ACTIVE TRANSPORTATION AND HEALTH: UNDERSTANDING THE IMPACT OF TRANSPORTATION-RELATED PHYSICAL ACTIVITY ON HEALTH

by

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DISSERTATION

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ABSTRACT

Active Transportation and Health: Understanding the Impact of Transportation-Related Physical Activity on Health

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Car-oriented infrastructure in the U.S. leads to physically inactive lifestyles and negative health outcomes. To promote physical activity, public health officials encourage active transportation, namely biking and walking on daily trips. Previous studies proved that both perceived or self-assessed and objective health measures should be used to understand individuals' health status. Therefore, this study uses the National Household Travel Survey (NHTS) data to understand the associations between perceived health and modal trip features including the number of trips, trip distance, and duration for auto, public transit, walk, and bike trips. Regarding the objective health, this dissertation uses one-week walking activities data of a sample population from two universities in the U.S. The walking records include the average resting heart rates and minute-by-minute measures of walking heart rates, burned calories, and the number of steps. The results show that individuals with longer auto trips show lower perceived health; however, the higher frequency and longer active transportation are linked to better perceived health. Also, the cross-analysis results on a sample from one of the universities show that perceived health is not necessarily associated with actual health measures of BMI and physical activity. Regarding the objective physical activity and health, the results show that underweight/normal people, compared with overweight/obese individuals, seem to have lower resting heart rates, longer duration of walking, and a significantly higher number of steps (mean and total). Moreover, the results of modeling the changes in the walking heart rates based on health and activity predictors show that overweight and obese individuals have small changes in walking heart rate due to age and high resting heart rates. On the other hand, greater changes in walking heart rates are observed among the healthier people (with lower resting heart rates), due to their large number of steps, and moderate-to-vigorous minutes of walking.

Key Words: Active Travel, Perceived Health, Objective Health, Physical Activity, Walking, Obesity, Heart Rate

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Chapter 1 Introduction

Nowadays, many societies are struggling with unhealthy lifestyle and physical inactivity due to eating unhealthy foods, not exercising, and lack of maintaining a healthy weight. However, a physically active lifestyle can help individuals to improve physical and mental health by managing body weight, body fat, blood pressure as well as depression, anxiety levels, and feelings of loneliness. The transportation planning agencies and cities can provide well-connected streets including safe pedestrian and bicyclist paths to promote an active and healthy lifestyle for individuals (Plan4Health, 2020). Active Transportation is the inclusion of walking and biking as non-motorized transportation options on trips. The literature also considers and supports public transit as a substantial source of physical activity, considering the remarkable amount of walking required as part of any public transportation trip (Chaix et al., 2014; Rissel et al., 2012). If active transportation is made affordable and convenient for all transportation users, it can have a great contribution to enhance physical activities among people and promote healthier lifestyles, recreation, and environmental protection.

The dependence on private vehicles for daily trips is one of the factors leading to an unhealthy lifestyle. According to previous studies (Dargay et al., 2007; Santos et al., 2011; Schipper, 2011), the U.S. has one of the highest auto ownership rates in the world. According to the National Household Travel Survey (NHTS-2009), the average vehicle ownership in the United States is 1.9 vehicles per household. Furthermore, private vehicle trips are accounted for 83% of all trips in the United States (Santos et al., 2011). This auto-dependent lifestyle causes physical inactivity, which results in cardiovascular diseases, obesity, and mental illnesses (Chakrabarti & Shin, 2017). Therefore, the reduction in the number of car trips can have a great contribution to a healthy and active life.

Active transportation is a good way to meet the physical activity levels recommended by health and physical activity associations. The recommended physical activity is to perform at least 150 minutes of moderate or 75 minutes of vigorous activity per week (World Health Organization, 2010). A well-established body of literature has demonstrated the health benefits of physical activity in general (Brown et al., 2007; Hamer & Chida, 2008; Hart, 2009), and active travel, in particular (Flint et al., 2014; Hu et al., 2003; Humphreys et al., 2013; Scheepers et al., 2015).

In the context of active transportation and public health, researchers applied two general methods to measure health outcomes from physical activities. The first group used a self-reported survey to estimate self-assessed or perceived health, such as (Humphreys et al., 2013; Scheepers et al., 2015). These two studies considered the individuals' health perception as an indicator of their general health. However, a more popular and accurate method of health measurement assesses physical activity and health indices through objective measures. For example, some research works studied the positive effects of active travel on obesity (Flint & Cummins, 2016; Lindström, 2008; Wen & Rissel, 2008) or showed the cardiovascular health benefits of walking and biking (Millett et al., 2013; Tajalli & Hajbabaie, 2017; Wennberg et al., 2006).

With this being said, this dissertation examines the effects of active transport on individuals' perceived and objective health. Chapter 2 considers the associations between walking and biking trip features, using travel frequency, duration, and distance, and evaluates whether different trip features of various modes have positive or negative effects on individuals' health perception. Then, Chapters 3 and 4 focus on studying the differences in objective physical health and activity measures such as resting and minute-by-minute heart rates and for different weight groups. In particular, chapter 4 investigates the predictors of health and physical activities based on changes in heart rates during walking activities.

Objectives

In the last two decades, active transportation has gained more attention since it stimulates people to be more involved in physical activity. The health outcomes of walking and biking, particularly in the context of transportation, whether perceived by individuals or measured through different methods (such as accelerometry) are extremely essential to public health experts, transportation engineers, and city/urban planners to collaborate in a way to encourage individuals towards healthier living. This dissertation has three broad objectives, each one having more specific objectives as follows:

a. To examine the effects of active trip features on perceived health
    - To estimate the effect of the associations between different trip modes features and self-assessment of health
    - To examine the effects of socio-demographics on individuals' health perception
    - To compare the associations between different features of trip modes (duration, distance, and frequency) on people's perceived health
b. To investigate the differences in physical health and activity levels between healthy and unhealthy weight groups
    - To examine which weight group (normal/underweight or overweight/obese) has better health in terms of physical activity and objective health measures
    - To conduct some cross-comparisons between the weight status and health indicators of individuals.
c. To understand the health outcomes of walking activities based on individual-level sociodemographic and health indicators

- To determine which physical activity or health measure has the largest effect on changes in walking heart rates
- To examine which activity and health predictors are associated with heart rate changes among different weight-resting heart rate groups

Methodology

This research seeks to examine the relationships between active transportation trip feature and the individuals' health perception. Using the household, person, and trip data collected from the National Household Travel Survey (NHTS 2017). This uses ordinal logit modeling to understand the significant associations among socio-demographic variables, trip features, and the individuals' self-assessed health. Also, this study collects a sample of faculty, staff, and students at two Universities and further investigates the relationships between perceived and objective health through a health-assessment and in-body examination data.

In chapter 3, this research examines the differences between the objective physical activity and health measure among two major weight groups, namely normal/underweight as healthy, and overweight/obese as an unhealthy weight group. The objective physical health measures include resting heart rate, minute-by-minute walking heart rate, and calories burned. The study examines the physical activity measures of moderate-to-vigorous percentages of walking, average, and total walking steps, as well as total walking minutes. The study uses the hypothesis tests and descriptive cross-table analysis to understand which weight group has healthier resting/walking heart rates and greater walking activity measures.

In chapter 4, the study uses Classification and Regression Tree (CART) to examine the associations between the physical activity and health measures identified in chapter 3 based on minute-by-minute changes in walking heart rates.

Chapter 2 The Effect of Transport Choice and Trip Features on Perceived Health

Introduction

Transportation infrastructure in the United States has a car-centric nature based on multilane highways and the lack of quality public transportation systems. Previous studies pointed out that the car-oriented infrastructure leads to physically inactive lifestyles and negative health outcomes including obesity, diabetes, muscular, and cardiorespiratory diseases. Based on (American Heart Association, 2018a), cardiovascular diseases are accountable for nearly 836,546 deaths in the U.S., which is equal to about one of every three deaths. According to the National diabetes statistics report (Centers for Disease Control and Prevention, 2017), 30.3 million Americans, which correspond to 9.4% of the U.S. population, had diabetes in 2015. Obesity represents another prevalent health risk factor affecting 87.5% of American adults. The proportions of overweight, obese, and severely obese U.S. adults are 26.1%, 43.5%, and 17.8%, respectively (Centers for Disease Control and Prevention, 2017). Several public health organizations recommend a minimum of 150 minutes per week of moderate physical activity or 75 minutes of vigorous activity to maintain good health (American Heart Association, 2018b; U.S. Department of Health and Human Services, 2008a). However, higher amounts of physical activity are associated with more health benefits including the reduction in obesity, and cardiovascular diseases.

Public health agencies view non-private modes of transportation such as walking, biking, and public transit, as a strategy to incorporate physical activity into daily travel activities. A well-established body of literature examined the positive association between active (walk/bike) modes and health measures, resulting in lower rates of obesity (Flint et al., 2014; Flint & Cummins, 2016; Humphreys et al., 2013; Samimi et al., 2009; Scheepers et al., 2015). One study (Wen & Rissel, 2008) examined the association between various transport modes to work and obesity using a sample of 6,810 Australian commuters. The results showed that men who commuted by car were about 40% more likely to be overweight and obese than those who cycled or used public transit. According to (Langerudi et al., 2015), a 1% increase in transit use reduced the likelihood of obesity and heart attack for 1.10% and 1.20%, respectively. (She et al., 2019) conducted an aggregated longitudinal study with the National Household Travel Survey (NHTS) 2001 and 2009 to examine the causal impacts of public transit usage on county obesity rates. Results showed that a 1% increase in public transit riders appeared to reduce the county population obesity rates by 0.473%. Also, active transportation modes were reported to be significantly associated with a lower risk of cardiovascular diseases (Bennett et al., 2017; Murtagh et al., 2015), and diabetes (Hu et al., 2003; Millett et al., 2013). The research of (Tajalli & Hajbabaie, 2017) indicated that the change of transportation mode from car to walking resulted in a 5.5%, 16.9%, and 4.4% reduction in obesity, high blood pressure, and diabetes, respectively.

However, researchers point out that clinically measured objective measures do not always represent individuals' self-assessment of health. Various researchers confirmed that poorer self-rated health is associated with chronic diseases (Banerjee et al., 2010; Jonnalagadda & Diwan, 2005; Maharlouei et al., 2016; Molarius & Janson, 2002) and disability (Damian et al., 1999; Goldberg et al., 2001). The literature largely agrees that persons with cardio-cerebral vascular diseases, visual impairment, and mental illness were more likely to have lower perceived health. Although the relationship between perceived health and objective health is not simple to understand, previous studies found that perceived health is a comprehensive measure on individual self-assessed health and is a significant indicator of the quality of life. (Kaplan & Camacho, 1983) showed their concerns about the significant emphasis on objective health measures and less focus on perceived health in medicine. They tracked mortality rates for nine years to investigate its association with perceived health ratings. Based on their results, strong relationships were observed between perceived health and mortality and that the perceived health is not entirely dependent on physical health status. (Shields & Shooshtari, 2001) showed that the reliability of self-reported health measures is as good as or even better than objective health measures to reflect individual chronic diseases and well-being. This is because unhealthy lifestyles such as smoking and irregular exercise are all associated with perceived health measures. (Hunt et al., 1980) found that perceived and objective health status is well-aligned among older adults even though socioeconomic status such as gender, age, and marital status are not indicators for better perceived health. Furthermore, (Piko, 2000) showed that four measures of psychological well-being, physical activity behavior, acute illness episodes, and the frequency of psychosomatic symptoms were significantly associated with perceived health. However, psychological well-being was showed to be the strongest predictor.

Previous studies pointed out that trip measures such as travel time, distance, and frequency of transportation mode affect health outcomes including perceived health. For example, (Hoehner et al., 2012) studied the individuals' longitudinal data of twelve Texas counties to examine the associations between car commuting distance and health measures. The results showed that long car trip duration resulted in lower cardiorespiratory fitness and higher metabolic risk. However, increasing the number of walking trips improves health. Also, (de Sá et al., 2015) used Brazilian metroplex household travel survey data to explore the associations of trip distance and mode changes on health. Results indicated that the combinations of shorter trip distance (for both car and active modes), fewer auto trips, and a higher number of walking trips lead to better health. Some studies (Langerudi et al., 2015; Samimi et al., 2009) showed that a 1% increase in average public transit use is associated with 0.09% and 1.43% increases in self-assessed health, respectively. (Bopp et al., 2013) found that active commuting resulted in better perceived health for those who walk or bike at least once a week. (Humphreys et al., 2013) showed that a larger amount of active commuting is remarkably associated with higher levels of perceived physical well-being; specifically, for those who involve with 45 minutes per week. However, (Scheepers et al., 2015) showed that walking is not significantly associated with perceived health measures, whereas biking is (Odds Ratio (OR) = 1.35). (Avila-Palencia et al., 2018) investigated the relationships between transportation mode choices (car, motorbike, public transport, e-bike, bicycle, and walking) and some health and social contact measures including perceived health in seven European cities using cross-sectional and longitudinal approaches. Results showed a positive association between an active mode and perceived health (OR = 1.07 for biking and OR = 1.01 for walking) and walking enhanced vitality while biking reduced perceived stress and improved mental health and vitality. Although previous researchers investigated the positive impacts of active commuting (Humphreys et al., 2013; Legrain et al., 2015) on perceived health, no consensus was observed on the significant trip determinants that influence perceived health.

Consequently, a gap remains in understanding the relationships between perceived health and trip measures. To the knowledge of the author, no study has considered the various trips features of duration, distance, and frequency for all the main modes (auto, public transit, walk, and bike) in a study. Therefore, this study aims to understand the relationships between a comprehensive set of trip features and perceived health by each transportation mode. Specifically, the study focused on various trip characteristics such as the number of trips, duration (hour), and trip length (in 100 miles) by different modes including auto, walk, bike, and transit to look into which trip measures are most significantly associated with self-assessed health. This study used the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration, 2018) to collect individuals' perceptions of health and trip behaviors. Furthermore, the research considered the built environment (living in urban vs. rural areas, population density, and employment density) and individual socioeconomic status reported in NHTS as well as trip features. Furthermore, this study conducted a health assessment survey and an in-body examination on a sample population from one university in Texas to examine the alignment between perceived health, objective health, and the use of active transportation. In the context of transportation planning and public policy, this examination can help metropolitan transportation organizations and cities to prioritize the public transit projects and active travel projects according to the current and required infrastructure within the budgeting policies of the states.

Data

Perceived health measures and associated sociodemographic data were collected from the last version of NHTS 2017 conducted by the Federal Highway Administration (FHWA). NHTS is the major national data source collecting the American public travel behavior based on demographic, economic, and cultural variations. NHTS 2017 includes data of 264,234 persons from 129,696 households in the U.S. The overall response rate is 15.6%, although, for different states, this rate varies from 11.9% to 24.1%. The new NHTS version adopted an Address-Based Sampling (ABS) method instead of sampling from potential residential telephone numbers (or random-digit dialing sample). This feature allows for the inclusion of cellphone-only households, which represent over half of the total households. Collection of data via mail-back recruit method and web response system as well as traditional telephone survey is another major change in the newly released NHTS versus the previous versions.

This study excludes individuals reporting to have medical conditions. The original 11 categories of income are merged into four groups (less than $25,000, $25,000-$49,999, $50,000-$99,999, $100,000 and higher) and the five categories of individuals' education are collapsed into three categories of high school or less, bachelor or some college, and graduate or professional. Also, built environment variables of population and employment densities are used. This study used four transportation modes– auto, public transit, walk, and bike – because of very low frequency in other options.

Trip features variables include the total number of trips, duration, and distance by mode. For each trip variable, this study calculated the total, average, and maximum statistical values. Then, the authors built a Pearson correlation table for the transport variables and eliminated the highly correlated variables. As a result, the study used the total number of trips (frequency), mean duration, and maximum distance for auto, public transit, bike, and walking trips for modeling. The dependent variable is the self-assessed health opinion responded in five categories (poor, fair, good, very good, and excellent). Poor and fair conditions are merged into one category, called relatively fair. Table 1 shows the descriptive statistics of the modeling variables.

Statistical Modeling

This study used an ordinal logit model to investigate the relationships of socio-demographics, physical activity, built environment, and trip features with the perceived health. The ordered logit model leverages the four ordinal levels of the perceived health variable using a single latent propensity to distinguish the varying orders of that variable (Eluru & Yasmin, 2015). To determine outcome probabilities, this propensity is segregated into categories as many as dependent variable alternatives. The developed model assumed that perceived health levels (y_i) are associated with an underlying continuous, latent variable (y_i^*), with the following linear function:

$$y_i^* = X_i\beta + \varepsilon_i, \text{for } i = 1, 2, \ldots, N \tag{1}$$

Table 2-1 Variables and Descriptive Statistics of NHTS Respondents

Variable	Description	n (%)	Mean	Standard deviation	VIF
Health	opinion of health (Dependent Variable)		1.93	0.87	
0: relatively fair (ref)		9,945 (5.6)			
1: good		44,001 (24.7)			
2: very good		72,489 (40.8)			
3: excellent		51,421 (28.9)			
Gender	gender		0.52	0.50	
0: male (ref)		85,359 (48.0)			
1: female		92,497 (52.0)			1.02
Age	person's age in years		50.45	18.17	1.08
Hisp	Hispanic or Latino origin of a person		0.08	0.28	
0: Not Hispanic/Latino (ref)		162,799 (91.5)			
1: Hispanic/Latino		15,057 (8.5)			1.03
Education	educational attainment of an individual		0.98	0.68	
0: high school or less (ref)		42,878 (24.1)			
1: bachelor or some college		94,990 (53.4)			1.62
2: graduate or professional		39,988 (22.5)			1.76
Income	household income		1.92	1.00	
0: less than $25,000 (ref)		21,417 (12.0)			
1: $25,000-$49,999		33,950 (19.1)			2.21
2: $50,000-$99,999		59,751 (33.6)			2.92
3: $100,000 and higher		62,738 (35.3)			3.16
Physical Activity	times of phyiscal activity during past week		2.82	3.30	1.03
Urb_Rur	Household in urban/rural area		0.77	0.42	
0: rural (ref)		39,627 (22.2)			
1: urban		138,229 (77.8)			1.25
Population Density	persons per square mile in the census tract		0.68	0.60	
0: 0-999 (ref)		68,910 (38.7)			
1: 1,000-9,999		96,430 (54.2)			1.48
2: 10,000 and more		12,516 (7.1)			1.93
Employment Density	workers per square mile in the census tract		0.91	0.75	
0: 0-249 (ref)		59,428 (33.4)			
1: 250-1,999		75,410 (42.4)			1.65
2: 2,000 and more		43,018 (24.2)			1.78
Auto					
Auto_fr	frequency of auto trips		3.83	2.44	1.13
Auto_max_dist	maximum auto trip distance (in 100 mile)		0.19	0.48	1.58
Auto_mean_dur	average auto trip duration (hour)		0.39	0.58	1.62
Public Transit					
Public_fr	frequency of transit trips		0.06	0.37	1.83
Public_max_dist	maximum transit trip distance (in 100 mile)		0.01	0.16	2.00
Public_mean_dur	average transit trip duration (hour)		0.03	0.24	3.00
Walk					
Walk_fr	frequency of walk trips		0.38	1.00	1.23
Walk_max_dist	maximum walk trip distance (in 100 mile)		0.01	0.12	1.03
Walk_mean_dur	average walk trip duration (hour)		0.06	0.24	1.17
Bike					
Bike_fr	frequency of bike trips		0.07	0.32	1.31
Bike_max_dist	maximum bike trip distance (in 100 mile)		0.01	0.02	1.15
Bike_mean_dur	average bike trip duration (hour)		0.01	0.09	1.41

$y_i^* = X_i\beta + \varepsilon_i$, for $i = 1, 2, \dots, N$ where
i $(i = 1, 2, \dots, N)$ = the individual;
X_i = vector of exogenous variables;
β = vector of unknown parameters;
ε_i = random disturbance term

Since the opinion of health in an ordered format is used as the dependent variable, it is also assumed that the vector of j $(j = 1, 2, \dots, J)$ and α_j are self-assessed health levels and the thresholds connected with these levels, respectively. The following relationship connects the unobservable latent variable (y_i^*) with the observable ordinal variable (y_i), through the thresholds:

$$y_i = j, \text{if } \alpha_{j-1} < y_i^* \leq \alpha_j, \text{for } j = 1, 2, \dots, J \tag{2}$$

p_{ij} , the probability that individual i perceives individual health level as j, can be computed as follows:

$$p_{ij} = p(y_i = j) = p(\alpha_{j-1} < y_i^* \leq \alpha_j) = F(\alpha_j - X_i\beta) - F(\alpha_{j-1} - X_i\beta) \tag{3}$$

where, $F(.)$ represents the standard logistic cumulative distribution function, which is computed based on Sigmoid function $(\frac{1}{1+e^z})$; p_{ij} is computed as follows:

$$p_{ij} = p(y_i = j) = \frac{\exp(\alpha_j - X_i\beta)}{(1 + \exp(\alpha_j - X_i\beta))} - \frac{\exp(\alpha_{j-1} - X_i\beta)}{(1 + \exp(\alpha_{j-1} - X_i\beta))} \tag{4}$$

Multicollinearity among independent variables is tested with Variance Inflation Factor (VIF) based on the inflated variance of the estimated coefficients. In general, VIFs exceeding 4 warrant more investigation, while the values of higher than 10 show serious multicollinearity and require the modification of variables (Hair et al., 2010). The association between trip variables and perceived health is tested through the Wald test (Wald Chi-Squared test) to ensure that each travel attribute is significant in the model. Using Maximum Likelihood Estimation (MLE), the coefficients estimates $(\hat{\beta})$ are divided by their standard errors $(\widehat{se}(\hat{\beta}))$ as follows (Wasserman, 2006):

$$W = \frac{(\hat{\beta} - \beta_0)}{\widehat{se}(\hat{\beta})} \sim N(0,1) \tag{5}$$

Since the parameter of interest is usually zero, the Wald statistics are simplified as follows.

$$W = \frac{\hat{\beta}}{\widehat{se}(\hat{\beta})} \sim N(0,1) \tag{6}$$

Survey for Validation

Previous studies confirmed that perceived health did not always align with objective health. This study conducted an online survey and an in-body examination with a sample population to validate the previous findings with local samples, comprised of 58 faculty members, staff, and students of the University of Texas at Arlington (UTA). This sample population was derived from the research project "Monitoring Daily Activities and Linking Physical Activity Levels Attributed to Transportation Mobility Choices and Built Environment" (Oh et al., 2019). In this project, a survey was designed to ask the participants about perceived health, socio-demographic status, daily commuting mode, and active minutes with moderate and vigorous physical activity (in minutes) they had in the week before the survey. The obtained active minutes were converted to physical activity levels based on the guidelines by (U.S. Department of Health and Human Services, 2018). Inactive individuals were considered as the ones without any activity. Insufficiently active individuals were the ones with less than weekly 150 minutes of equivalent moderate activity PA. Of note, every one minute of vigorous physical activity was considered as two minutes of moderate physical activity (U.S. Department of Health and Human Services, 2018). Also, active and highly active people consisted of those with 150-300 and more than 300 minutes per week, respectively.

In-body examination collected objective health measure, BMI ($\frac{\text{weight}}{\text{height}^2}$), in which weight and height were measured in kg and meter, respectively. The study used four BMI categories of underweight (less than 18.5), normal (between 18.5 and 24.9), overweight (between 25 and 29.9), and obese (30 and higher). Table 2 shows the distribution of the sample population. In-body examination collected objective health measure, BMI ($\frac{\text{weight}}{\text{height}^2}$), in which weight and height were measured in kg and meter, respectively. The study used four BMI categories of underweight (less than 18.5), normal (between 18.5 and 24.9), overweight (between 25 and 29.9), and obese (30 and higher). Table 2 shows the distribution of the sample population.

Model Results

Before modeling, multicollinearity between independent variables was checked by Variance Inflation Factor (VIF) test (refer back to Table 1) and confirmed that all the VIF values were less than 4, indicating that multicollinearity does not exist among the variables (Hair et al., 2010). McFadden measure (likelihood ratio chi-square), and Akaike Information Criterion (AIC) was used as the fitness measures and the model is statistically significant at $\alpha = 0.01$ level. Table 3 presents the coefficients, odds ratio, and confidence intervals (CI) for all the independent variables. The result of the Wald test showed that model with trip attributes by each mode (Auto, transit, walk, and bike) provides better results to predict the dependent variable (perceived health) than the model only including socio-demographics, and built environment. Females are more likely to have higher perceived health. Age is negatively associated with health as commonly revealed in previous studies (Ermagun & Levinson, 2017; Humphreys et al., 2013; Kent et al., 2019). Similar to the studies (Ermagun & Levinson, 2017; Langerudi et al., 2015; Scheepers et al., 2015; She et al., 2017, 2019; Tajalli & Hajbabaie, 2017), this study found that individuals with higher family income and educational attainment tend to have better self-assessed health.

Table 2-2 Survey Samples

Variable	n (%)
Gender	
male	31 (53.4%)
female	27 (46.6%)
Age	
18 - 25	27 (46.6%)
26 - 49	25 (43.1%)
50 - 64	6 (10.3%)
65 and above	0 (0.0%)
Race	
American Indian or Alaskan Native	0 (0.0%)
Asian / Pacific Islander	22 (37.9%)
Black or African American	7 (12.1%)
Hispanic American	6 (10.3%)
White / Caucasian	22 (37.9%)
Other	1 (1.7%)
Education	
some high school education, but no diploma	0 (0.0%)
high school graduate with a diploma or equivalent (e.g. GED)	1 (1.7%)
some college credits, but no Bachelor's degree	13 (22.4%)
bachelor's degree or higher	44 (75.9%)
Status (Position)	
faculty	6 (10.3%)
staff	15 (25.9%)
student	37 (63.8%)
Income	
Less than $30,000	37 (63.8%)
$30,000 - $50,000	14 (24.1%)
$50,000 - $100,000	7 (12.1%)
More than $100,000	
Having Driver's License	
Yes	47 (81.0%)
No	11 (19.0%)
Weight Status (BMI)	
underweight	1 (1.7%)
normal	20 (34.5%)
overweight	22 (37.9%)
obese	15 (25.9%)
Physical Activity Level	
inactive	7 (12.1%)
insufficiently active	15 (25.9%)
active	25 (43.1%)
highly active	11 (18.9%)
Commuting Mode	
car	35 (60.4%)
bike/walk	23 (39.6%)
Perceived Health	
bad	4 (6.9%)
fair	15 (25.9%)
good	35 (60.3%)
excellent	4 (6.9%)

Individuals with a greater amount of physical activity (light/moderate, and vigorous) per week also tend to consider themselves healthier. Hispanics are more likely to have lower perceived health, which was also indicated in the study of (Ermagun & Levinson, 2017). The model also shows that people living in more densely employed areas have better perceived health.

Results indicate that higher car usage is linked with better perceived health (OR = 1.01). Although this might seem unusual, previous studies found that driving could be beneficial for reducing physical stress levels (Ellaway et al., 2003; G. Williams et al., 2008). Although (Avila-Palencia et al., 2018) found conflicting results and showed that car driving negatively affects self-assessed health (OR = 0.98), the results came from the model only using the trip frequency by mode. In the model of this chapter, the average auto trip time is negatively connected with health perception (OR = 0.98). In other words, individuals with less mean car trip duration have a higher health perception. An explanation for that is individuals with longer trip duration were more likely to live in rural and suburban areas, which is associated with less walkable/bikeable features of the built environment (Hoehner et al., 2012). However, this finding is consistent with the findings that smaller amounts of auto travel time are connected to higher life satisfaction and better health status (Morris, 2015; Oliveira et al., 2015). The developed model shows that frequent use of public transit is highly associated with lower perceived health (OR = 0.96). A likely explanation is that transit users are largely lower-income populations who are more likely to assess themselves unhealthy. Although average transit time is not a significant variable to explain perceived health, the maximum transit trip distance is significantly associated with higher perceived health (OR = 1.23). Both walking and biking frequency are positively associated with perceived health (OR = 1.05 for walking and OR = 1.18 for biking).

Table 2-3 Ordered Logit Model for Perceived Health

Variable		Coefficient	OR	95% CI
Intercept 1		2.95***	19.07	(18.15 , 20.03)
Intercept 2		0.81***	2.24	(2.14 , 2.35)
Intercept 3		-1.11***	0.33	(0.31 , 0.34)
Gender	male (ref)			
	female	0.10***	1.11	(1.09 , 1.13)
Age		-0.03***	0.98	(0.97 , 0.98)
Hisp	Not Hispanic/Latino (ref)			
	Hispanic/Latino	-0.13***	0.88	(0.85 , 0.90)
Education	high school or less (ref)			
	bachelor or some college	0.21***	1.23	(1.21 , 1.26)
	graduate or professional	0.54***	1.71	(1.67 , 1.76)
Income	less than $25,000 (ref)			
	$25,000-$49,999	0.44***	1.56	(1.51 , 1.61)
	$50,000-$99,999	0.72***	2.04	(1.99 , 2.11)
	$100,000 and higher	1.13***	3.09	2.99 , 3.19)
Physical Activity		0.10***	1.10	(1.10 , 1.10)
Urb_Rur	rural (ref)			
	urban	-0.01	0.99	(0.96 , 1.02)
Population Density	0-999 (ref)			
	1,000-9,999	-0.02	0.98	(0.96 , 1.01)
	10,000 and more	-0.11***	0.90	(0.85 , 0.94)
Employment Density	0-249 (ref)			
	250-1,999	0.05**	1.05	(1.02 , 1.09)
	2,000 and more	0.06**	1.06	(1.02 , 1.10)
Auto_fr		0.01***	1.01	(1.01 , 1.02)
Auto_max_dist		0.04**	1.04	(1.02 , 1.07)
Auto_mean_dur		-0.02*	0.98	(0.96 , 0.99)
Public_fr		-0.04*	0.96	(0.93 , 0.99)
Public_max_dist		0.21**	1.23	(1.07 , 1.42)
Public_mean_dur		-0.04	0.96	(0.91 , 1.03)
Walk_fr		0.05***	1.05	(1.04 , 1.07)
Walk_max_dist		0.01	1.01	(0.94 , 1.08)
Walk_mean_dur		0.16***	1.17	(1.12 , 1.22)
Bike_fr		0.17***	1.18	(1.15 , 1.22)
Bike_max_dist		0.03	1.03	(0.68 , 1.56)
Bike_mean_dur		0.26***	1.30	(1.15 , 1.46)
McFadden R square		0.143		
AIC		413,119.2		
Likelihood Ratio Chi-2		-206,559.6		
Wald Test Result for trip attributes (d.f. = 12)	χ-square = 1008.1	P-value = 0.000		

*Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05*

Many studies (Avila-Palencia et al., 2018; Humphreys et al., 2013; Schauder & Foley, 2015; Scheepers et al., 2015) found similar results. However, maximum active travel distance is not a significant variable affecting perceived health. Biking frequency, compared to walking frequency, is more likely to be associated with higher perceived health (regression coefficients of 0.17 for bike versus 0.05 for walk) due to the greater intensity of exercise associated with cycling versus walking (Voss et al., 2015). The studies (Smith, 2017; Willis et al., 2013) showed that cyclists have the highest well-being, and are the most satisfied travelers, in comparison to other modes' users. The model also indicates that both average walking duration and biking duration are significantly associated with higher health perception (OR = 1.17 for walk and OR = 1.30 for bike). The developed ordered model concludes different trip features, socio-demographics, and built envornment variable, which seems to be more inclusive than the previously developed models in terms of the number and type of the variables included in the modeling.

Survey findings

Table 4 compares perceived health, objective health (BMI), and physical activity levels, collected from the survey and in-body examination with the local sample of UT Arlington. The highest proportion (29%) are categorized as normal weight and good health, followed by overweight and good health (22%). Only one person (2%) belongs to the lowest BMI category. Among the survey participants, 34% is overweight and 26% is obese; however, 68% of overweight participants felt their health is good or excellent, which is much higher than those who answered to bad (0%) or fair (32%) categories. Also, only 27% of obese participants answered their health as bad. The researchers also compared the perceived health and physical activity. Overall, 12% and 26% of the population has inactive and insufficiently active physical activity. Among them, 60% indicated that their health is good or excellent, which is much higher than those who answered that their health is bad or fair. The results show that 76% of active and 64% of highly active individuals indicated they are in good or excellent health condition; the rate of active respondents with good perceived health is also almost four times the active ones with excellent perceived health. The number of people who engage with low levels of physical activity but indicate a good perception of health is eight times those who had bad perceived health with the same activity level. Regarding the travel mode, 60% and 40% of participants commute by car and active modes, respectively. While 57% of car commuters have a good/excellent perceived health, 73% of active commuters evaluated their health to be good and excellent. The overall results show that perceived health is not always aligned with objective health measures such as BMI and physical activity level. However, our sample showed that transportation-related physical activity is consistent with higher perceived health.

Table 2-4 Comparisons among Self-assessed Health, Weight, Physical Activity and Trip Mode to Work

	Perceived Health				Total (%)
	Bad	Fair	Good	Excellent	
BMI					
Underweight	0	0	1	0	1 (2%)
Normal	0	2	17	1	20 (34%)
Overweight	0	7	13	2	22 (38%)
Obese	4	6	4	1	15 (26%)
Physical Activity					
Inactive	1	1	5	0	7 (12%)
Insufficiently Active	1	6	8	0	15 (26%)
Active	1	5	15	4	25 (43%)
Highly Active	1	3	7	0	11 (19%)
Transport Mode					
Car	3	10	20	2	35 (60%)
Bike/Walk	1	5	15	2	23 (40%)

Conclusion

This paper examines how trip attributes are associated with perceived health, which represents general health status. This study used NHTS 2017 to collect individual-level data of perceived health, trip attributes including trip duration, distance, and frequency for auto, public transit, and active transportation. The results showed that individuals with longer auto trips tend to show lower perceived health; however, the higher frequency and longer active transportation are linked to better perceived health. The survey with local samples showed that perceived health is not necessarily associated with actual health measures of BMI and physical activity. The results of this chapter can contribute to the development of performance measures for each transportation mode by assigning considering different weights for the various trip features of travel time, distance, and frequency regarding each mode. Also, these results help the researcher of active travel to developing an index based on the weights of different trip features.

Future studies will collect longitudinal health and activity data including various objective measures of health. This will allow the researchers to explore further associations and causalities among perceived and objective health, and physical activity including transportation activity. The authors will also consider adding much detailed activity data such as minute-by-minute accelerometer-based walking/biking activities to examine their relation to perceived health.

Chapter 3 Physical Health and Activity Measures across Healthy and Unhealthy Weight Groups

Background

Among the many public health challenges threatening most of the societies, physical inactivity is one of the most serious issues. Being physically inactive is a major but modifiable risk factor for non-contagious diseases, such as heart disease, diabetes, obesity, stroke, hypertension, and some cancers (Lachat et al., 2013). According to the World Health Organization (WHO), the fourth and fifth leading risk factors for non-communicable diseases are physical inactivity and overweight/obesity (World Health Organization, 2009). These two are responsible for a total of 11% in annual deaths. Obesity is also an important cause of heart disease (Healthline, 2018), which plays a leading role in total deaths in the United States. Consequently, individuals should be engaged in physical activities to prevent the risk factors leading to cardiovascular disease.

The World Health Organization (WHO) defines physical activity as any type of movement in the body, which is made by skeletal muscles and needs energy expenditure (World Health Organization, 2018). Physical activity is a major solution to maintain a healthy weight. Also, according to (Centers for Disease Control and Prevention, 2020a) the main weight groups in terms of body mass index (BMI) are: underweight (BMI less than 18.5), normal (BMI between 18.5 and 24.9), overweight (BMI between 25 and 29.9), and obese (BMI equal to 30 and higher). According to (Blanchard et al., 2005) people with normal weight spend more time on physical activity than overweight individuals. Also, based on the same reference, overweight people tend to do more physical activity than obese individuals. According to the studies (Hagströmer et al., 2010; Tudor-Locke et al., 2010), individuals with higher body mass index (BMI) tend to be less engaged in physical activity. Furthermore, (Hansen et al., 2013) indicate that in comparison with normal-weight people, overweight and obese individuals walk fewer steps and are engaged in less overall physical activity and physical activity of at least moderate intensity.

Physical activities have a broad range, including traveling, working, doing household chores, playing, etc. Nevertheless, walking is the simplest and most prevalent form among the U.S. adults and those who meet the aerobic physical activity guideline (Kruger et al., 2008). Walking as a moderate-intensity physical activity received attention in the 1990s (U.S. Department of Health and Human Services, 1996). According to (Lee & Buchner, 2008), walking can provide light-intensity (such as strolling while window shopping), moderate-intensity, and vigorous-intensity (e.g. fast walking) impacts. To resolve the mentioned physical inactivity issue, public health agencies need to promote more walking among adults. Therefore, as a viable strategy to meet the physical activity guidelines, adults need to enhance walking in terms of level and frequency (Paul et al., 2015). The literature has shown that brisk walking is a safe and healthy measure to prevent the risks of a sedentary lifestyle among unfit people, which can also result in the reduction of chronic disease rates (Lee & Buchner, 2008).

People with different socio-demographics were showed to have different activity levels. According to (U.S. Department of Health and Human Services, 2020), about 3 out of 10 U.S. adults report being inactive during their leisure time. Also, female, older, African-American, and Hispanic individuals with lower education levels remain less likely to meet the aerobic requirements of the 2008 Physical Activity Guidelines for Americans. Well-established literature shows that regular physical activity helps to reduce the risk factors for high blood pressure, heart diseases, stroke, some cancers, type 2 diabetes, and depression (U.S. Department of Health and Human Services, 2008a). WHO recommended having a minimum of 150 minutes of moderate or 75 minutes of vigorous physical activity per week to stay healthy (World Health Organization, 2010). However, any amount of moderate-to-vigorous physical activity can gain health benefits for individuals (U.S. Department of Health and Human Services, 2018).

With all being said, this chapter attempts to answer some research questions. This study uses a health measure, resting heart rate (RHR), as an index showing the number of heartbeats per minute while at rest. Resting heart rate is a common indicator of wellness due to the inter-relationship between physical exercise, resting heart rate, and overall health (Nealen, 2016). This chapter examines if the levels of a physical health measure, namely resting heart rate vary among normal/underweight individuals and overweight/obese people. Then, this research examines if physical activity measures vary among individuals from different weight groups (different BMI). Since walking is the most accessible and least expensive form of active travel, the investigation of the differences between walking's activity and health indicators among adults within different weight groups is of great importance for the transportation and public health experts to estimate the benefits associated with adding extra walking trips of various bouts and intensity levels to each weight group's daily routine. Also, this chapter investigates whether the higher mean ratio of moderate-to-vigorous walking among the overweight/obese group, compared to the normal/underweight group is statistically significant. This chapter further evaluates if the normal/underweight people have a better situation in terms of physical activity measures of burned calories, walking minutes, number of steps per walking minutes. To do that, this chapter starts with a review of previous studies on the effects of walking on health measures and variability in heart rates. Then, the data source and methodology are presented. Following the data section, the modeling approach (hypothesis tests) and discussion on the results are introduced. Finally, conclusion and future research are discussed in this chapter.

Literature Review

Grouping individuals based on their weight status requires a health indicator. Given that obesity is one of the most critical concerns in the context of public health, body mass index (BMI = $\frac{\text{Weight}}{\text{Height}^2}$) has progressively gained global acceptance for the measurement of overall health in general and particularly obesity (Bhurosy & Jeewon, 2013). This increased popularity of BMI is due to its direct connection to health risks and mortalities in many societies, irrespective of age, gender, and ethnic group (Muralidhara, 2007). According to one study (Hall & Cole, 2006), BMI is the best anthropometric measure of body fatness for public health issues. Even though BMI does not directly measure body fat, it can be a measure of extra body weight and it has been illustrated to correlate with body fat (Nihiser et al., 2007). According to some studies (Muralidhara, 2007; Nihiser et al., 2007), since the direct methods of body-fat measurements, such as skin fold, and underwater weighing are very expensive and require more time, facilities and trained staff, BMI has been accepted as the most widely used measure for weight-related health risks. Nevertheless, researchers argue that BMI may not be necessarily the best measure of weight-related health status especially in terms of disease risks (Lee et al., 2008) since BMI cannot distinguish between fat and muscle. As muscle is heavier than fat, BMI may group more toned people in the overweight category, although they have low-fat levels (Sifferlin, 2013). The study of (Ahima & Lazar, 2013) shows that BMI cannot be the most accurate measure, as it does not differentiate between different types of fat. Besides, (Shmerling, 2016) believes that since BMI is only a measure of one's size, it does not measure health or a physiological state related to the presence or absence of diseases. One who smokes and has a normal BMI may be more vulnerable to cardiovascular death than someone who has a high BMI but is a physically fit non-smoker. However, other researchers believe that among the predictors of type 2 diabetes, waist, waist-to-hip ratio, and BMI are all equally associated (Qiao & Nyamdorj, 2010; Vazquez et al., 2007). However, BMI still remains the most common predictor of obesity.

Long-term weight regulation is a function of physical activity patterns (Cooper et al., 2000). Previous studies have used different indices to measure physical activity levels and fitness. These measures include steps per day (Tudor-Locke et al., 2010; Wyatt et al., 2005), steps per minute (Cooper et al., 2000), duration of different walking intensities, namely, light, moderate, and vigorous (Cooper et al., 2000; Tudor-Locke et al., 2010), and resting heart rate (RHR). According to (American Heart Association, 2015b), the resting heart rate for most men and women is 60 to 100 beats per minute. Generally, higher resting heart rates occur with poorer physical fitness, higher values of blood pressure, and higher values of body weight (Jensen et al., 2013). It is suggested to measure the resting heart rate in the morning before getting up and drinking coffee (American Heart Association, 2015a). Resting heart rate is a risk factor and can predict cardiovascular morbidity (Morcet et al., 1999). Also, RHR is an independent risk factor for heart failure (Nanchen et al., 2013). Some factors that impact resting heart rate like age, gender, height, and race are non-modifiable; however, the lifestyle factors of smoking, alcohol, and mental stress remain modifiable (Ehrenwald et al., 2019). Physical fitness is among the modifiable factors of resting heart rate. Usually, fit individuals have lower resting heart rates with values of less than 60 beats per minute (Machowsky, 2013). Also, more fit people can perform a particular physical activity at a lower minute-by-minute heart rate than less fit individuals due to the better performance of oxygen pumping procedure by heart (Machowsky, 2013).

Previous studies have examined the differences between physical activity and fitness measures among various weight groups. For example, the study of (Wyatt et al., 2005) conducted a combination of a telephone survey and a 4-day accelerometry through a step counter on 742 subjects, including 40% normal weight, 47% overweight, and 13% obese in Colorado. The results showed that on average, the individuals had 6,804 steps per day. Also, obese individuals walked 2000 steps fewer than normal-weight ones. In the study of (Cooper et al., 2000), the physical activities of 72 participants were measured for 7 days through minute-by-minute accelerometry. The results indicate that despite no significant difference in the steps per minute among normal and overweight individuals, obese participants were significantly less active than non-obese ones during weekdays (279.1 ± 77.5 vs. 391.3 ± 139.4 counts per minute) and weekends (222.3 ± 93.9 vs 368.2 ± 177.5 counts per minute). Also, in terms of the duration of moderate-intensity levels of physical activity, the non-obese (BMI < 30) and obese individuals (BMI ≥ 30) showed to have respectively 39.8 ± 19.5 and 31.3 ± 14.0 minutes of walking during weekdays and 30.8 ± 24.4 and 15.0 ± 12.2 during weekends. Using the 2005-2006 National Health and Nutrition Examination Survey (NHANES) data, (Tudor-Locke et al., 2010) examined the physical activity/inactivity profile for 1,016 normal weight, 1,195 overweight, and 1,242 obese U.S. adults (totally 3,522) aged 20 and above. In their study, physical activity was measured based on some indicators, such as activity counts (number of right hip movements recorded by Actigraph AM-7164 accelerometers) per day, uncensored or raw steps per day, censored (raw steps minus those steps taken at an intensity < 500 activity counts/minute), uncensored/censored steps per minute, and length of sedentary, low, light, moderate, and vigorous intensity. The analysis results showed that the indicators of physical walking were different across various weight BMI categories. To be precise, the total number of steps per day was 7,190 ± 157, 6,879 ± 140, and 5,784 ± 124 for normal, overweight, and obese people, respectively. In terms of moderate-walking intensity, normal weight, overweight, and obese individuals spent 25.7 ± 0.9, 25.3 ± 0.9, and 17.3 ± 0.7 minutes/day, respectively. Furthermore, the duration of vigorous-intensity walking was 7.3 ± 0.4, 5.3 ± 0.5, and 17.3 ± 0.7 minutes per day for normal weight, overweight, and obese individuals. As can be seen from the previous studies, overweight/obese individuals, compared to normal/underweight ones, are less active in most of the physical activity measures.

However, previous studies fail to include both groups of physical activity and health measures and examine the differences between healthy weight (normal and underweight) and unhealthy weight (overweight and obese) individuals. According to one study (Hansen et al., 2013), to develop an understanding of obesity, it is important to have the information on physical activity measures of overall walking, intensity-specific walking, and the number of steps across different weight groups. To be more precise, the literature has shown higher health care charges associated with being overweight/obese versus normal/underweight (Anderson et al., 2005) and being more engaged in physical activity versus being insufficiently active or inactive (Carlson et al., 2015; Chevan & Roberts, 2014). Also, this understanding is useful for public health experts in the planning of interventions to enhance physical activity and prevent weight gain in the general population. Therefore, this study attempts to find if significant differences between the walking activity and health measures among normal/underweight people and overweight/obese individuals exist.

Data

Physical Activity Study

The required data of this chapter and chapter four are derived from a research project titled "Monitoring Daily Activities and Linking Physical Activity Levels Attributed to Transportation Mobility Choices and Built Environment" (Oh et al., 2019). This project, which was a collaboration between Western Michigan University (WMU) and the University of Texas at

Arlington (UTA), was funded by the U.S. Department of Transportation (DOT) through the Transportation Research Center for Livable Communities (TRCLC) at WMU. This project aimed to identify and categorize the health outcomes from daily physical and travel activities. For this purpose, the research team developed an initial survey to pre-screen the participants. This short survey included questions about age, gender, main daily transportation modes, and approximate daily commuting travel time. Also, the respondents were surveyed about the type, frequency, and duration of every physical activity they had for the week before the survey day.

After comparing the number of survey participants based on the two criteria of main transportation mode and being physically active (at least 150 minutes of weekly physical activity) 120 participants, namely a total of 60 faculty members, staff and students from each school were selected for the main part of the study. The selected participants were asked to fill out the main survey. Regarding this survey, they had a choice to fill out an online or a written self-reported survey, including socio-demographics (age, gender, education, etc.), physical activity (type, duration, and estimated level of intensity from 1 to 10) during the week ending to the survey, and daily transportation modes (type, and travel time). Furthermore, for each participant the following health intake measurements were conducted in the Biomechanical Laboratory for WMU participants and the Kinesiology Department for UTA ones:

- height
- weight (traditional and digital scales)
- body fat percentage (digital scale and hand-held body fat monitor)
- body mass index (BMI, through the hand-held body-fat monitor)
- girth measurements (abdomen as the smallest girth around the abdomen and hip as the largest girth around the buttocks)

The data of participants' trips modes and purposes were collected through a developed cell phone application called "Physical Activity Through Smart Travel Activity" or "PASTA" (Oh et al., 2019). Also, each participant received a Fitbit Charge 3 to collect the physical activity indices of active minutes, daily steps, total and burned calories, and heart rates in a 60-second time intervals for the six months of April 2019 through September 2019.

Data Processing

This study collected the physical activity and health measures of the selected participants for the week of June 2-8, 2019. This dataset is composed of the data of 95 participants from the Physical Activity Study (Oh et al., 2019) after excluding those individuals with missing data during the study period. The physical activity and health measures include the average resting heart rates and minute-by-minute measures of walking heart rates, burned calories, and the number of steps. Based on the guidelines of the U.S. Department of Health and Human Services, health-related outcomes are improved by physical activities of at least 10 minutes. However, any length of moderate-to-vigorous physical activity can contribute to health benefits associated with the accumulated volume of physical activity (U.S. Department of Health and Human Services, 2018). Therefore, this study considers walking activities of 5 minutes and longer and excludes walking activities shorter than 5 minutes.

In terms of BMI, the participants are grouped into two categories of underweight/normal and overweight/obese. Most studies consider overweight and obese people in an unhealthy weight group when investigating relationships between physical activity and obesity. Also, due to the small sample size, underweight participants (n=2) were included in the normal weight category. Using the recommendation of the American Heart Association (AHA), the study measures the daily resting heart rates for individuals after the wake-up time in the morning (American Heart Association, 2015a). The individuals' wake-up time was found by the number of steps that suddenly increased in the morning. The resting heart rate for everyone was calculated as the average values of the RHR for the mentioned week.

This study requires an approach to determine the intensity levels of walking minutes for the minute-by-minute moderate-to-vigorous walking data of individuals. This study uses the American Heart Association (AHA) approach to compute the ratio of one's heart rate at any minute to his/her maximum heart rate. Then, using the thresholds by the (American Heart Association, 2015a) the intensity of walking at any given minute is determined according to table 1. The maximum heart rate is calculated from the age-based formula (Fox & Haskell, 1971), according to equation 1:

$$\text{Heart Rate}_{\text{max}} = 220 - \text{Age} \tag{1}$$

Table 3-1 The intensity of walking as a percentage of maximum heart rate according to (American Heart Association, 2015a)

Heart rate as a percent of Maximum Heart Rate (220 – Age)	The intensity of Physical Activity
Heart rate: less than 50% of HR_{max}	Light
Heart rate: equal to or greater than 50% and less than 70% of HR_{max}	Moderate
Heart rate: greater than 70% of HR_{max}	Vigorous

This study uses the individuals' steps per minute to categorize different walking intensities. According to (Lobby, 2020; Tudor-Locke et al., 2018), the numbers of walking steps per minute from the regular slow walking and running are 60 and 180, respectively; therefore, the data set excludes all minute-by-minute records of activities that have the number of steps below 61 or above 179. This task was done to include only those records matching the walking activities of individuals.

Burned calories per minute are the difference between minute-by-minute total calories (obtained by Fitbit Charge 3) and basal metabolic rate (BMR) per minute. The BMR per day for men and women is calculated by equations 2 and 3, which are the revised formulae of Harris-Benedict by (Mifflin et al., 1990). The BMR per minute is computed by dividing BMR by 1440 daily minutes ($24 \text{ hr } \times 60 \text{ minutes}$).

$$\text{Men: BMR} = 10 \times \text{weight (kg)} + 6.25 \times \text{height (cm)} - 5 \times \text{age (years)} + 5 \tag{2}$$

$$\text{Women: BMR} = 10 \times \text{weight (kg)} + 6.25 \times \text{height (cm)} - 5 \times \text{age (years)} - 161 \tag{3}$$

Table 2 illustrates the categorical descriptive statistics of the 95 respondents of the sample study, as well as the U.S population. Also, the numerical physical activity and health measures of the participants can be seen in table 3. As can be seen, the participants' ages range from 17 to 60. Regarding gender distribution, almost 62% of the participants were men. However, in the United States, the percentages of men (49.2%) and women (50.8%) are very close. In terms of BMI, overweight individuals ($25 \leq \text{BMI} \leq 29.9$) represent the greatest portion of the sample population with 39%. Also, the percentage of healthy weight (normal and underweight) adults is 32%, which is much less than the proportion of individuals with unhealthy weight (68%). Table 2 shows that the percentages of weight groups in the sample population are very similar to the corresponding percentage in the U.S. population. For example, 32% and 68% of the participants are in healthy and unhealthy weight groups, these percentages are 28.4% and 71.6%, for the U.S. population. Nevertheless, the perceived health seems to be very different among this study's participants and the U.S. population. As can be seen, while 26% of the sample consider themselves with fair health, this health category includes 7.7% of the U.S. people. Also, although 23.7% of the U.S. people have a good perception of their health, only 23.7% of the selected participants are grouped in the good health category. Table 3 indicates that resting heart rates are as low as 49 and as high as 84, with an average of 66.1. Moreover, although the total number of steps per walking activity has a high standard deviation (929.1), the standard deviations for the physical activity measures of the mean number of steps and total moderate-to-vigorous walking minutes are quite low, with the values of 12.8 and 9.8, respectively.

Table 3-2 Descriptive statistics of the categorical attributes of the sample study and U.S. characteristics

Variable	Description and frequency	Relative Frequency (%). the U.S.
gender	**female** *36(38%)* **male** *59(62%)*	female 50.8% male 49.2%
weight group	**underweight** BMI<18.5 *2(2%)* **normal** 18.5≤BMI≤24.9 *28(29%)* **overweight** 25≤BMI≤29.9 *37(39%)* **obese** 30≤BMI *28(29%)*	underweight 1.5% normal 27.7% overweight 31.8% obese 39.8%
perceived health	**bad** 5*(5%)* **fair** 25*(26%)* **good** 53*(56%)* **excellent** 12*(13%)*	poor 2.2% fair 7.7% good 23.7% very good 31.1%
resting heart rate level	**Low** RHR<55 *10(11%)* **Medium** 55≤RHR<70 *53(56%)* **High** 70 ≤ RHR *32(34%)*	–

Descriptive Analysis

Tables 4 and 5 show the cross-comparisons of weight versus resting heart rate level and perceived health of individuals. The tables show some compatibility between individuals' weight status, resting heart rate, and health perception. As can be seen, while only 7% of the participants with healthy weight have a high resting heart rate, 93% of them are grouped into low/medium RHR category. Among the unhealthy weight group, 46% have a high resting heart rate. The perceived health and weight comparisons show that 90% of the normal/underweight people assess themselves with having good or excellent health status. Also, 42% of individuals with unhealthy weight perceive to have bad/fair general health.

Table 3-3 Descriptive statistics of the numerical attributes of the sample study

Variable	Description and frequency	Min	Max	Mean	Standard Deviation
age	Numerical from 17 to 60	17	60	30.1	10.7
BMI	Numerical from 17.4 to 42.7	17.4	42.7	27.7	5.7
resting heart rate (RHR)	Numerical from 49 to 84	49	84	66.1	7.4
basal metabolic rate (BMR) per minute of walking activity	Numerical from 0.83 to 1.74	0.8	1.7	1.2	0.2
total calories burned per walking activity	Numerical from 5.4 to 637.5	5.4	637.5	53.1	61.1
mean number of steps per walking activity	Numerical from 61.3 to 146.5	61.3	146.5	87.9	12.8
total number of steps per walking activity	Numerical from 123 to 9814	123	9814	835.4	929.1
moderate-vigorous walking minutes	Numerical from 5-min to 53.3 min	5	100	11.5	9.8
weekly percentage of moderate-to-vigorous walking to total walking	Numerical from 9.2% to 100%	9.2%	100%	81.2%	18.5%

Table 3-4 comparisons among weight group and resting heart rate level

resting heart rate group	weight group	
	healthy weight (normal/underweight)	unhealthy weight (overweight/obese)
high (RHR ≥ 70)	7%	46%
Low/medium (RHR < 70)	93%	54%
total	100%	100%

Table 3-5 comparisons among weight group and self-assessed health (survey)

perceived health	weight group	
	healthy weight (normal/underweight)	unhealthy weight (overweight/obese)
bad/fair	10%	42%
good/excellent	90%	58%
total	100%	100%

Table 3-6 comparisons among walking heart rate and calories burned within different bouts among weight groups

Weight Group	Walking duration T	Walking heart rate			
		Mean	Std. Dev	Min	Max
Overall	0 < T < 5 min	96.6	12.8	49	153
	5 min ≤ T < 10 min	103.1	11.1	63.3	186.2
	10 min ≤ T < 15 min	106.9	11.0	65.1	165.9
	15 min ≤ T < 20 min	109.6	10.8	75.7	144.5
	20 min ≤ T	112.3	12.3	83.8	154.8
healthy weight (underweight/normal)	0 < T < 5 min	93	13.0	54	141
	5 min ≤ T < 10 min	100.6	12.1	63.3	148.8
	10 min ≤ T < 15 min	105.7	11.2	65.1	144.6
	15 min ≤ T < 20 min	112.0	10.6	94.5	143.6
	20 min ≤ T	111.7	12.5	83.8	144.3
unhealthy weight (overweight/obese)	0 < T < 5 min	98.3	12.3	49	153
	5 min ≤ T < 10 min	104.2	10.5	70.0	186.2
	10 min ≤ T < 15 min	107.6	10.9	79	165.9
	15 min ≤ T < 20 min	108.3	10.7	75.7	144.5
	20 min ≤ T	112.7	12.2	85.8	154.8
Weight Group	**Walking duration T**	**Calories burned**			
		Mean	**Std. Dev**	**Min**	**Max**
Overall	0 < T < 5 min	7.87	5.36	1.04	40.95
	5 min ≤ T < 10 min	26.85	13.03	5.39	78.74
	10 min ≤ T < 15 min	53.76	20.12	12.66	146.72
	15 min ≤ T < 20 min	84.00	27.66	22.44	180.74
	20 min ≤ T	188.82	110.98	47.43	637.50
healthy weight (underweight/normal)	0 < T < 5 min	7.26	4.99	1.04	31.74
	5 min ≤ T < 10 min	24.23	13.05	5.39	75.33
	10 min ≤ T < 15 min	49.24	17.53	12.66	81.98
	15 min ≤ T < 20 min	80.84	24.43	22.44	123.32
	20 min ≤ T	190.53	113.67	47.86	599.08
unhealthy weight (overweight/obese)	0 < T < 5 min	8.17	5.51	1.29	40.95
	5 min ≤ T < 10 min	28.02	12.86	5.69	78.74
	10 min ≤ T < 15 min	56.15	21.00	14.63	146.72
	15 min ≤ T < 20 min	85.77	29.27	27.20	180.74
	20 min ≤ T	187.63	109.62	47.44	637.50

This paper uses hypothesis tests to investigate the differences in resting heart rate as a baseline health indicator and walking-related activity measures among the weight groups of normal/underweight and overweight/obese. Figure 1 shows the frequency distribution plots of these measures. Resting heart rate records seem to be roughly normally distributed with the highest frequency at RHR = 66. The percentage of individuals with high resting heart rates (RHR ≥ 70) is three times greater than that of small resting heart rate (RHR < 55). However, 105 beats per minute are the walking heart rate with the highest frequency (around 700) among the walking records of at least five minutes. Regarding the moderate-to-vigorous walking to total walking, the graph shows that the highest frequency of walking activities (with at least 5 minutes) had about 0.9 of moderate-to-vigorous intensity level. Moreover, the mean walking steps per minute of walking is approximately 95 for most of the walking activities.

As can be seen from figure 1, three measures of calories burned, total walking steps, and total walking minutes have a very similar frequency distribution plot, which is of a long-tail distribution kind. These three unsymmetrical plots illustrate that many occurrences of walking records seemed to have been conducted within small calories, a low number of steps, and very short bouts. It is obvious that in terms of calories burned, total walking steps, and total walking duration and with a reasonable approximation, a very small number of the walking activities occurred far from the mean or central values of each measure. On the contrary, very few percentages of the walking activities were undertaken within a small ratio of moderate-to-vigorous intensity, meaning that most of the walking activities had at least 0.9 of moderate plus intensity.

Hypothesis Tests Results, and Discussion

Using the records of the 95 participants, this chapter conducts hypothesis tests for the resting heart rate and the ratio of moderate-to-vigorous walking. Furthermore, using 1362 walking records (5 minutes and longer) of participants, the hypothesis tests are conducted for the following physical activity measures: calories burned, average walking heart rate, average walking steps, total walking steps, and total walking minutes. The following shows the hypothesis tests for each physical activity and health measure assuming unequal variances.

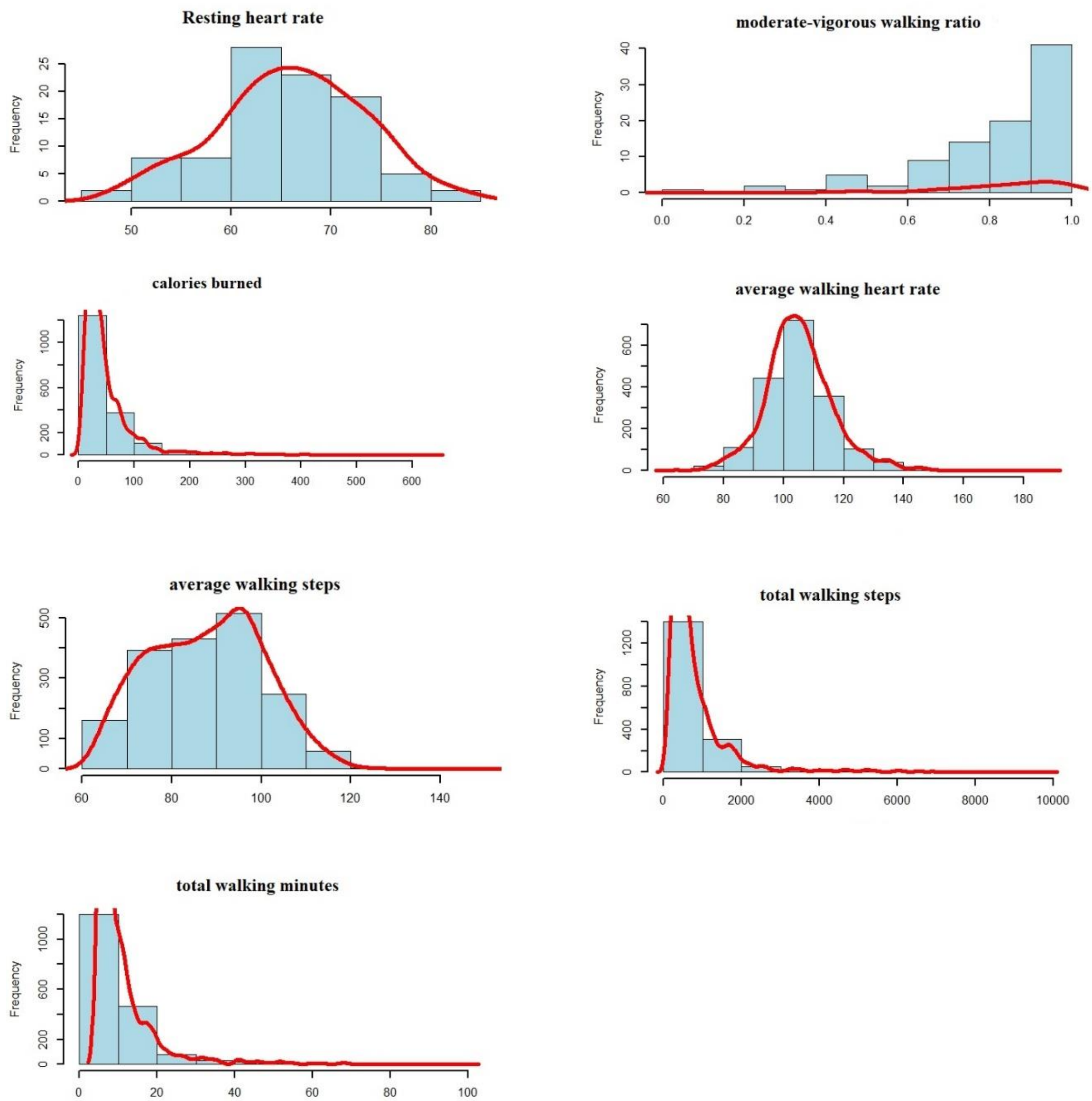

Figure 3-1 comparisons among walking heart rate and calories burned within different bouts among weight groups

Firstly, for each measure, null and alternative (research) hypotheses of the t-test are defined. Then, the statistics of the test are shown in a table. These statistics include: the frequency for the weight groups (underweight/normal and overweight/obese); mean and variance for each weight group; t-statistic for the test, which is computed by equation 4, and finally t-critical and p-value for one-sided or two-sided tests

$$\mathrm{t-statistic} = \frac{\overline{x_1} - \overline{x_2}}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \tag{4}$$

In which,

n_1, n_2 represent the number of observations for G1 and G2, respectively.

$\overline{x_1}$, $\overline{x_2}$ are related to the mean for G1 and G2.

s_1, s_2 show the standard deviations for G1 and G2.

Physical health condition measures

Resting heart rates

This hypothesis test aims to understand if the individuals in the healthy weight (normal/underweight) group have lower resting heart rates than those in the unhealthy weight (overweight/obese) group. Therefore, the null and research hypotheses for one-tail t-test are defined as follows:

H_0: it is assumed that the mean resting heart rates for underweight/normal weight group is greater than that of the overweight/obese group.

H_1: it is hypothesized that the mean resting heart rates for the normal/underweight weight group are smaller than the RHR of overweight/obese group.

Table 3-7 Hypothesis test for resting heart rate

	Underweight-Normal	Overweight-Obese
Mean	60.7	68.6
Variance	37.4	41.5
Observations	30	65
t Stat	-5.8351	
P(T<=t) one-tail	0.0000	
t Critical one-tail	1.6698	

Table 7 shows the results of the t-statistic and p-value for the one-tail t-test. The normal/underweight participants have a statistically lower resting heart rate than overweight/obese ones. These results are consistent with those of many other studies (Ehrenwald et al., 2019; Mitchelmore, 2016; Shekokar et al., 2013), showing a negative association between BMI and resting heart rates. The paper (Shekokar et al., 2013) showed that individuals with a BMI of ≥ 25 kg/m^2 had a significantly higher resting heart rate compared to normal-weight subjects. However, the study of (Quer et al., 2020) found a U-shape relationship between resting heart rate and BMI and showed that the lowest RHR was associated with a BMI of 21 for women and 23 for men.

Ratio of moderate-to-vigorous walking

The purpose of this one-tail hypothesis test is to compare the proportions of moderate-to-vigorous walking (to total walking) between the two independent groups of normal-underweight and overweight-obese individuals. The intensity level of physical activity is directly dependent on heart rates. Therefore, the overweight/obese weight persons who perform an exercise at higher heart rates are expected to have a higher moderate-to-vigorous walking ratio than normal and underweight ones.

The mean of the moderate-to-vigorous walking ratio for normal-underweight (p_1), and overweight-obese (p_2) group are calculated based on the moderate plus walking minutes and total walking minutes for each group as follows:

$$p_1 = \frac{7407}{10589} = 0.699 \quad \text{and} \quad p_2 = \frac{11775}{15343} = 0.767$$

Now, the null and research hypotheses for the proportion hypothesis test are described as:

H_0: the null hypothesis states that the mean ratio of moderate-vigorous walking minutes to total walking minutes among the normal-underweight group is greater than the mean ratio of the overweight-obese group, or $p_1 > p_2$

H_1: it is assumed that the mean ratio of moderate-vigorous walking minutes to total walking minutes for overweight-obese subjects is higher than this ratio among normal-underweight ones or $p_2 > p_1$

Then, the z-statistic for hypothesis testing is computed by equation 5:

$$\text{z} - \text{statistic} = \frac{\widehat{p_1} - \widehat{p_2}}{\sqrt{\hat{p}(1-\hat{p})(\frac{1}{n_1} + \frac{1}{n_2})}} \qquad (5)$$

Where, $\widehat{p_1}$ and $\widehat{p_2}$ are the proportions of success (here, the moderate-to-vigorous walking to total walking minutes) for the normal-underweight and overweight-obese groups, respectively. $\hat{p}$ is the proportion of moderate-to-vigorous walking for the pooled sample. $\hat{p}$ is calculated by summing all of the moderate-to-vigorous walking minutes by the total walking minutes as follows:

$$\hat{p} = \frac{7407 + 11775}{10589 + 15343} = 0.7397$$

Then, z-statistic is calculated as -12.2575. Since the z-statistics is greater than the $z_{0.05}$=1.96, then reject the null hypothesis (H_0), so, it can be stated with 95% significant confidence level that the mean ratio of moderate-to-vigorous walking among the unhealthy weight (overweight-obese) group is higher than the mean ratio of moderate-plus walking among the healthy (normal-underweight) group. Since the Fitbit smartwatch was a reward for the selected participants of the study to stay in the project until the end, the overweight and obese subjects might have been more motivated for weight loss by being involved in more moderate-to-vigorous physical activity including walking. However, the results of the study of (Cheah et al., 2019) on a national sample of 10,141 Malaysians show that the highest amount of moderate-to-vigorous physical activity was among overweight and normal people, respectively. Besides, obese individuals had a greater amount of moderate-to-vigorous physical activity than the underweight group in the Malaysian study.

Physical activity measures

<u>Calories burned per walking activity</u>

This study also assumes that the overweight/obese individuals burn more calories per minute than normal/underweight counterparts from walking activities based on the higher moderate-to-vigorous physical activity ratio of unhealthy weight group, compared with unhealthy weight group. Therefore, the hypotheses for this one-tail t-test are stated as:

H_0: it is assumed that overweight/obese individuals burn fewer calories than normal/underweight ones during walking.

H_1: it is hypothesized that the calories burned during walking activities are greater among overweight/obese individuals than normal/underweight people.

Table 3-8 Hypothesis test for calories burned per minute

	Underweight-Normal	Overweight-Obese
Mean	4.1	4.6
Variance	2.6	3.0
Observations	420	942
t Stat	-5.7774	
P(T<=t) one-tail	0.0000	
t Critical one-tail	1.6460	

According to the p-values and t-statistic for this hypothesis based on table 8, it can be stated that with a 95% confidence level the mean of the calories burned per minute among the overweight-obese (unhealthy) individuals is greater than this mean among the normal-underweight (healthy) people. This result complies with the results of (Loftin et al., 2010), in which an increase in body weight is associated with an increase in calories burned.

Average heart rate per walking activity

This test aims to examine whether the overweight/obese participants have higher walking heart rates than the normal/underweight individuals, due to being engaged in more moderate-to-vigorous physical activity. Therefore, the hypotheses for this one-tail t-test are introduced as:

H_0: it is assumed that the average heart rate per walking activity is smaller among overweight/obese participants than normal/underweight ones.

H_1: The research assumption is that the average heart rate per walking activity among the overweight-obese group is larger than this rate among the underweight-normal weight group.

Table 9 illustrates a statistically significant greater walking heart rate for overweight/obese people than normal/underweight individuals. For the following measures of average steps, total steps, and minutes per walking activities, no assumption is made on the direction of the hypotheses.

Table 3-9 Hypothesis test for average heart rate

	Underweight-Normal	Overweight-Obese
Mean	104.1	106.0
Variance	159.6	122.4
Observations	420	942
t Stat	-3.1106	
P(T<=t) one-tail	0.0010	
t Critical one-tail	1.6463	

In other words, it is assumed that the number of walking steps (mean and total), and walking minutes are statistically different among healthy and unhealthy weight groups, and the author does not have any preliminary assumption on if each physical activity measure is greater among one of the mentioned weight groups. Therefore, a two-tailed t-test is conducted for each measure.

Average steps per walking activity

H_0: The null hypothesis states the lack of a statistically significant difference between the mean number of steps per walking activity among unhealthy and healthy weight groups.

H_1: it is assumed that the average number of walking steps is not the same among overweight/obese and normal/underweight people.

Total steps per walking activity

H_0: it is hypothesized that the total number of steps per walking activity is not statistically different among unhealthy and healthy weight groups.

H_1: it is assumed that it is a difference between the total steps per walking activity among underweight-normal weight and overweight-obese groups.

Minutes per walking activities

H_0: it is assumed that the difference between the minutes per walking activities for the underweight-normal weight group and the overweight-obese group is equal to zero.

H_1: The alternative hypothesis says that the difference between the minutes per walking activities for the underweight-normal weight group and the overweight-obese group is not equal to zero.

Tables 10, 11, and 12 indicate the results of the two-tail t-test for the mean steps, total steps, and total minutes per walking activities, respectively.

Table 3-10 Hypothesis test for average steps

	Underweight-Normal	Overweight-Obese
Mean	89.2	87.2
Variance	162.2	162.6
Observations	420	942
t Stat	3.0246	
P(T<=t) two-tail	0.0025	
t Critical two-tail	1.9620	

Table 3-11 Hypothesis test for total steps

	Underweight-Normal	Overweight-Obese
Mean	961.6	773.1
Variance	1279005.6	646871.8
Observations	420	942
t Stat	3.6517	
P(T<=t) two-tail	0.0003	
t Critical two-tail	1.9626	

Table 3-12 Hypothesis test for minutes of walking

	Underweight-Normal	Overweight-Obese
Mean	12.1	10.6
Variance	123.8	72.7
Observations	420	942
t Stat	2.8738	
P(T<=t) two-tail	0.0041	
t Critical two-tail	1.9624	

The results show that normal/underweight participants, compared to overweight/obese ones have different (higher) amounts of physical activity measures of steps per walking (total and average), and total walking minutes. The direct relationship between the number of steps and duration of walking has been previously studied. For example, according to (Schutz et al., 2014), an increase in the number of steps per day is linearly associated with an increase in walking duration. In that study, 55 normal-weight and overweight women were categorized into three groups of walking, including 30, 60, and 90 minutes per day for five days a week and in four weeks. The results showed that walking steps increased from 10,000 steps/day for the 30-minute prescription to 14,000 for the 90-minute prescription. Also, the studies of (Hagströmer et al., 2010; Tudor-Locke et al., 2010) indicate a decrease in overall physical activity with increasing BMI. Moreover, (Hansen et al., 2013) show that obese individuals have 19% and 25% less physical activity in comparison with normal-weight people, on weekdays and weekends, respectively. However, one study (Williams, 2012) shows that walking distance compared with walking duration represents a better assessment of walking activity. The results of (Williams, 2012) showed that while walking distance among women was connected with a 1.7 times reduction in odds of being overweight/obese/extremely obese, the corresponding value was 2.2, 2, and 2.3 among overweight, obese, and extremely obese men.

Nevertheless, a one-tail t-test for the physical health measures shows that the resting heart rate, the ratio of moderate-to-vigorous walking, and the average walking heart rate have a different situation than physical activity measures. According to the results, the overweight/obese individuals have higher resting heart rates, average walking heart rates, and the ratio of moderate-to-vigorous walking (but with the weak significance of 90% confidence level) compared to normal/underweight participants. Also, according to the results, no statistically significant difference in the calories burned was observed between the participants in different weight categories.

Manova test

This test conducts a multivariate analysis of variance test for the difference in means on two or more dependent variables (in this study health and physical measures), simultaneously. In fact, in the Manova test, all the measures are combined in one variable. Then, this new variable is used as the outcome in the model. Therefore, the Manova test is conducted on all the physical activity measures, together. In other words, the measures of calories burned per minute, average walking heart rate, average steps per minute, total steps per minute, and total walking minutes are considered in multivariate space. Therefore, the null and alternative hypotheses for the Manova test are as follows:

H_0: it is hypothesized that no difference exists in the multivariate means of physical activity measures among healthy (normal-underweight) and unhealthy (overweight-obese) weight groups. Or, the multivariate physical activity means of healthy and unhealthy weight groups are equal.

H_1: it is assumed a statistically significant difference lies between the multivariate means of the physical activity measure among healthy and unhealthy weight groups.

The result of the Manova test shows a p-value of 0.0000, saying this test is statistically significant at a 99% confidence level. This shows that the multivariate means of physical activity measures (all together) are not the same among healthy weight and unhealthy weight groups.

Conclusion

This chapter examines the differences in walking activities and health measures among the faculty, staff, and students of two U.S. schools. The sample population was categorized into two weight groups, namely healthy weight group (underweight/normal participants with body mass index less than 25) and unhealthy weight group (overweight/obese individuals with BMI equal or greater than 25). In terms of physical activity, the present chapter shows a decrease in the levels of physical activity measures with increasing BMI. In fact, for the bouts of $\geq$ 5 walking minutes, underweight/normal people have a significantly higher number of steps (mean and total) and longer duration of walking compared with overweight/obese individuals. Regarding health measures, underweight/normal individuals had lower resting heart rates than the overweight and obese group. However, a really small difference was observed between the average walking heart rates across the two weight groups.

This findings of this chapter help the researchers on the interdisciplinary of transport and cardiovascular health to do longitudinal studies to examine the walking activity measures (the number of steps and walking minutes, …) for the active commuting trips among healthy and unhealthy weight groups and conduct some statistical analysis and comparisons related to cardiovascular risk factors (BMI, different blood pressures) over a more prolonged time among the mentioned groups. The mentioned analyses and comparisons can have a key contribution to determine the economic burden of low active commuting levels by the calculation of direct healthcare costs, productivity losses, and disability-adjusted life-years attributable to physical inactivity (Ding et al., 2016).

The findings of this study must be interpreted considering the following limitations. This chapter and the following use the most prevalent index, namely BMI to identify and categorize the participants in terms of weight group. However, this method’s reliability has been challenged by many studies due to the inclusion of muscle mass (Frankenfield et al., 2001; James, 2004). Furthermore, another limitation is the use of a commercial-grade wearable device (Fitbit Charge

3). The reason is that the recorded heart rates of individuals through this device might not be as precise as the heart rates by electrocardiogram, although the previous studies have shown that this difference is quite small (Quer et al., 2020). Also, the inclusion of special socio-demographic groups of people is another limitation in this study. In fact, this study was conducted on the university community, which are more educated than the average person in the U.S. Therefore, future studies can have more generalizable results if they are conducted on a more socio-demographically representable sample.

Future studies can consider resting heart rate over time for people with different fitness levels. Different studies have worked on the change of resting heart rate for various weight groups over time (Quer et al., 2020). However, considering the effect of physical activity level as well as body mass index to categorize people and conducting a longitudinal study over the groups can be one topic for future studies. The findings of this study can be applied in active transportation planning and public health interventions to increase the moderate-to-vigorous walking to fight against the highly critical issue of obesity.

Chapter 4 The Association between Walking Heart Rates and Health-Fitness Predictors

Background

Many studies show an insufficient amount of physical activity among people. According to (U.S. Department of Health and Human Services, 2017), only one in three Americans meet the recommended amount of physical activity and 28% of the U.S. population (aged 6 and over) are not active at all. One of the purposes of physical activity interventions is to inspire sedentary individuals to adopt a more active lifestyle (Cropley et al., 2003). Many reasons for inadequate activity levels exist, but one of the most prevalent apologies for exercise reduction is injury (Cropley et al., 2003; Sallis et al., 1990). According to one study (Waehner, 2019), lack of enjoyment, motivation, sufficient time, commitment, knowing how to exercise, seeing changes in the body as well as having kids stressed, tired, sore, and an inability to afford a gym membership are the top reasons individuals are not involved in an exercise. Also, based on (Mailey et al., 2014), family responsibilities make scheduling physical activity hard for married individuals. Nevertheless, if individuals include daily moderate-to-vigorous physical activities, such as climbing stairs, gardening, brisk walking, yard work, etc. they can overcome the mentioned inactivity.

Physical inactivity represents one of the most serious public health concerns facing health organizations worldwide. Regarding public health, being physically inactive has been perpetually associated with seven major chronic diseases including coronary heart disease, hypertension, stroke, colon cancer, breast cancer, type 2 diabetes, and osteoporosis (Humphreys et al., 2013). Physically inactive people also have a higher probability of obesity, which is also a significant risk factor for chronic diseases (Brown et al., 2007). Based on the World Health Organization, physical inactivity accounts for 6% of global deaths, which ranks it as the fourth leading cause of global mortality. Also, physical inactivity contributes to 21-25% of breast and colon cancers, 27% of diabetes, and 30% of ischemic heart disease (World Health Organization, 2019). According to the Centers for Disease Control and Prevention (CDC) (Centers for Disease Control and Prevention, 2017), chronic diseases, including heart disease, cancer, and diabetes, account for seven out of ten deaths among Americans and represent 75% of US healthcare spending. According to the (U.S. Department of Health and Human Services, 2018), about half of the U.S. adult population has one or more preventable chronic diseases, but regular physical activity can have a positive impact on seven out of ten of the most prevalent chronic diseases. According to the CDC, in 2015-2016, the prevalence of obesity reached 39.8 % among U.S. adults, aged 20 and over, and 20.6% among adolescents, aged 12-19 years. Also, 30.3 million (9.4%) of the U.S. population had diabetes in 2015 (Centers for Disease Control and Prevention, 2017). With the aforementioned disease rates, it seems essential for everyone to take physical inactivity seriously.

As mentioned earlier in this dissertation, walking and biking on daily trips, either commuting or non-commuting, is the healthiest mode of transportation. Given that transport is an essential part of everyone's daily life and leisure physical activity may be burdensome to keep in long term (Sallis et al., 1992), being more involved in active commuting is a feasible approach, which encourages individuals to enhance their levels of activity (De Nazelle et al., 2011). However, although physical exercise as part of one's daily routine such as walking and biking to mandatory activities may easily increase physical activity levels, most areas lack the infrastructure that encourages active transportation and requires long commuting travel distance, leading to private vehicle use for most trips/activities. Therefore, providing more walkable/bikeable and transit-oriented infrastructures in the urban areas, the individuals get motivated to use public transit and active modes, particularly for daily commuting trips. In this way, they are more likely to be engaged in at least 30-minute physical activity, which is recommended by many health and physical activity agencies (American Heart Association, 2018b; U.S. Department of Health and Human Services, 2008b).

Many researchers have worked on the health benefits of active travel. The association between active transport and obesity has been largely studied (Bassett et al., 2008; Flint et al., 2014; Flint & Cummins, 2016; Frank et al., 2004; Humphreys et al., 2013; Lindström, 2008; Scheepers et al., 2015; Tajalli & Hajbabaie, 2017; Wen & Rissel, 2008). Moreover, many researchers (Bennett et al., 2017; Hu et al., 2003; Millett et al., 2013; Murtagh et al., 2015; Tajalli & Hajbabaie, 2017; Wennberg et al., 2006) studied the connection between active commuting and other health measures/outcomes, such as blood pressure, diabetes, and cardiovascular diseases. Another health measure, resting heart rate (RHR), which measures the number of one's heartbeats per minute at rest, can be an indicator of one's health and fitness level (Quinn, 2019). For example, (Zhang et al., 2016) showed that resting heart rate values of 80 and above indicate an increase in cardiovascular risk and all-cause mortality. Furthermore, this risk is highest when the resting heart rate goes above 90. Also, an increase in fitness levels causes the resting heart rate to lower (Bumgradner, 2019). Therefore, resting heart rate can be used to represent one's health.

While vigorous physical activities, such as running and cycling, have the largest impact on health outcomes, moderate ones including brisk walking can still affect. Generally, any moderate-to-vigorous walking causes an increase in minute-by-minute heart rate; however, this increase is not the same for different levels of intensity. For example, the change of heart rate due to walking at low speeds (60 steps per minute) is less than the change at running (220 steps per minute). The literature appears to lack an examination of the effect of personal characteristics (e.g. sociodemographic variables, physical health measures, and physical activity levels) on the change in minute-by-minute walking heart rates. Therefore, this study investigates the role that the resting heart rates of individuals play in the change of their minute-by-minute heart rates due to walking. The authors also examine other factors, such as BMI, and physical fitness and activity levels (e.g. walking steps and moderate-to-vigorous minutes of walking) to determine their impacts on the changes in minute-by-minute heart rates. Knowing the changes in the walking heart rates helps the researchers in modeling and analyzing the effects of transportation-related walking on cardiovascular health over time. This chapter starts with a review of previous studies on the effects of walking on health measures and variability in heart rates. Then, the data source and methodology are presented. Following the data section, the modeling approach and discussion on the results are introduced. Finally, conclusion and future research are discussed in this chapter.

Literature Review

Compared with other physical activity types, which require equipment and gym membership, walking offers a simple approach to exercise (Hart, 2009). Regardless of the purpose, overall walking (utilitarian and recreational) negatively correlates with cardiovascular risk factors and all-cause mortality (Hamer & Chida, 2008). Also, based on (Hart, 2009), the many health benefits associated with walking include: strengthening muscles, enhancing cardiovascular fitness, controlling weight, increasing bone density, and improving one’s psychological state, and improving the regulation of lipids, insulin, and glucose. However, incorporating walking and cycling on trips, namely active travel, allows individuals to integrate physical activity into a sedentary lifestyle. A well-established body of literature between the positive associations of active travel and important health outcomes exists (Rojas-Rueda et al., 2011; Woodcock et al., 2009). (Hu et al., 2003) examined the relationship of type 2 diabetes with occupational, commuting, and leisure-time physical activity among 14,290 Finnish adults (without a history of cardiovascular disease). They categorized the active commuting into three groups of none, 1 to 29 minutes, and more than 30 minutes, and the results showed the hazard ratios of diabetes linked for these categories as 1.00, 0.96, and 0.64, respectively. In another study, (Hu et al., 2005) focused on the associations between active travel and the risk of stroke for 47,721 Finnish individuals (25 to 64 years of age without a history of cancer, coronary heart disease, and stroke). These results show the hazard risks of ischemic stroke associated with 0, 1-29 min, and ≥30 minutes of active commuting as 1.00, 0.93, and 0.86 respectively. (Frank et al., 2004) examined the relationships between the built environment, and residential locations, and walking travel on BMI and obesity for 10,878 individuals in 13 counties of Georgia, Atlanta. The results showed that every additional one hour of walking for transportation is linked with a 4.8% reduction in the likelihood of obesity (OR = 0.952, 95% CI (0.910-0.997)). As can be seen, even shorter bouts of walking have health benefits.

Furthermore, many monetary benefits seemed to be associated with physical activity. According to (Pratt et al., 2000), physically active individuals spend $1,019 on their annual mean healthcare costs while physically inactive individuals spend $1,349. Also, controlling for physical activity levels and body mass index (BMI), being physically inactive, overweight, and or obese is associated with 23.5% of annual healthcare costs (Anderson et al., 2005). Based on the results of (Carlson et al., 2015), the mean per capita difference between annual healthcare expenditures of inactive versus active adults is $1,437, and insufficiently active versus active individuals is $713. Nevertheless, (Chevan & Roberts, 2014) state that it is unlikely to be healthcare cost savings due to physical activity in the short-term. Besides, knowing the positive impacts of active travel can have policy implications for the provision of related infrastructure.

The health measures (indices) of BMI and physical activity levels may impact the health benefits an individual receives from walking. Studies show that BMI alone does not provide a complete representation of health and the effects of physical activity vary for people with different weight status. The studies of (Lee et al., 1998; Lee & Paffenbarger, 2000) indicated that overweight but fit men have a similar or lower risk of all-cause mortality compared with normal-weight unfit men. Examining metabolic risk factors for 176 men and 217 women for 5.6 years, (Ekelund et al., 2007) show that a 100 J.kg fat-free mass $(FFM)^{-1}$ increase in physical activity energy expenditure is linked with improved metabolic risk factors, independent of the change in body fatness. On the contrary, some research papers (Mora et al., 2006; Weinstein et al., 2004) showed that high values of BMI have a higher influence than physical activity on the increase in cardiovascular outputs. (Hu et al., 2004) showed that only a small difference between the risks of hypertension between overweight physically highly active women and healthy weight physically inactive women occur with hazard ratios of 0.65 and 0.68, respectively. (Jackson et al., 2014) measured the risk of diabetes for 10,339 Australian women at three-year intervals for 14 years. The results showed that the risk of hypertension for obese highly active women and obese inactive women were respectively, 3.4 times (OR = 3.43, 95% CI 2.68-4.39) and 4.9 times (OR = 4.91, 95% CI 3.92-6.13) smaller than healthy weight highly active women. (Menai et al., 2017) examine the associations between objectively measured walking steps and blood pressure for 9,238 individuals among 37 countries in the world. The results showed that among overweight and obese people, reduced blood pressure was significantly associated with a one-month increase of more than 3,000 steps; however, this relationship was not significant for normal-weight individuals. This study fails to specify the intensity and bouts of walking which is linked to the blood pressure reduction. As can be seen, people with different health (BMI in this study) may not receive the same benefit from physical activity.

Physical activity, including moderate-to-vigorous walking, causes the heart rate to change rapidly. Heart rate variability or the variation of heart period or heart rate can be a reflection of the autonomic nervous system (Akselrod et al., 1981; Chan et al., 2007). According to (Quintana et al., 2016), the variability in heart rate is complicated coordination of autonomic, respiratory, circulatory, endocrine, and mechanical effects over time, but physical activities influence heart rate variability to a large extent (Chan et al., 2007; Rennie et al., 2000). Different physical activities cause the heart rate to show various features during those activities, which also reveals the autonomic shift in response to change in physical activity (Chan et al., 2007). According to (Yuchi & Jo, 2008), different variables including age, gender, and ambient temperature hydration, affect the relationship between heart rate and physical activity, although a direct rule behind this link is not easy to discern. One of the health implications of heart rate variability is that it is a noninterfering measure of autonomic dysfunction and a risk factor for cardiovascular disease (Chandra et al., 2012). Also, according to (Yuchi & Jo, 2008), the association between physical activity and heart rate is a potential predictor having applications in the areas of cardiopathy research and diagnosis, heart attack warning indicator, sports capability measure, and mental activity evaluation. However, in the context of transportation engineering and particularly active commuting, this relationship is of great importance to estimate the energy expenditure related to walking, biking, and using public transit, and consequently, the health benefits of each mode. For example, the variations of heart rate help to increase the accuracy of Metabolic Equivalents (METS) due to the linear relationships between heart rate and energy expenditure (Lee et al., 2010).

According to (Hart, 2009), the frequency and intensity of walking can increase or decrease the likelihood of health benefits; more-vigorous walking of longer duration increases the likelihood of the benefits and less-vigorous walking of shorter duration decreases the likelihood of these benefits. Besides, some studies on active travel and obesity provide different suggested values of daily active travel giving the highest benefit. For example, while (Humphreys et al., 2013) shows that participating in at least 45 minutes of daily active commuting is associated with the largest health benefits, according to (Chapman, 2019), if someone walks 30 minutes daily for four days a week, he/she can burn an extra 20,000 to 40,000 calories per year, which is equal to a six to twelve-pound weight loss with the same food diet. The intensity of physical activity has a great role in the calories burned and the potential health benefits. One way to check the intensity of any physical activity is to measure one's minute-by-minute heart rates and determine the intensity based on the established target zones by the physical activity and or health organizations (Ehrman et al., 2018). Two major categorizations for the heart rates during moderate-to-vigorous physical activity exist. According to the American Heart Rate Association, while during a moderate-intensity activity, the minute-by-minute heart rates are in the range of 50-70% of maximum heart rate, the target heart rate for vigorous physical activity is 70-85% of maximum heart rate (American Heart Association, 2015a). However, the Centers for Disease Control and Prevention (CDC) adopts the groupings of Physical Activity Guidelines Advisory by the U.S. Department of Health and Human Services. According to this classification, the (Centers for Disease Control and Prevention, 2020b), the ranges of minute-by-minute heart rates for moderate and vigorous physical activities are respectively, 64-76% and 77-93% of maximum heart rate.

This study selects the change in the difference between walking HR and resting HR as the health output for this chapter. This study concentrates on the effect of physical activity measures of steps per walking minutes, and the duration of moderate-to-vigorous portions of walking on heart rate changes. To do that, this study not only uses physical activity (leisure, transportation, and exercise,) data of people over 1 week instead of a cross-section, but it also uses the revealed physical activity data, measured by accelerometer-based method (Fitbit Charge 3), instead of a self-reported activity.

Data

As was mentioned in the previous chapter, the data comes from a U.S. DOT-funded research project (Oh et al., 2019) on the associations between daily physical activities and transportation mobility choices. Due to the very low frequency of underweight group's individuals (n=2) and their walking activities (n=14), the individuals with BMI < 18.5 are considered in the normal weight group. The categorization of participants in terms of weight (BMI) and resting heart rates appear in table 1. This table indicates that the normal-weight and obese participants consist of an almost equal proportion of the sample population with 32% and 29%, respectively. Also, just a little more than half of the sample (55%) are individuals with medium resting heart rates.

Table 4-1 Cross-table of individuals in terms of weight and resting heart rate (RHR)

Attribute	**low RHR (< 55)**	**medium RHR (55 ≤ < 70)**	**high RHR (70 ≤)**	**Total**
Normal (BMI < 25)	9 (9%)	19 (20%)	2 (2%)	**<u>30 (32%)</u>**
Overweight (25 ≤ BMI ≤ 29.9)	2 (2%)	25 (26%)	10 (11%)	**<u>37 (39%)</u>**
Obese (30 ≤ BMI)	0 (0%)	8 (8%)	20 (21%)	**<u>28 (29%)</u>**
Total	**<u>11 (12%)</u>**	**<u>52 (55%)</u>**	**<u>32 (34%)</u>**	

The data includes 1,362 walking activities of at least five minutes, which were collected from 95 individuals. For modeling, 70% of this data including 953 records of walking activities are considered for training the model. Also, 30% of the total number of walking records, namely 409 records are accounted for testing the model performance. Tables 2 and 3 and show the descriptive statistics of the walking activities measures for the training and testing datasets, respectively.

Table 4-2 Descriptive statistics of the walking activities in training data (n=1271)

Variable	Min	Max	Mean	Standard Deviation
Steps/minute	61	179	118.6	23.9
Moderate-vigorous walking minutes	5	100	11.4	10.2
Mean heart rate per walking activity	84.3	186.2	108.9	10.5

Table 4-3 Descriptive statistics of the walking activities in testing data (n=544)

Variable	Min	Max	Mean	Standard Deviation
Steps/minute	74	161	115.9	21.3
Moderate-vigorous walking minutes	5	71	11.2	8.9
Mean heart rate per walking activity	86.3	154.8	109.0	9.4

Modeling and Discussion

This study uses one of the supervised machine learning algorithms, called Classification and Regression Tree (CART) (Breiman et al., 1984), which can be used in both regression and classification problems. Decision trees where data are sorted based on the predictor variables use observations of predictor variables to make conclusions about a target variable. The decision tree models including CART are very good at capturing the non-linearity in the dataset. Also, using the CART model eliminates the need for data standardization, since the Euclidean distance or other measuring factors between the data are not calculated by tree models (Sharma, 2019). According to (Yadav, 2019), CART models due to very well handling of non-linear relationships, having high accuracy, better stability, and ease of interpretations are mostly applied in non-linear decision making with linear decision platforms. The dependent variable in this chapter is the change in walking heart rates, in contrast with the resting heart rate. Due to having a continuous and non-linear nature, the regression decision tree is used.

Using the concepts of a recursive partition and Rpart library in R programing language, the predictor space is divided into high dimensional rectangles of $R_1, R_2, \ldots, R_j$ so that the residual sum of squares according to equation (1) is minimized:

$$\text{Residual Sum of Squares (RSS)} = \sum_{j=1}^{J} \sum_{i \in R_j} (y_i - y_{R_j}^{\wedge})^2 \qquad (2)$$

In equation (1), $y_{R_j}^{\wedge}$ is the mean response or the training data within the j^{th} rectangle. Given that the above optimization is computationally infeasible, a top-down, greedy approach, called "recursive binary splitting" is taken. To address the problem of overfitting, cost complexity pruning is applied to a large tree, which was grown on the training data to obtain a sequence of best subtrees.

This study aims to estimate the difference between the walking heart rate and resting heart rate for the moderate-to-vigorous walking activities of the sample population based on measures related to individuals' physical conditions or their activity levels. Among the physical conditions, this study uses predictor variables of age, gender, body mass index, and resting heart rate. Also, the physical activity measures of individuals' number of steps and moderate-to-vigorous walking minutes per walking activity are examined. Therefore, the dependent variable of this study is the difference between min-by-min heart rate and resting heart rate ($\Delta HR = HR_{min-by-min} - HR_{Rest}$)

The original dataset includes 1362 records of the min-by-min walking activities of 5 minutes and longer for the 95 participants of the study. Using the Rpart library and affiliated packages in R software, with the 953 records of walking activities (5 minutes and longer) the recursive binary partitioning model is trained. Then, using 30% of the dataset, namely 409 walking records, the training model is used to predict the estimated y values for the test data and to check the performance of the trained model. Then, using cost complexity pruning, the cost complexity parameter (cp) for this tree is achieved at the size of 9. Figure 1 shows the pruned regression tree for the training data. Also, figure 2 indicates that the relative error is minimized at a pruned tree with 9 terminal nodes. Moreover, the percentages of walking activities within each leaf mean value (($\Delta \mathrm{HR} = \mathrm{HR}_{\mathrm{min-by-min}} - \mathrm{HR}_{\mathrm{Rest}}$), based on the weight and resting heart rate can be seen in table 4.

The pruned tree is formed based on the resting heart rate, age, moderate-to-vigorous walking minutes, and the number of steps per walking minutes. This tree has 9 leaves or terminal nodes, which are numbered from 1 to 9 in figure 1. In the first step, the root node (node 0) is divided into two child nodes, which are the walking activities for the individuals with resting heart rates of 71 and above on the left side and the ones with resting heart rates of less than 71 on the right side.

The results of the training model show that the left side of the tree belongs to those walking activities that were mainly conducted by individuals who have high (unhealthy) resting heart rates. Interestingly, the tree indicates that for the unhealthy heart rate group (RHR > 71), only one physical activity measure, namely steps per minute impacts the walking heart rates. Nevertheless, both measures of steps per minute and moderate-vigorous minutes are affecting the walking heart rates of healthy individuals (RHR < 71).

The mean difference between walking and resting heart rates for the activities of the unhealthy group is 27.8, 34, and 40.5 for the terminal nodes 1, 2, and 3, respectively. According to the results, within leaf 1 ($\Delta \mathrm{HR}_{\mathrm{mean}} = 27.8$), 91% of the walking records were reported by the obese-high RHR group, and the remaining 9% by the overweight-high RHR. This shows that this small change in walking heart rates can be due to the lower intensity of walking and the large resting heart rates of those individuals. This situation also happens among the walking records in terminal node 2 ($\Delta\mathrm{HR}_{\mathrm{mean}} = 34.0$), in which 65% and 34% of these total walking activities were done by obese-high RHR and overweight-high RHR persons. Similarly, higher percentages of walking records in leaf 3 (with mean y value of 40.5) were conducted by obese-high RHR (55%) and overweight-high RHR (36%), while only 9% of these walking records were reported among normal-high RHR people.

Also, on the left side of the tree (higher heart rates), age (as a physical condition) is affecting the upper levels of categorization. In other words, the younger individuals (age < 42) than older ones (age ≥ 42) are more involved in higher intensity levels of walking. This can be seen by comparing a larger $\Delta\mathrm{HR}_{\mathrm{mean}}$ for leaf 2 and leaf 3 (34.0 and 40.5), in comparison with that of leaf 1 (27.8). The mean values in leaves 1, 2, and 3 indicate that the change in walking heart rates for unhealthy individuals (RHR ≥ 71) is small.

The walking activities of healthier individuals (RHR < 71) group on the right side (terminal nodes 4 to 9). The considerable importance of physical activity measures on the change in walking in heart rates can be seen by the effects of moderate-to-vigorous walking minutes and steps per minute predictors as the first and second variables on splitting the walking records. The tree indicates that on the right side, within the leaves with the lower change in their mean walking heart rates, like terminal nodes 4 ($\Delta\mathrm{HR}_{\mathrm{mean}}$ = 36.0), and 6 ($\Delta\mathrm{HR}_{\mathrm{mean}}$ = 45.9) the highest percentage of walking activities was done by normal-medium RHR and normal-low RHR individuals, with 41%, 23%, and 29%. Healthy weight and fit people likely engage in physical activities (including walking) within lower heart rates. However, the greatest percentages of walking activities occur in leaves with higher mean y values, namely terminal nodes 7, 8, and 9 are conducted by the overweight-medium RHR group. According to table 4, these percentages are 38%, 41%, and 40%, respectively.

The results of this model have implications in the context of active transportation. The urban planning policies considering components of shorter blocks (Ewing & Cervero, 2010), bike networks including bike paths, bike lanes, and local streets with low speeds and motorized traffic volumes (Buehler & Dill, 2016), street connectivity (Galvez et al., 2010), and in general, community-scale urban design and land use policies (Heath et al., 2016) can all greatly contribute to higher levels of active transportation among the individuals, particularly the sedentary ones. This will help the individuals to walk/bike on safe, walkable, and bikeable infrastructures on commuting trips, leading to better health outcomes. Higher levels of active transportation in terms of intensity, steps, minutes particularly among overweight and obese individuals can have important roles in the improvement of cardiovascular health outputs.

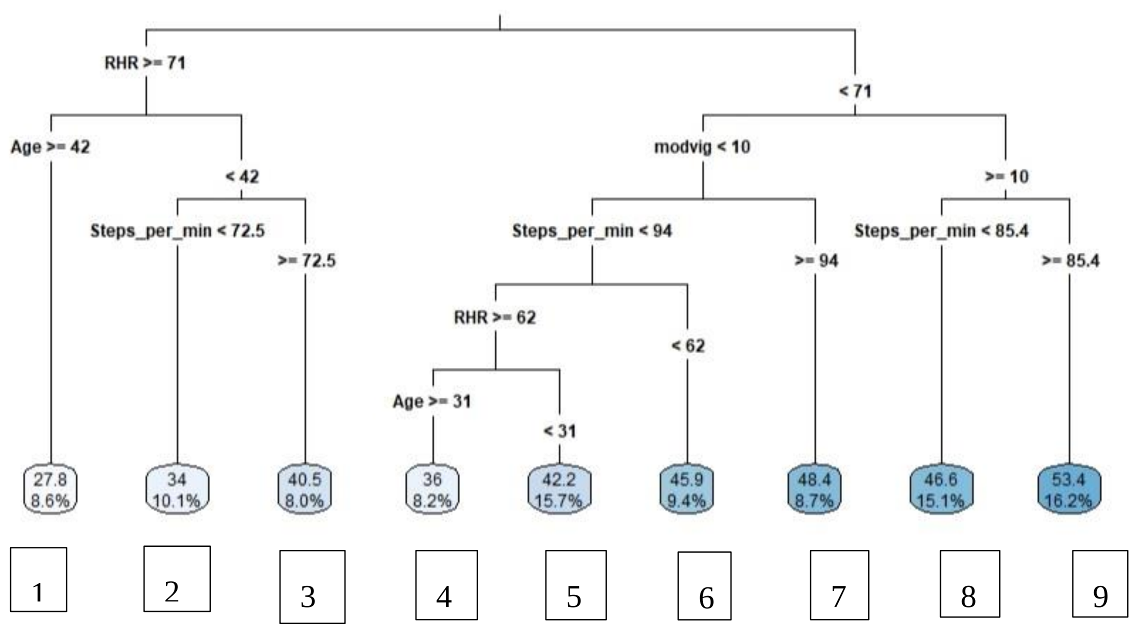

Figure 4-1 Pruned regression tree

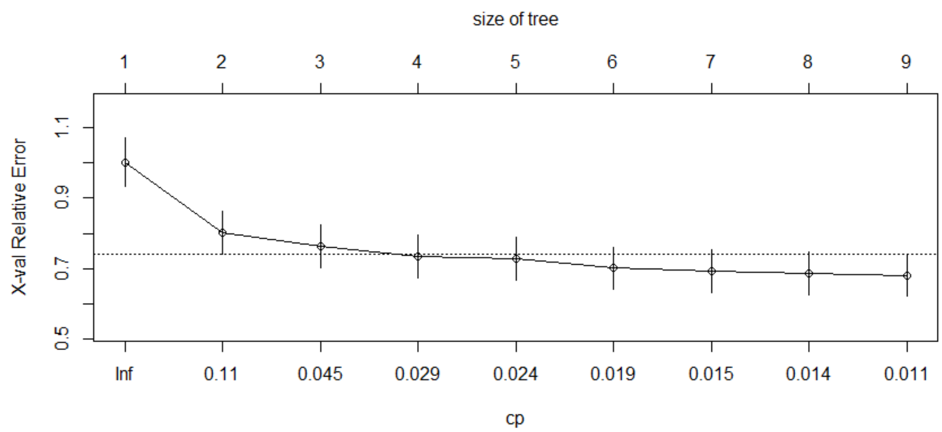

Figure 4-2 Relative error of the regression tree model in terms of different values of tree size and complexity parameter

Table 4-4 Percentage of walking activities within each leaf mean value, weight-RHR group populations

Terminal node	Terminal node mean	Normal-Low RHR	Normal-Medium RHR	Normal-High RHR	Overweight-Low RHR	Overweight-Medium RHR	Overweight-High RHR	Obese-Medium RHR	Obese-High RHR	Total
1	27.8						9%		91%	100%
2	34.0			1%			34%		65%	100%
3	36.0		41%			32%		6%	21%	100%
4	40.5			9%			36%		55%	100%
5	42.2		22%	3%		55%	7%	13%		100%
6	45.9	23%	29%		3%	23%		21%		100%
7	46.6	8%	38%		1%	38%	6%	8%	2%	100%
8	48.4	7%	29%		4%	41%	4%	14%	1%	100%
9	53.4	10%	34%		5%	40%	5%	6%	1%	100%

To assess the prediction performance of the trained regression tree, two statistical evaluation indicators of Mean Absolute Percentage Error (APE) and Mean Square Error (MSE) are calculated for both training and testing trees. APE and MSE are computed by equation 2 and 3:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\Delta HR_{actual} - \Delta HR_{mean\ estimated}}{\Delta HR_{actual}}\right| \times 100\% \qquad (2)$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\Delta\mathrm{HR}_{\mathrm{actual}} - \Delta\mathrm{HR}_{\mathrm{mean\ estimated}})^2 \tag{3}$$

In which, **n** is the number of walking activities in training, testing, or a given health population group. Also, $\Delta\mathrm{HR}_{\mathrm{actual}}$ and $\Delta\mathrm{HR}_{\mathrm{mean\ estimated}}$ are respectively the actual and predicted difference between walking and resting heart rate in each walking activity **i**.

The results of the above equations show that MSE for the model estimated by training dataset and predicted test dataset are 87.0 and 83.5, respectively. Also, The APE values for the training and test models are 16.04% and 16.97%, respectively.

Conclusion

This study investigates the physical condition and physical activity measures affecting the change in the walking heart rates as a health/fitness outcome. The implication of walking heart rate in transportation planning studies is the inclusion of active trip modes (walking and biking) as the healthiest modes of travel in state and regional transportation plans. Active traveling is more beneficial for individuals with lower physical conditions, namely the ones with larger resting heart rates and body mass index since the studies have proved that these persons have less physical activity during their daily routine rather than physically active and healthy individuals.

The focus of this study is on walking as the simplest form of physical activity. Many previous studies have shown the benefits of walking, particularly with higher intensity (moderate-to-vigorous) and in longer bouts (at least 10 minutes). Using the walking activities of at least 5 minutes, this chapter shows that resting heart rate is the most important predictor of changes in walking heart rates. Also, smaller changes in walking heart rate, being observed among overweight and obese individuals with high resting heart rates (RHR $\geq$ 71), are mostly affected by physical conditions of individuals' resting heart rate and age. On the other hand, healthier people (RHR <71) have greater heart rate changes during walking, which is mostly impacted by their physical conditions, including the number of steps, and moderate-to-vigorous minutes of walking. This study helps transportation engineering researchers to estimate the health benefits in terms of cardiovascular outputs for active trips, particularly the commuting ones due to their daily and regular nature.

This study has some limitations, which can be improved for future studies. First, this study solely investigates walking activities. However, consideration of walking and biking, particularly in commuting trips (as the most frequent trip) and observing the trend of minute-by-minute heart rate for different weight-resting heart rate groups might be an interesting topic. Working on 30-second time windows instead of one-minute provides researchers with a more accurate estimation of this health outcome and its confounding factors. Finally, another appealing research topic might be on the effects of individuals' activeness, namely "inactive", "insufficiently active", "active", and "highly active" as well as their weight on another health outcome, such as calories burned for various walking activities.

Chapter 5 Concluding Remarks

Cardiovascular diseases including coronary artery diseases, heart attack, heart failure, and stroke are the leading causes of death in the U.S. Many health conditions, such as high blood pressure, diabetes, and obesity increase the risk for the mentioned diseases. The vehicle-based nature of today's lifestyle enhances physical inactivity, which itself is a key avoidable contributor to obesity, diabetes, and high blood pressure. However, the inclusion of walking, biking, and use of public transit in the trip activities, particularly daily commuting trips may help individuals to achieve the minimum recommended amount of physical activity, and consequently a better health situation.

In the context of public health, two complicated while interrelated concepts of objective health versus perceived (or self-assessed) health have been discussed extensively. Although perceived health is measured through self-reported surveys, both surveys and experimental measurement methods can gauge objective health status. In the context of transportation engineering, all main transportation modes, namely automobile, public transit, walking, and biking can have both positive and negative impacts on self-assessed and objective health measures. Therefore, the second chapter of this study is assigned to the effects of various trip features, namely duration, distance, and frequency on people's perceived health status in the United States. Using the comprehensive household, person and trip data of the latest National Household Travel Survey (NHTS), NHTS 2017, this dissertation uses the socio-demographics (age, gender, median household income, etc.), built environment (population residential and employment density), and the trip features of frequency, maximum distance, and mean duration (all in one week) of individuals' trips. The results show that while individuals having a longer duration of transit and car trips have poorer perceived health, individuals with more frequent and longer bike and walk - or active - trip times have better perceptions of their health status. Also, the results of the ordinal logit model indicate that being female, young, physically active, and more educated (graduate degree and higher) contribute to having higher self-assessed health. To further investigate the results of this model, a health-assessment survey is conducted within a local sample population of the faculty members, staff, and students from the University of Texas at Arlington (UTA). This cross-analysis between the perceived health and three measures of weight (calculated by BMI), physical activeness, and transportation mode (auto vs. active) shows that perceived health may not necessarily comply with the objective health since a high percentage of overweight individuals believed to have good or excellent health. This topic helps the researchers of transportation planning and public health to design surveys that incorporate questions on various trip features by each mode. Then, they can adopt performance measures for each transportation mode by assigning different weights to the trip features of each trip mode.

Therefore, this dissertation chooses walking as the simplest form of physical activity, weight group, and resting heart rate as the predictors of objective health to further investigate the effects of walking activities on changes in the walking heart rate as a health indicator. Analyzing the minute-by-minute accelerometry data of one week from a sample population of individuals from two U.S. universities shows that healthy weight (normal-underweight) individuals seem to be more physically active than unhealthy weight (overweight-obese) people. To be more precise, the results of the hypothesis tests illustrate that the healthy weight group has a higher ratio of moderate-to-vigorous walking with a greater number of walking steps and longer walking duration in comparison with unhealthy weight people. In terms of health status, the results of the hypothesis tests and cross-comparison analyses indicate that the individuals within the normal-underweight group have a lower resting and walking heart rate than overweight-obese ones. Also, healthy people, compared with unhealthy ones had lower minimum and maximum heart rates.

Then, in the fourth chapter, the physical condition and physical activity predictors of changes in walking heart rates are examined. Consequently, one type of supervised machine learning algorithm, namely classification and regression decision tree (CART) is applied to those minute-by-minute data. According to the results, the resting heart rate is the most significant contributor to changes in walking heart rates. Also, in comparison to the unhealthy weight group (overweight-obese), the larger changes in walking heart rates are observed among healthy individuals (normal-underweight). These larger changes were mostly linked with healthy individuals' physical conditions, namely the number of steps and moderate-to-vigorous minutes of walking. On the other hand, the small changes in the walking heart rates of overweight-obese people were mostly impacted by their resting heart rates and age. The implication of this topic is to alarm the transportation planning/engineering agencies to provide urban areas with more walkable/bikeable infrastructure, such as street connectivity, separated bike lanes, pedestrian overpasses/underpasses to facilitate the active trips for different pedestrians/bike commuters. Also, given that most commuters in walkable/bikeable cities, such as San Francisco, Portland. are active commuters, developing public health models to estimate the population-level health gains being made by switching from private vehicles to active modes is very essential in this context.

This research has some limitations, which can be removed during future studies. This study uses BMI as the health predictor to identify and categorize individuals for analysis. However, health is a function of many factors, including hereditary, environmental. Future studies can apply a cardio-vascular health indicator rather than sole BMI to group individuals. This health indicator will categorize the individuals considering the risk factors of BMI, waist circumference, resting heart rate, blood pressure, cholesterol, and blood glucose. Furthermore, this potential research can collect the longitudinal minute-by-minute data for a period longer than one week, which was the case of this study. This longitudinal study is better to consider 30-second instead of one-minute time windows to account for more accurate observations of heart rate, given that heartbeat changes rhythm is different among various individuals. These Longitudinal data being collected over prolonged periods help to do interpersonal and intrapersonal analyses of risk factors regarding individuals' active transportation behavior. Furthermore, data collection procedures that capture active minutes, and different transportation walking (commute vs. utilitarian), as well as the physical health and activity measures of this study, might have interesting results for future studies. Another limitation of this study is the use of a cross-sectional data set (NHTS) to examine the individuals' perceived health. However, people's health perception can be variable over time as a result of variations in their physical activity and health.

Generally, one key topic in the current research topics in transportation engineering is the relationship between transportation and health, due to the aftermath of transportation engineering/planning projects on humans as the users of the system and the interaction between humans and transportation systems. Therefore, the most significant implication of this dissertation as the interdisciplinary context of transportation, public health, and policy might be healthcare savings due to active travel. Since active travel is associated with increased physical activity levels and improved health outcomes, the findings of this study, particularly those related to the associations between resting heart rates and physical activity as well as the changes in the walking heart rates among different weight groups can be used to develop healthcare cost-saving models. The prevalence of cardiovascular diseases is associated with considerable healthcare expenditure. However, developing a model to estimate the reduction in these costs as a result of active trips can be very helpful, because it can remove some uncertainties regarding the cost benefits of active transportation.

Chapter 6 References

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