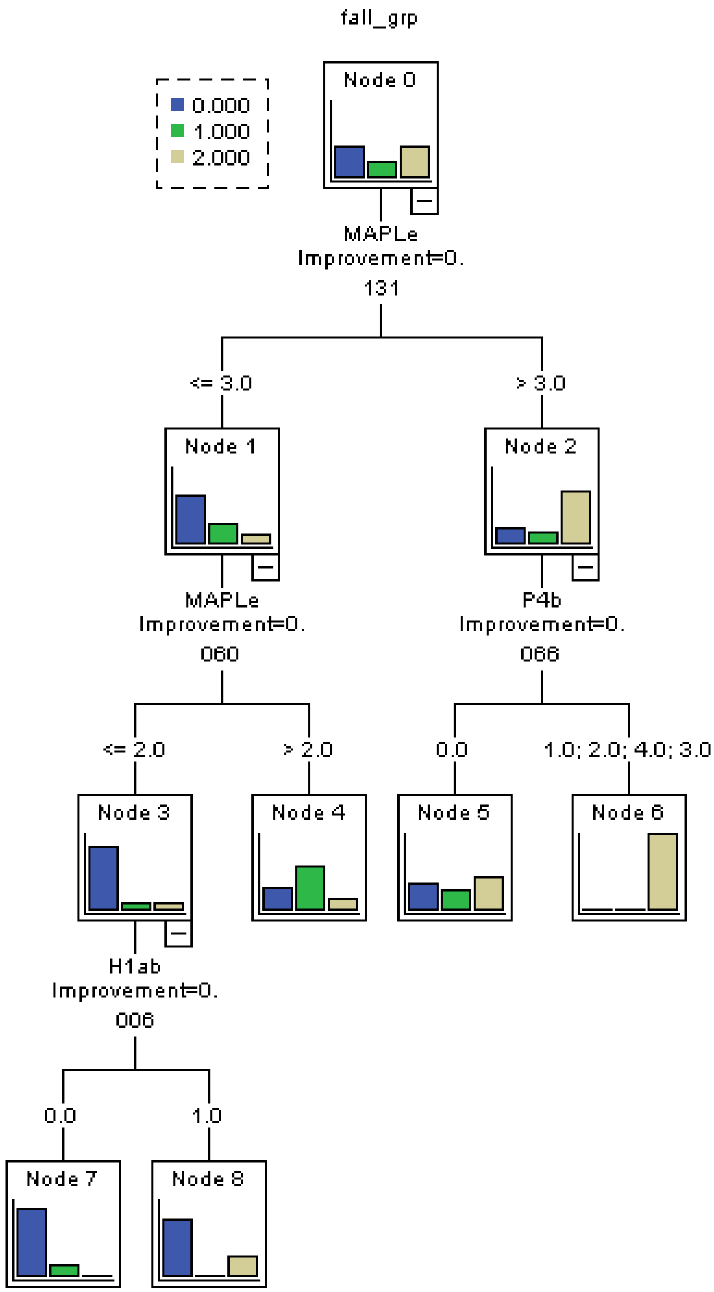


Figure 34: The Tree Diagram (Model: DT_RAIHC)

Table 22: The Confusion Matrix (Model: DT_RAIHC)

Classification

Observed	Predicted 0	Predicted 1	Predicted 2	Percent Correct
0	10	2	4	62.5%
1	1	4	3	50.0%
2	1	1	14	87.5%
Overall Percentage	30.0%	17.5%	52.5%	70.0%

Growing Method: CRT

Dependent Variable: fall_grp

5.2.2.3 The Combination of Wearable and the RAI-HC Data Set

5.2.2.3.1 Proportional Odds Model (POM_Combo)

The same feature selection technique was finally applied on the combination of wearable and the RAI-HC data set. The best subset of four features selected in the final regression model (POM_Combo) included MAPLe, the number of emergency room visits without an overnight stay (P4b), daily awake time, and the median of daily average HR (HR_Median). The proportional assumption was not rejected based on the statistical test (p = .453). The overall classification accuracy was 62.5%, with accuracies of 75.0%, 37.5%, and 62.5% in classifying the non-faller, single faller and recurrent faller group, respectively. Table 23 shows the classification results with a confusion matrix for model POM_Combo.

Table 23: The Confusion Matrix (Model: POM_Combo)

Confusion Matrix (POM_Combo)				
	Predicted Group			
Group	0	1	2	Total
0	12	2	2	16
1	3	3	2	8
2	3	3	10	16
Total	18	8	14	40

5.2.2.3.2 Decision Tree Model (DT_Combo)

The independent variables used on the tree model based on the combination of both data set (DT_Combo) match those of the regression model POM_Combo (MAPLe, the number of emergency room visits without an overnight stay (P4b), daily awake time, and the median of daily average HR (HR_Median)). The first split was performed on MAPLe, and followed by the number of emergency room visits without an overnight stay (P4b) and the median of daily average HR (HR_Median) on the second level. The next split was on HR_Median, and finally performed on daily awake time (see Figure 35). The overall classification accuracy was 80.0%, with accuracies of 87.5%, 50.0%, and 87.5% in classifying the non-faller, single fallers and recurrent faller group, respectively (see Table 24).

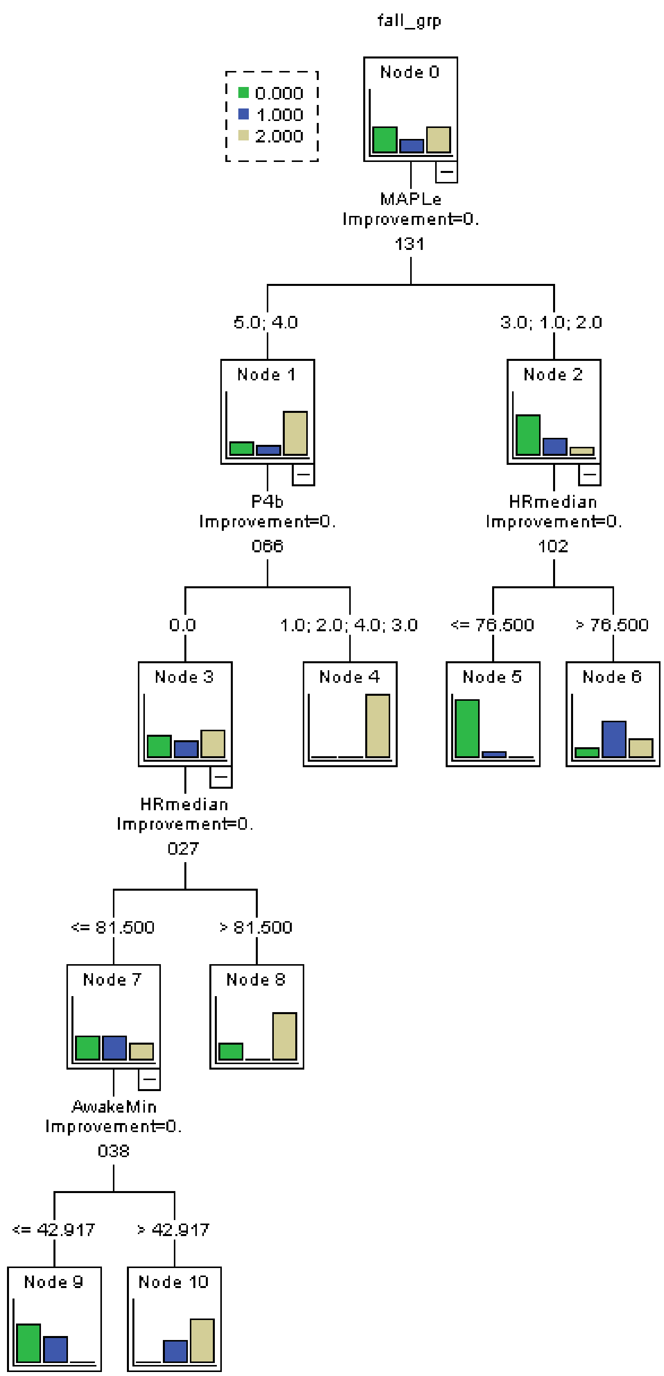


Figure 35: The Tree Diagram (Model: DT_Combo)

Table 24: The Confusion Matrix (Model: DT_Combo)

Classification

Observed	Predicted			
	0	1	2	Percent Correct
0	14	1	1	87.5%
1	3	4	1	50.0%
2	0	2	14	87.5%
Overall Percentage	42.5%	17.5%	40.0%	80.0%

Growing Method: CRT

Dependent Variable: fall_grp

5.2.2.4 Models Assessment

The proportional odds model derived from the RAI-HC data set exclusively outperformed that of wearable data, with overall classification accuracy of 57.5% vs. 50.0%, and different with-in group accuracies. The decision tree models (DT_Wearable, DT_RAIHC, and DT_Combo) showed better overall classification performances in comparison with their corresponding proportional odds models (POM_Wearable, POM_RAIHC, and POM_Combo), with overall accuracies of 77.5% vs. 50.0% (Wearable), 70.0% vs. 57.5% (the RAI-HC), and 80.0% vs. 62.5% (Combo), respectively (see Table 25).

The decision tree model DT_Combo including the predictors from both wearable and the RAI-HC data sets achieved the best overall accuracy (80.0%), with a better generalization error (Std. Error = .063). However, comparatively low accuracy of classifying the single faller group was identified in all models, except for the tree model DT_Wearable derived from wearable data exclusively.

Table 25: The Classification Performance Matrix for All Models in Study II

Classifier	Model	Classification Accuracy			
		Overall	**G_0 (Non-Faller)**	**G_1 (Single Faller)**	**G_2 (Recurrent Faller)**
LR	Wearable	50.0%	80.0%	38.5%	25.0%
	Computer_MDSHC	52.5%	50.0%	50.0%	56.3%
	RAIHC	57.5%	62.5%	37.5%	62.5%
	Combo	62.5%	75.0%	37.5%	62.5%
DT	Wearable	77.5%	93.3%	92.3%	41.7%
	RAIHC	70.0%	62.5%	50.0%	87.5%
	Combo	80.0%	87.5%	50.0%	87.5%

6. Discussion

6.1 General Discussion

The findings in this thesis are largely consistent with other studies that have examined risk factors of falling in community-dwelling older adults [27, 31, 64, 66, 73, 75, 76]. In Study I, the predictors remained statistically significant in both the human feature selection (POM_Human_MDSHC) and computer feature selection models (POM_Computer_MDSHC) based on the MDS-HC items included short-term memory problem (B1a), ADL self-performance on transfer dependency (H2b), ADL decline compared to status 90 days ago (H3), primary modes of locomotion (indoors) (H4a), stair climbing (H5), bladder continence in last 7 days (I1a), worsening of bladder incontinence as compared to status 90 days ago (I1b), unsteady gait (K6a), and limit going outdoors due to fear of falling (K6b). More predictors were incorporated into the regression model by human feature selection based on evidence in the literature, including assessment on hearing/vision/cognitive impairment/disease/health conditions/lifestyle/medication/living environment. However, computer feature selection with utilizing the best subsets algorithm was more in favor of the IADL and ADL self-performance and the service utilization section. For example, the number of emergency room visits without an overnight stay (P4b) and the overall change in care needs as compared to status of 90 days ago (P6) were selected by the algorithm and proven to be strong predictors of fall risk classification, but were omitted by human feature selection.

The results in this study demonstrated that males were more susceptible to falls than females, such that in the recurrent faller group, males were 1.51 times more likely to experience a fall (G_2: OR = 1.51; 95% CI, 1.46-1.56) (Table 5). This finding is different from most of the literature on fall risk assessment, which revealed that being female is more likely to fall than being male [11, 42, 68, 82]. This discrepancy may be attributable to the reluctance of males to report history of falls, females' tendency to have osteoporosis or take certain medications that can increase the incidence of falls, or fear of falling of females to limit their PA levels [73]. Another reason may be in line with the difference in study population; while this study targeted individuals who received HC services, the majority of falls studies in the literature may well have evaluated general geriatric populations.

The MDS-HC system, a standardized, comprehensive assessment, has been widely used in Canadian nursing homes and continuing care facilities [79]. With over 400 data items in the MDS-HC, it contains rich information of each HC resident's overall assessment on functional, medical, psychosocial, and cognitive status [79] as listed on Table 1 above. It has proven to be a solid foundation, based on which CAPs and a variety of summary scales and algorithms at clinical settings were developed with reliability and validity [79]. For example, cADL, assessing the activities of daily living, not only incorporates several key assessments on the MDS-HC items, such as changing decision making, ADL decline, admitted to hospital, overall change in care needs, etc. but also takes ADL hierarchy and Cognitive Performance Scale (CPS) into consideration. It makes the cADL a comprehensive and powerful CAP in addressing the person's independence of carrying out essential tasks in day-to-day living [80].

The results in this study supported the important role of CAPs/Scales as one of the major components of the RAI-HC instrument, which helps to evaluate an individual's health conditions and clinical status upon assessment. In particular, a decision support tool MAPLe (scores ranging from 1 rep. low priority to 5 rep. very high priority client), a measure of medical complexity and health instability using the CHESS (scores ranging from 0 rep. stable to 5 rep. highly unstable) [73, 81], and Urinary Incontinence CAP, which is designed to improve urinary function and to prevent worsening of function, were significant predictors in the classification models in this study. In one research, Teo et al. examined the association between sleep problems or urinary incontinence and falls in older women [34], and the results were in consistent with this study, indicating both factors are correlated with the incidence of falls in the aging population. These CAPs/Scales are as good as "gold standard" measures in the industry, assessing individuals' health conditions by category (severity of impairment or risk of problems), with reflection to the clinical findings in a variety of domain areas [79].

The classification performances of the four proportional odds models for logistic regression in Study I were fairly close. In general, the overall accuracies were 68.2-71.5%, with much higher accuracies classifying the non-faller group (93.3-96.6%) vs. recurrent faller (20-46%) and single faller group (0.01-5.5%). The poor classification performance on the single faller and recurrent faller groups was partly due to the unbalanced size of each group in the RAI-HC data set, i.e. lower frequency of single fallers (16.4%) and recurrent fallers (15.7%) vs. non-fallers (68.0%). One approach by stratifying/bootstrapping and matching the size of each group in the training and test set may improve the classification performance [86]. Blagus and Lusa showed that comparing to enlarging the sample size of a minority group, the downsizing procedure performed on a majority group may be more effective, given the discrepancy of sample size between groups was not too severe [87].

Another possible reason of imbalanced accuracies between groups lied in the characteristics of data. For example, there may be overlapping of the single faller and/or recurrent faller/non-faller group in feature spaces, which resulted in the ambiguous boundary between the single faller and recurrent faller/non-faller group. The underestimated boundary of the single faller group may cause poor classification performance within this particular class. As a linear classifier, the logistic regression performance was affected by the complexity of data itself. A more comprehensive model such as random forest (RF) or neural network (NN) algorithm may perform better than that of the logistic regression classifier for the large RAI-HC data set.

In discriminating the faller and non-faller groups, all four logistic regression models built in Study I had good SPE (87.2-90.0%) but low SEN (32.6-49.0%), as well as higher NPVs (73.9-78.6%) and relatively lower PPVs (60.0-64.1%). The statistical test results indicated a good accuracy of identifying non-fallers (87.2-90.0%, SPE) but lower accuracy in discriminating the fallers (32.6-49.0%, SEN). The NPVs were higher than PPVs, revealing that among those HC clients who were predicted as non-fallers, the probability of being non-fallers (73.9-78.6%) was higher than the probability of being fallers (60.0-64.1%) among those who were predicted as such.

The overall classification accuracy was quite close for both models derived from the MDS-HC items (LR_Human_MDSHC vs. LR_Computer_MDSHC) (71.5% vs.72.0%), and so were the AUC (0.726 vs. 0.730), SEN (32.6% vs. 34.0%), SPE (89.8% vs. 90.0%), PPV (60.0% vs. 61.5%), NPV (73.9% vs. 74.3%), and the Brier score (0.187 vs. 0.186). The classification performance of the computer feature selection model based on the CAPs/Scales

(LR_Computer_CAPScales) outperformed those of the two models derived from the MDS-HC items (LR_Human_MDSHC/LR_Computer_MDSHC), with higher overall classification accuracy (73.2% vs. 71.5%/72.0%), slightly larger AUC (0.730 vs. 0.726/0.730), and lower Brier Score (0.181 vs. 0.187/0.186). So were the SEN (39.6% vs. 32.6%/34.0), PPV (62.5% vs. 60.0%/61.5%), and NPV (75.9% vs. 73.9%/74.3%). The logistic regression model built on all available items on the RAI-HC data set (LR_Computer_All) achieved the best performance in distinguishing fallers and non-fallers, with the highest overall classification accuracy of 75.1%, the largest AUC of 0.769, and the lowest Brier Score of 0.171, indicating the best calibrated predictions among the four models in Study I (see Table 13).

It was hypothesized that there were differences in PA, HR and SP among the three faller groups in the target population. The statistical test results revealed a significant difference of PA, including daily steps, daily distance, and daily activity time between groups. The findings are consistent with the literature regarding PA and falls (Section 2.2), i.e. the decline of PA is associated with the increased occurrence of falls [23, 26, 27]. However, further pairwise analyses on all possible group comparisons (G_0 vs. G_1, G_0 vs. G_2, and G_1 vs. G_2) indicated that the actual differences in the means between each pairwise comparison were not detectable for interpreting effect size. It also revealed that over the 7-day study period, the PA pattern (daily steps) of the single faller group was similar to that of the recurrent faller group based on the split plot of mean daily steps by group (Figure 16). Due to the small sample size, the detection of significant differences of HR and SP patterns between groups was not realized in this study. Nevertheless, the split plots of mean daily resting HR and daily sleep duration by group (Figures 23 and 32) showed that the non-faller and single faller group shared some similarities (trend or mean range) of these two measurements.

Although the classification models derived from the small RAI-HC data set outperformed that of wearable data exclusively, the wearable components still possess certain predictive powers with relevance and importance in fall risk classification. For instance, the daily walking HR and daily activity time extracted from the smart wearable were identified as best subset of features in building the classification models on wearable data. Likewise, incorporating the daily awake time and the median of daily average HR into the final models POM_Combo and DT_Combo based on the combination of wearable and the RAI-HC data set achieved the best classification performance than that of each individual data set exclusively. The findings of this study confirmed that wearable data associated with continuous measurements of PA, HR and SP may play a supplementary role in facilitating fall risk stratification. Future fall risk assessment studies should consider leveraging wearable technologies to supplement resident assessment instruments.

In principle, the logistic regression algorithm searches for a single linear decision boundary in the feature space [84]. Regression models are likely to suffer from poor performance or even become invalid when there exists highly nonlinear relationships between variables [84]. In addition, regression analyses usually take the form of producing predicted probabilities in order to get an estimate of confidence in the classification [85]. This becomes more critical with small sample size, as it is more likely that certain regions in the feature space are less represented than others. In this study, the total sample size was 40, with the proportion of three faller groups $G_0 : G_1 : G_2 = 2:1:2$. The G_1 was likely to be less represented in the feature space than the other two groups. As discussed above in the results (Section 5.2.1), this particular group shared the similarities of HR and SP measurements with the non-faller group (Figures 23 and 32); however, it differed from the non-faller group by PA measurement (Figure 16). Thus, the classification performance of this particular group was poor while fitting the logistic regression models.

The decision tree algorithm essentially partitions the feature space into half using linear decision boundaries that are aligned with axis [84]. It is good for data points that are not easily separated by a single hyperplane [84]. If the features are known nonlinearly related, the trees outperform logistic regression. Decision trees do not require any assumptions of linearity in the data; instead, trees are created based on actual values of attributes. The first few splits performed on trees represent the most valuable features within the data set. In this study, the most influential features that affect the falls frequency were MAPLe on the RAI-HC data set and daily walking HR derived from the wearable components on each corresponding tree model DT_RAIHC and DT_Wearable.

6.2 Strengths and Limitations

6.2.1 Strengths

No prior research, to my knowledge, has combined off-the-shelf wearable sensor-derived data with the interRAI assessment system to examine the characteristics of different faller groups in community-dwelling older people, or to build fall risk classification models with the combination of both wearable and the interRAI data set. There was a gap in knowledge necessary to understand the association of PA, HR, SP and different fall frequencies in the target population. This thesis project was a small pilot towards a better understanding of this relationship, with continuous measurements using a smart wrist-worn device commercially available. Furthermore, identifying single fallers from the aggregation of fallers cohort and examining the unique characteristics of this sub-group of fallers would contribute to early detection and early prevention in mitigating the risk of recurrent falls.

Although the selected smart wearable is not medical device for monitoring health conditions, it can provide general information regarding PA, HR and night SP data representing an individual's overall health and fitness objectively. Participants may benefit from this study as the smart wearable tracks information about their PA, HR and SP patterns. Using the device may increase the participants' awareness of daily activity level and provide motivation to exercise, which is recommended to reduce the risk and incidence of falls. Hence, it may very well promote a more active lifestyle, with a positive influence on older adults' quality of life (QoL).

In addition, this study compared the classification performance in classifying older adults into the non-fallers, single and recurrent fallers group between wearable sensor-derived data and the RAI-HC assessment system. Wearable data may play a supplementary role in facilitating fall risk classification. The combination of wearable data and the RAI-HC system provided a better classification model and decision support to the community/society in fall risk assessment and assisting independent living older adults. It may help develop proactive care plans for the older population, especially those at high risk for falls.

6.2.2 Limitations

The limitations of this study included small sample size, limited study period and lack of follow-up observation, which may lead to selection and systematic bias. Since participants were recruited from a limited number of geographical areas in the KWCG communities, they may not represent the entire older population in Canada. A selection bias may be introduced to this study.

In addition, the limited generalizability of this study may impact the evaluation of a broad interpretation of the results to other older population groups, such as hospital inpatients, or nursing home residents.

Although by recruiting a total number of 40 participants, the similarities and differences in PA, HR and SP among three faller groups can be evaluated, a larger sample size would increase precision and permit the detection of small differences between groups. Moreover, a 7-day wearable data collection appeared to be sufficient to assess the average PA reflecting a habitual level of a person's activity, which was in accordance with current recommendations [47-49]. However, a longer duration of data collection is preferable for a better precision of the estimates.

The selected wearable device is capable of monitoring sleep patterns at night with auto sleep detection; however, it cannot distinguish short period or fragmented sleep. As such, daytime napping cannot be separated from periods of extreme inactivity in this study. In addition, specific sleep disorders were not captured, either. During the experimental period, it was noticed that the smart wearable was less sensitive in counting steps with people who have extreme slow gait speed or use a walker. Therefore, there may be some underestimates of steps for participants who use a walker as assistive device. One participant who was unable to wear the band on his wrist was offered an alternative option by wearing it as a necklace. However, the SP measurements with this option may not be as accurate as the wrist-worn method, as the sensor may roll off from the body while tossing over in bed.

When evaluating sensor-derived fall risk assessment, clinical assessments have been the predominating criterion method. However, false positives and false negatives from clinical assessments introduce inaccuracies [8]. Therefore, using prospective occurrence of falls when categorizing individuals into different faller groups would be the preferred criterion method. Furthermore, classification models are better tested in a large, prospective clinical trial to evaluate their true potential. However, due to time and budget constraints, a follow-up observation to assess prospective fall events was not performed in this study.

In the model building process of this study, a potential limitation existed due to the use of single-predictor-association-with-response step for screening out predictors. In the univariate analysis, only statistically significant variables with the default p value of 0.05 were selected in multivariate analysis. When the correlation between the outcome variable and a predictor is confounded and the confounder is not properly controlled, this approach would reject potential important variables [93]. Screening out predictors with univariate analysis often fails to control confounders or inter-correlations between predictors, resulting in biased and distorted estimation of the effects with poor model fitting or overfitting [93, 94]. Applying shrinkage methods in full models that include all predictors selected based on domain knowledge would be a good modeling strategy in small data sets [94].

6.3 Public Health Implications

From a public health perspective, studies on fall risk assessment seek to answer two key questions: 1) how to identify individuals at high risk for falls; and 2) how to mitigate such risk? The practical implications of this thesis come in the form of: i) investigating the similarities and differences among different faller groups by leveraging wearable technologies and resident assessment instruments; and ii) generating classification models for community-dwelling older people (prevention-based).

By obtaining a better and fuller understanding of fall risks and varying characteristics of older population with different fall histories, more informed suggestions can be made for individuals in the general public and clinical settings (treatment based). In particular, this thesis provides a necessary baseline from which comparative characterization and fall risk research studies can rocket.

Moreover, the results of this thesis project can be used by communities/societies in better shaping or modifying their existing fall prevention programs. Indirectly, the HR monitored at home or community-based settings have the potential to supplement the routine nursing observations in clinical and hospital settings. It may support better care in older adults by reducing unnecessary clinician visits and health care expenditures spent to measure physiological signals.

6.4 Future Directions

While the two parallel studies in this thesis revealed some practical and enlightening findings, they also had a few limitations. For example, Study II suffered from restricted generalizability due to the homogenous sample from community-based settings within a limited number of geographical areas; likewise, performance and motivational biases may have influenced the findings. Further, it has not yet known the true potential of the fall risk classification models without being tested in a large, prospective clinical setting.

Future studies are needed to work around these limitations. For instance, more studies on essentially all types of older populations are warranted, including clinical inpatients, LTC, or other institutional residents. Additional follow-up observations in future studies would help to examine the true potential of the classification models. Moreover, sensor-derived characterization of PA in future research aiming to evaluate an appropriate level of PA in fall prevention in the aging population will be realized with more objective, well-designed empirical studies.

Furthermore, it may also be interesting to uncover potential influences of cultural, genetic, and mental factors on the effects for falls by leveraging wearable technologies. Studies utilizing a variety of cognitive and mood measures might uncover some potential benefits in understanding the physiological mechanisms of which trigger a fall. A combination of computerized algorithms with machine learning techniques and physiological measures of cognition and mood would be compelling.

Additional modeling and analytic methods can be considered in future work. For example, time series analysis tracking the trajectories of PA, HR and SP in the 7-day period or even predicting/forecasting the future trajectories of different faller groups is possible. A linear mixed-effects model would be a good approach to compare the effect of three groups on PA, HR and SP measured repeatedly over time. Furthermore, the problem of imbalanced data among three faller groups can be addressed by stratifying/bootstrapping and matching the size of each group in the training and test set [88, 89]. Lastly, other machine learning algorithms such as RF or NN may lead to better classification performance [88, 89].

The study results revealed that the single faller group shared the similarities with both the non-fallers and recurrent fallers, which resulted in the ambiguous boundary in feature spaces, affecting the classification performance on this particular class. Future work should consider dichotomizing the three-level outcome in two different ways, i.e. examining the risk factors for non-fallers/single fallers (0/1 fall) vs. recurrent fallers ($\geq$ 2 falls), and non-fallers (zero falls) vs.

fallers (≥ 1 fall) [73]. At baseline, the predictors for the risk of falling (0 vs. ≥ 1 fall) would serve as a knowledge base for further understanding of the risk factors associated with multiple (≥ 2) falls. The characteristics of this subgroup of fallers (single fallers) would be better assessed with such a dichotomous outcome than the three-group classification performed within this study.

7. Conclusions

Most fall risk assessment studies have focused on discrimination between non-fallers and fallers in older adults, by comparing their balance evaluation, postural stability, and various physical function tests. Although it is important, further examination and classification of characteristics among different faller groups would be more beneficial.

The primary objective of this thesis project was to investigate the similarities and differences in PA, HR and SP among three different faller groups in a sample of older people living in community, with continuous measurements using the Mi Band, an off-the-shelf smart wrist-worn device. A second aim was to assess the risk factors for falls in the target population, build fall risk classification models and evaluate the classification performance based on: i) wearable data exclusively, ii) the RAI-HC assessment system exclusively, and iii) the combination of wearable and the RAI-HC data set.

In doing so, a community-based cross-sectional study (Study I) utilizing the RAI-HC data set was first conducted, examining the risk factors for falls. The results revealed that unsteady gait, ADL decline, ADL self-performance on transfer dependency, short-term memory problem, primary modes of locomotion (indoors), stair climbing, bladder continence, and limit going outdoors due to fear of falling remained statistically significant in both the human and computer feature selection models derived from the MDS-HC items. MAPLe, CHESS, ADL CAP, Cognitive CAP, and Urinary Incontinence CAP selected from the CAPs/Scales made strong predictors in classifying the three faller groups. The computer feature selection model based on the CAPs/Scales outperformed the two models derived from the MDS-HC items with a better classification performance. The final model built on all available items on the RAI-HC data set achieved the best performance in classifying the three faller groups.

In parallel, an experimental study (Study II) was designed and implemented to address the primary objective as discussed above. The study design was the first to take into consideration of leveraging the smart wearable with the interRAI system in fall risk classification. Overall, the results revealed that the difference of PA among three faller groups was statistically significant, although the HR and SP data were not significantly different in comparing the groups. It also confirmed that the wearable data can be applied to the fall risk classification modeling, and the decision tree model derived from the combination of wearable data and the RAI-HC data set achieved the best classification performance. These findings contributed interesting and novel details about the hypotheses test, and provided a more sophisticated perspective on falls study in general.

Recently, fall risk assessment protocols have been increasingly integrated with wearable technologies. This shift has been shown to be beneficial for improving fall risk prediction. The wearable components associated with continuous measurements of PA, HR and SP in commercially available wearable devices appear to play a supplementary role in facilitating these benefits.

Moreover, the findings within this thesis are substantial for developing a better knowledge base of the fall prevention practice, which hold great promise for boosting the QoL of many individuals. More generally, research of this field is implicated in providing an empirical basis for public health promotions and interventions involving fall risk assessment and prevention. It is hoped that more studies continue to proliferate in order to obtain a comprehensive perception on this field.

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Glossary

App/ Application	A type of software that enables a user to perform a specific task or set of tasks on a computing device.
Backward Elimination	"Backward elimination, which involves starting with all candidate variables, testing the deletion of each variable using a chosen model comparison criterion, deleting the variable (if any) that improves the model the most by being deleted, and repeating this process until no further improvement is possible[6]."
Berg Balance Test	"The Berg Balance Scale (or BBS) is a widely used clinical test of a person's static and dynamic balance abilities, named after Katherine Berg, one of the developers. For functional balance tests, the BBS is generally considered to be the gold standard[7]."
Biomarker	"In medicine, a biomarker is a measurable indicator of the severity or presence of some disease state. More generally a biomarker is anything that can be used as an indicator of a particular disease state or some other physiological state of an organism[8]."
Brier Score	"A proper score function that measures the accuracy of probabilistic predictions[9]."
Cross-Validation	"Cross-validation, sometimes called rotation estimation, is a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set[10]."
CSV Format	"In computing, a comma-separated values (CSV) file stores tabular data (numbers and text) in plain text. Each line of the file is a data record. Each record consists of one or more fields, separated by commas. The use of the comma as a field separator is the source of

[6] https://en.wikipedia.org/wiki/Stepwise_regression

[7] https://en.wikipedia.org/wiki/Berg_Balance_Scale

[8] https://en.wikipedia.org/wiki/Biomarker_(medicine)

[9] https://en.wikipedia.org/wiki/Brier_score

[10] https://en.wikipedia.org/wiki/Cross-validation_(statistics)

	the name for this file format. CSV is a common data exchange format that is widely supported by consumer, business, and scientific applications[11]."
Decision Tree	"A decision support tool that uses a tree-like graph or model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility[12]."
End-Stage	"The last phase in the course of a progressive disease. As in end-stage liver disease, end-stage lung disease, end-stage renal disease, end-stage cancer, etc. The term "end stage" has come to replace "terminal"[13]."
Exercise	"A subcategory of physical activity that is planned, structured, repetitive, and purposeful in the sense that the improvement or maintenance of one or more components of physical fitness is the objective[14]."
Fall	"A fall is an event which results in a person coming to rest inadvertently on the ground or floor or other lower level[15]."
Feature Selection	"In machine learning and statistics, feature selection, also known as variable selection, attribute selection or variable subset selection, is the process of selecting a subset of relevant features (variables, predictors) for use in model construction[16]."
Frailty	"A clinical syndrome in which three or more of the following criteria were present: unintentional weight loss (10 lbs in past year), self-

[11] https://en.wikipedia.org/wiki/Comma-separated_values

[12] https://en.wikipedia.org/wiki/Decision_tree

[13] http://www.medicinenet.com/script/main/art.asp?articlekey=30946

[14] http://www.who.int/dietphysicalactivity/pa/en/

[15] http://www.who.int/violence_injury_prevention/other_injury/falls/en/

[16] https://en.wikipedia.org/wiki/Feature_selection

	reported exhaustion, weakness (grip strength), slow walking speed, and low physical activity[17]."
Logistic Regression	"A regression model where the dependent variable is categorical[18]."
Neural Network	"A computational model used in computer science and other research disciplines, which is based on a large collection of simple neural units (artificial neurons), loosely analogous to the observed behavior of a biological brain's axons[19]."
Non-Faller	People who have no (zero) falls in last 90 days.
Older Adults/ Older People/ Senior	Person with the chronological age of 65 years or older.
Parasympathetic	Pertaining to a division of the autonomic nervous system
Physical Activity	"Any bodily movement produced by skeletal muscles that requires energy expenditure[20]."
Proportional Odds Model	"An ordinal regression model—that is, a regression model for ordinal dependent variables[21]."
Random Forest	"An ensemble learning method for classification, regression and other tasks[22]."
Recurrent Faller	People who have two or more (≥ 2) falls in last 90 days.

[17] Frailty in older adults: evidence for a phenotype. Retrieved from: http://www.ncbi.nlm.nih.gov/pubmed/11253156

[18] https://en.wikipedia.org/wiki/Logistic_regression

[19] https://en.wikipedia.org/wiki/Artificial_neural_network

[20] http://www.who.int/topics/physical_activity/en/

[21] https://en.wikipedia.org/wiki/Ordered_logit

[22] https://en.wikipedia.org/wiki/Random_forest

Sensitivity	"One of statistical measures of the performance of a binary classification test, also known in statistics as classification function. Sensitivity (also called the true positive rate, or the recall in some fields) measures the proportion of positives that are correctly identified as such[23]."
Single Faller	People who have one (1) fall in last 90 days.
Smartphone	A cellular phone that has the ability to perform complex computing tasks.
Smart Wearable Device	A user worn accessory, with integrated electronic and computing technologies, that captures or reports on some form of data.
Specificity	"One of statistical measures of the performance of a binary classification test, also known in statistics as classification function. Specificity (also called the true negative rate) measures the proportion of negatives that are correctly identified as such[24]."
Stressor	A stimulus that causes stress.
Sympathetic	Pertaining to the sympathetic nervous system

23 https://en.wikipedia.org/wiki/Sensitivity_and_specificity

24 https://en.wikipedia.org/wiki/Sensitivity_and_specificity