Title: Wearable Device Users with and without Disabilities and their Physical Activity Behaviors.

The importance of physical activity is well documented (Haskell et al., 2009a; McReynolds & Rossen, 2004; Steinbeck, 2001). Despite physical activity’s benefits, many individuals are not meeting current weekly physical activity guidelines recommending \( \geq 150 \) minutes of moderate or \( \geq 75 \) minutes of vigorous aerobic physical activity and 2 or more days of muscle-strengthening activities (Carlson et al., 2010; Tucker et al., 2011; Whitfield, 2019; Zenko et al., 2019). Individuals with disabilities are less likely to meet physical activity guidelines compared to individuals without disabilities (Hilgenkamp et al., 2012; Jung et al., 2018; McKeon et al., 2013; Temple & Walkley, 2003; Wouters et al., 2019) due to various built- and social-environment barriers (Bodde & Seo, 2009; Rimmer & Rowland, 2008; Rimmer et al., 2004, 2008). Wearable devices have been proposed as a potential intervention for promoting physical activity among individuals with and without disabilities (Stragier et al., 2016; Wu & Liu, 2020). Numerous studies have found that wearable device
usage may improve physical activity levels of users (Coughlin & Stewart, 2016). However, these studies were often conducted in controlled settings, where participants were provided a wearable device to use, and typically included additional intervention components, such as group exercise, personal training sessions, and educational classes to promote physical activity (Coughlin & Stewart, 2016). Little is known about the physical activity levels of wearable device users with disabilities. The purpose of this study was to examine the associations between wearable device usage and physical activity levels of individuals with and without disabilities in free-living. The aims of this study were to 1) compare physical activity levels between wearable device users and non-users with and without disabilities and 2) compare physical activity levels between wearable device users who track their physical activity with and without disabilities to those who do not track physical activity.

Manuscripts detailed herein utilized 2017 Behavioral Risk Factor Surveillance System (BRFSS) data from the following states: California, Connecticut, Florida, Louisiana, Nebraska, Oregon, Tennessee, and Texas. Physical activity analytic outcomes included continuous variables of physical activity/week (mins), vigorous physical activity/week (mins), and energy expenditure during physical activity (metabolic equivalent [MET]xminutes/week) and binary physical activity variables of engagement in leisure physical activity, engagement in > 300 minutes of equivalence combination of moderate and vigorous physical activity/week, meeting aerobic physical activity guidelines, and meeting both aerobic and muscle-strengthening physical activity guidelines. Participants were classified as individuals with disabilities if they reported any of the following: visual impairments, hearing
impairments, cognitive disability, independent living disability, self-care disability, and mobility disability. Individuals who reported using wearable devices were considered wearable device users; otherwise, participants were considered non-users. Wearable device users were further categorized as users who do or do not track physical activity based on self-report. Linear regression was used to model continuous physical activity variables and logistic regression was used for binary physical activity variables. Primary independent variables included disability status and wearable device usage. An interaction term between disability status and wearable device usage was included in all models. Statistical modelling used specialized procedures for complex survey data incorporating primary sampling unit identifiers, strata information, and sampling weights.

Analyses indicated that wearable device usage and tracking physical activity with wearable devices was not associated with greater time spent in physical activity (i.e., physical activity/week (mins) and vigorous physical activity/week (mins)) but was associated with a greater likelihood of engaging in leisure physical activity. Among wearable device users, individuals with disabilities were less likely to engage in physical activity and meet physical activity guidelines when compared to those without disabilities. Moreover, no interaction effects between disability status and wearable device usage to track physical activity was observed. While using wearable devices and tracking physical activity with wearable devices was associated with a higher odds of engaging in physical activity, further research is needed to examine the effect of wearable devices on increasing time spent in free-living physical activity. Additional studies are needed to determine the effectiveness and feasibility of using
wearable devices for promoting physical activity among individuals with various types and diagnoses of disabilities.
Wearable Device Users with and without Disabilities and their Physical Activity Behaviors

by
Willie Leung

A DISSERTATION

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APPROVED:

Major Professor, representing Kinesiology

Head of the School of Biological and Population Health Sciences

Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Willie Leung, Author
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CONTRIBUTION OF AUTHORS

This project is a production of the intellectual environment of a collaboration of researchers who have contributed in various degrees to the conceptualization of the research concept and study, the experimental design, and analytical methodology. Willie Leung conceptualized this project, collected data, conducted data analyses, interpreted the findings, and drafted the manuscripts. Megan MacDonald, Ph.D., assisted in conceptualizing the project, interpreting findings, and providing editorial comments and suggestions on the final draft. John Schuna, Ph.D., assisted in conceptualizing the projects, data analyses, interpretation of findings and provided editorial comments and advice on the final draft.
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Chapter 1. General Introduction
Wearable Device Users with and without Disabilities and their Physical Activity Behaviors

The benefits of physical activity are well documented (Haskell et al., 2009; McReynolds & Rossen, 2004; Steinbeck, 2001) and include better weight management, lower blood cholesterol, lower blood pressure, bone strengthening, improved musculoskeletal adaptations, reduced risk of cardiovascular disease and certain types of cancers, reduced stress, better emotional regulation, reduced risk for depression, and increased social functioning (Eime et al., 2013; Singh, 2002; Tak et al., 2013; Warburton et al., 2006).

Yet, even with the known benefits of physical activity, there is a paucity of US adults meeting current physical activity guidelines, which has led to the emergence of physical inactivity as a major public health concern (Centers for Disease Control and Prevention [CDC], 2019; Kohl et al., 2012; World Health Organization, 2020). Current physical activity guidelines for adults recommend a minimal weekly accumulation of 150 minutes of moderate or 75 minutes of vigorous aerobic physical activity along with 2 days of muscle-strengthening physical activity (2018 Physical Activity Guidelines Advisory Committee, 2018). Currently, across the US, fewer than 50% of adults meet physical activity guidelines (Carlson et al., 2010; Tucker et al., 2011b; Whitfield et al., 2019; Zenko et al., 2019b).

Individuals with disabilities are less likely than the general population to meet physical activity guidelines (Hilgenkamp et al., 2012; McKeon et al., 2013; Temple & Walkley, 2003; Wouters et al., 2019), and they engage in less moderate-to-vigorous physical activity (Jung et al., 2018). Individuals with disabilities face barriers to physical activity such as inaccessible physical environments, limited relevant
assistive technology, negative attitudes towards disability, lack of transportation, and lack of trained professionals working with individuals with disabilities in exercise settings (Bodde & Seo, 2009; Rimmer et al., 2004; Rimmer & Rowland, 2008; Rimmer et al., 2008). These barriers limit the ability of individuals with disabilities to participate in recreational and other physical activity opportunities (Clemente, 2017; Martin, 2013; Shields & Synnot, 2016; Úbeda-Colomer et al., 2019; van Schijndel-Speet et al., 2014).

One approach to overcome physical inactivity in the general population is wearable device usage (Stragier et al., 2016; Wu & Liu, 2020). Herein, wearable devices are defined as body-worn electro-mechanical devices that monitor physical activity patterns and provide automated real-time feedback; the devices may also include interactive behavior change tools via a smartphone or web-based platform (Brickwood et al., 2019b; Henriksen, Mikalsen, et al., 2018). Wearable devices may also refer to electro-mechanical devices that are easily worn and removed and do not require specialized equipment, such as a harness or adhesive dressing (Brickwood et al., 2019b; Hickey & Freedson, 2016; Wu & Liu, 2020). Wearable devices typically include an accelerometer sensor to track movement patterns (Aroganam et al., 2019; Henriksen, Mikalsen, et al., 2018). These devices can output various physical activity metrics, such as steps, distance, heart rate, physical activity minutes, and estimated caloric energy expenditure (Coughlin & Stewart, 2016; Wu & Liu, 2020).

Wearable devices are emerging as an intervention tool for motivating individuals to improve their physical activity and reduce sedentary behavior (Bassett, 2012; Jo et al., 2019; Melton et al., 2016; Mercer et al., 2016; van Mierlo et al.,
These devices may increase motivation toward physical activity, thereby proving useful for individuals lacking motivation to be physically active (Rupp et al., 2016). As such, wearable devices may serve as important facilitators of physical activity behavior change (Phillips et al., 2018). In recent years, wearable devices have gained popularity (Carrington et al., 2015; DasMahapatra et al., 2018; Hyde et al., 2020; Omura et al., 2017) and many individuals use these devices to monitor their daily physical activity patterns (Aroganam et al., 2019; Wu & Liu, 2020). Compared to traditional physical activity interventions designed for increasing physical activity, such as educational classes, or group/one-on-one exercise sessions, wearable devices are less resource-intensive and time-consuming to operate (Coughlin & Stewart, 2016; Michaelis et al., 2016). Moreover, wearable devices, including smartphones and smartphone activity tracking applications (Lunney et al., 2016), are the top fitness trend since 2016, according to a survey conducted by the American College of Sports Medicine (Kercher et al., 2021; Thompson, 2019, 2021).

Past literature details how wearable devices have been utilized in intervention studies for promoting physical activity and healthy lifestyles (Hartman et al., 2018; Hickey & Freedson, 2016; Strath & Rowley, 2018). A meta-analysis of 28 studies found a significant increase in daily step count and moderate and vigorous physical activity among adults without disabilities using wearable devices as either the only intervention component or as part of a broader intervention (Brickwood et al., 2019b). In an intervention targeting adults with Down syndrome (DS) by Ptomey et al. (2019), 27 participants with DS increased their physical activity levels after participating in online group exercise sessions, attending personalized educational
classes, tracking physical activity levels with a Fitbit Charge HR, and doing weekly homework assignments involving physical activity. In another intervention utilizing wearable devices and rehabilitative exercise, 20 participants with cerebral palsy between 10 to 20 years old increased their daily step count by an average of 138.8 steps and walking distance by an average of 43.74 miles after eight weeks of using wearable devices (Sharan et al., 2016). Current evidence demonstrates the feasibility of using wearable devices in promoting physical activity among individuals with and without disabilities.

Numerous studies utilizing wearable devices among individuals with and without disabilities have demonstrated increased physical activity in response to intervention. However, most of these studies were conducted in controlled environments rather than in free-living settings. In addition, participants in most of these intervention studies were provided wearable devices to use and followed instructions on when to use the wearable devices, limiting the relevance of such findings to normal daily usage with personal wearable devices. It is also unclear whether participants in these studies continued to use the wearable devices after completing the intervention. Moreover, most interventions utilizing wearable devices used additional intervention strategies aimed at improving physical activity, such as one-on-one meetings, educational classes, and group exercise. Only one study (Jauho et al., 2015) in the meta-analysis by Brickwood et al. (2019) used wearable devices as a standalone intervention component. Similar results were found in a systematic review by Coughlin et al. (2016) across six pre-/post-test trials and seven randomized controlled trials, where increased physical activity levels were observed among all included
studies but additional intervention strategies were employed beyond wearable device usage. Both studies indicated that wearable devices contributed to increased physical activity. However, both the meta-analysis and the systematic review highlighted the lack of studies examining wearable device usage as the sole intervention strategy when attempting to modify physical activity behaviors. As such, there remains a need to evaluate the associations between physical activity and wearable device usage in free-living settings among individuals with and without disabilities.

From a surveillance perspective, physical activity levels of wearable device users in free-living environments are relatively unknown. Despite this, it is known that individuals with and without disabilities are using or willing to use wearable devices (Block, 2017; Carrington et al., 2015; Omura et al., 2017). Moreover, population-level uptake of wearable devices continues to increase in the US. The 2018 Government & Academic Omnibus Survey found 21.7% of American adults are currently using wearable devices (Hyde et al., 2020), an increase from the 2015 HealthStyles online survey in which 12.5% of non-institutionalized US adults reported using wearable devices (Omura et al., 2017). Yet, there remains a paucity of literature investigating the association between wearable device usage and physical activity behavior in free-living.

Individuals with disabilities are less likely to engage in moderate-to-vigorous physical activity and meet physical activity guidelines than individuals without disabilities (Jung et al., 2018). Based on current literature, using wearable devices can potentially increase the physical activity levels of individuals with disabilities in controlled environments (Nsubuga et al., 2006). However, data from free-living can
better represent how individuals with and without disabilities may be using wearable devices (Nsubuga et al., 2006).

Given the need for a better understanding of the associations between wearable device usage and physical activity levels, the purpose of this study was to examine these associations among individuals with and without disabilities in free-living. This work addressed the following specific aims and research questions:

**Aim 1**: To compare physical activity levels between wearable device users with and without disabilities and non-users with and without disabilities (Ch. 2).

**Question 1**: Do physical activity levels differ between wearable device users and non-users?

**Hypothesis 1**: Wearable device users will have significantly higher physical activity levels than non-users.

**Question 2**: Among those with disabilities, do physical activity levels differ between wearable device users and non-users?

**Hypothesis 2**: Wearable device users with disabilities will have significantly higher physical activity levels than non-users with disabilities.

**Aim 2**: To compare physical activity levels between wearable device users who track physical activity with and without disabilities and wearable device users who do not track physical activity levels with and without disabilities (Ch. 3).

**Question 1**: Do physical activity levels differ between wearable device users who track physical activity and those who do not track physical activity?
Hypothesis 1: Wearable device users who track physical activity will have significantly higher physical activity levels than users who do not track physical activity.

Question 2: Among those with disabilities, do physical activity levels differ between wearable device users who track physical activity and those that do not track physical activity?

Hypothesis 2: Wearable device users with disabilities who track physical activity will have significantly higher physical activity levels than users with disabilities who do not track physical activity.
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Chapter 2. Manuscript 1

Population-based Physical Activity Outcomes of Wearable Device Users and Non-users With and Without Disabilities
Abstract

There is an increased interest in using wearable devices to promote physical activity. Previous intervention studies have demonstrated that wearable device usage can increase physical activity of individuals with and without disabilities. However, little is known about the physical activity levels of wearable device users in free-living settings. The purpose of this study was to compare physical activity levels between wearable device users and non-users with and without disabilities in free-living. Using data from the 2017 Behavioral Risk Factor Surveillance System in eight states, various continuous and binary physical activity outcomes were compared between wearable device users and non-users across disability status using linear and logistic regression models. Primary sampling unit indicators, strata information, and sample weights were used in analyses to account for the data’s complex survey design. In total, 19.6% (95% CI [17.7, 22.0]) of individuals were wearable device users. Among wearable device users, 82.2% (95% CI [78.8, 85.0]) were individuals without disabilities. Results indicated that wearable device users were more likely to engage in leisure physical activity than non-users (OR = 1.39, 95% CI [1.01, 1.90]). However, there was no significant difference between wearable device users and non-users in time spent in physical activity. Individuals with disabilities were less likely to engage in leisure physical activity (OR = 0.40, 95% CI [0.29, 0.55]) and meet aerobic physical activity guidelines (OR = 0.45, 95% CI [0.33, 0.60]) when compared to individuals without disabilities. No significant interaction between wearable device usage and disability status was found across all models. Results highlighted that wearable device users were more likely to engage in physical activity than non-users,
but mean durations spent in physical activity were not different between users and non-users. Further studies are needed to examine the associations between wearable device usage and various types and diagnoses of disabilities.
Introduction

In recent years, wearable devices have diffused through our society for their ability to track various health-related parameters (Erdmier et al., 2016; Omura et al., 2017). Wearable devices are noninvasive technologies typically taking the form of small hardware worn at various body locations. Wearable devices are commonly used for tracking and monitoring physical activity metrics such as distance walked, number of steps taken, time spent in physical activity, heart rate, $O_2$ saturation, and calories burned (Düking et al., 2018; Kaewkannate & Kim, 2016).

Wearable devices have been one of the most popular trends in the physical activity and fitness industry for the past several years (Thompson, 2019). The general public typically uses wearable devices to monitor personal fitness and the fitness and health of others (Lunney et al., 2016). There are a variety of brands and models of wearable devices, such as the Fitbit Charge (Fitbit Inc., San Francisco), Withings Pulse HR (Withings, Issyles-Moulineaux, France), Garmin Vivofit (Garmin Ltd., Lenexa, KA), and Apple Watch (Apple®, Cupertino, CA), to name a few.

While wearable devices can often monitor multiple aspects of health (e.g., sleep, nutrition, physical activity), wearable device users primarily utilize such devices for tracking physical activity (Tokuçoğlu, 2018). The ability to wirelessly sync information recorded from wearable devices to smartphone applications allows users to access their physical activity data in real-time and receive direct feedback about their physical activity levels (Erdmier et al., 2016; Kaewkannate & Kim, 2016). This real-time access feature is a convenient method for tracking physical activity compared to older methods such as exercise diaries (Buchowski et al., 2004) and
retrospective questionnaires (Lamb & Brodie, 1990; Washburn & Montoye, 1986), which required individuals to input and calculate physical activity summarizations themselves (Kaewkannate & Kim, 2016). Collectively, the abovementioned capabilities and features of modern wearable devices have contributed to their popularity and uptake within the broader population.

In addition to passive collection of pertinent health-related data, wearable device usage can also serve as an intervention in and of itself and is typically viewed as a low-cost alternative to resource-intensive physical activity interventions (Chen et al., 2017; Patel et al., 2015). Previous findings from a systematic review by Coughlin and Stewart (2016) suggested that wearable devices positively affect physical activity levels. A subsequent meta-analysis by Brickwood et al. (2019b) further investigated the effectiveness of wearable device interventions aiming to increase physical activity. Results of the meta-analysis indicated that wearable device interventions significantly increased daily steps (SMD = 0.23, 95% CI [0.15, 0.32], \( p < .001 \)) when compared to a no intervention control with an approximate adjusted increase of 627 steps/day (95% CI [417, 862]; Brickwood et al., 2019). Brickwood et al. (2019) also found that wearable device users had increased minutes/day in moderate-to-vigorous physical activity (MVPA) compared to the control group (SMD = 0.28, 95% CI [0.14, 0.41], \( p < .001 \)). Increased energy expenditure was also observed among wearable device users when compared to controls (SMD = 0.32, 95% CI [0.05, 0.58], \( p = .02 \); Brickwood et al., 2019). Current evidence supports the notion that wearable device usage can lead to increased physical activity levels.
Many published studies of wearable devices have focused on convenience samples from the general population without specifically identifying and assessing individuals with disabilities. As noted in the systematic review by Coughlin and Stewart (2016) examining wearable device usage for physical activity promotion, none of the evaluated studies included individuals with disabilities. Individuals with disabilities are a marginalized group experiencing numerous health-related disparities (Krahn et al., 2015; Reichard et al., 2011), such as limited access to preventive services, higher odds of chronic disease development, and physical activity disparity (Jung et al., 2018; Pharr & Bungum, 2012). Individuals with disabilities have fewer opportunities to participate in physical activity and engage in less physical activity when compared to their peers without disabilities. Individuals with disabilities are less likely to meet current aerobic physical activity guidelines calling for 150 minutes of moderate physical activity/week, 75 minutes of vigorous physical activity/week, or an equivalent combination of moderate and vigorous physical activity (Stanish et al., 2019; Zhao et al., 2011). Previous studies have evaluated wearable device usage for promoting and measuring physical activity among individuals with disabilities (Rum et al., 2021). For example, Olson et al. (2019) investigated the effectiveness of the Fitbit Charge HR (Fitbit Inc., San Francisco) for increasing physical activity among college students with disabilities. The study found that college students with disabilities using the Fitbit Charge HR spent more time in very active minutes than controls after 12 weeks of intervention. In a separate study, participants with Down syndrome (N = 27; mean age = 27.9 years) increased their physical activity using various approaches, including the Fitbit Flex (Fitbit Inc., San Francisco), online
exercise classes, individual counseling, and physical activity-related homework (Ptomey et al., 2019). Additional findings from Ptomey et al. (2019) indicated that participants enjoyed using the Fitbit Flex and perceived that the device helped motivate them to increase their physical activity. Moreover, another study among adults with intellectual disabilities (N = 3) found that using the Fitbit Flex and setting weekly goals increased average daily step counts (Leon-Barajas, 2018).

While the empirical literature base relevant to wearable devices and disabled individuals is growing, there is a paucity of published studies examining the relationship between physical activity levels and wearable device usage among individuals with disabilities in free-living settings. That said, many disabled individuals in the general public are using wearable devices (Omura et al., 2017), including individuals with multiple sclerosis (Block et al., 2017), those who are wheelchair users (Carrington et al., 2015), individuals with physical disabilities (Agyeman & Al-Mahmood, 2019), and individuals with Parkinson’s disease (Pastorino et al., 2013). Using information and data from observational studies in free-living rather than intervention studies depicts better representations of the natural behaviors of individuals within populations (Nsubuga et al., 2006). Additionally, many intervention studies evaluating wearable device usage among individuals with and without disabilities are limited by small sample sizes (Coughlin & Stewart, 2016). Moreover, most studies evaluating wearable device usage as a means to promote physical activity employed additional intervention strategies and components, such as one-on-one meetings, educational classes, and group exercise (Brickwood et al., 2019). For example, in the interventions conducted by Ptomey et
al. (2019) and Pope et al. (2019), an increase in physical activity levels among participants using wearable devices in combination with other strategies was found. Despite these intervention-related data, there remains a limited understanding of the associations between wearable device usage and physical activity among individuals with and without disabilities in free-living.

As wearable devices grow in popularity, there is a burgeoning need to elucidate the associations between wearable device usage and physical activity among individuals with and without disabilities in free-living settings. Therefore, the purpose of this study was to compare free-living physical activity levels between wearable device users and non-users with and without disabilities. It was hypothesized that wearable device users, with and without disabilities, would have significantly higher physical activity levels than non-users.

**Methods**

**Design**

This study used data from the 2017 Behavioral Risk Factor Surveillance System (BRFSS), a national survey of US adult residents assessing health-related risk behaviors, chronic health conditions, and preventive services. The Centers for Disease Control and Prevention (CDC) funds BRFSS and collects data in all 50 states, the District of Columbia, and three US territories (Centers for Disease Control and Prevention (CDC), 2020). BRFSS completes more than 400,000 participant interviews each year via telephone using Random Digit Dialing (RDD) techniques on both landline and cell phone blocks. Data from BRFSS can be generalized to the non-institutionalized US population of adults over 18 years.
For the purpose of this study, only the 2017 BRFSS data from the following eight states were included in analyses: 1) California, 2) Connecticut, 3) Florida, 4) Louisiana, 5) Nebraska, 6) Oregon, 7) Tennessee, and 8) Texas. The 2017 BRFSS was unique in that it collected information regarding wearable device usage; however, this data collection was part of an optional add-on module that only some states chose to use. A search for the wearable device usage data was conducted on the BRFSS webpage of all 50 states, the District of Columbia, and three US territories to determine which entities collected information regarding wearable devices. Of note, the District of Columbia did collect data on wearable device usage; however, those data have not been publicly released due to unspecified quality control issues (T. Garner, personal communication, May 13, 2020). To facilitate analysis of the collected data, individual state BRFSS data were merged with the larger national 2017 BRFSS data set using anonymized participant identification numbers. The total analytic sample from the eight states included 10,911 adults. Participants provided informed consent before participating in the survey. This secondary analysis of BRFSS data was reviewed by the Oregon State University - Institutional Review Board (IRB) which determined that the data acquisition and analyses were exempt from IRB review.

**Measures**

Seven physical activity outcomes variables were analyzed. Outcomes included continuous variables of 1) physical activity minutes/week, 2) minutes spent in vigorous physical activity/week, and 3) MET×minutes/week (MET = metabolic equivalents), and categorical variables of 1) engaging in leisure physical activity, 2)
participating in > 300 minutes of moderate physical activity or vigorous equivalent of physical activity (one vigorous equivalent physical activity minute = two moderate physical activity minutes)/week, 3) meeting aerobic physical activity guidelines, and 4) meeting both aerobic and strength physical activity guidelines.

The physical activity minutes/week variable was calculated by BRFSS. This variable was calculated for each individual by summing time spent per week in their two most commonly engaged-in leisure physical activities. The following information were collected by BRFSS to estimate physical activity minutes/week: 1) physical activity type, 2) physical activity intensity based on MET levels, 3) minutes spent in activity, and 4) weekly activity frequency. An allowable upper limit of 2,520 minutes of physical activity/week was set to provide a maximum bound encompassing realistic values for weekly physical activity volume (Tucker et al., 2011). Vigorous physical activity minutes/week was calculated in the same manner as physical activity minutes/week while restricted to consideration of vigorous intensity activities only (≥ 6 METs). We calculated METxminutes/week based on the 1) minutes spent in activity, 2) frequency of activity/week, and 3) MET levels of the activity based on the 2017 BRFSS data of the two most engaged-in leisure physical activities reported by participants. Estimated MET levels of each activity were included in the 2017 BRFSS data set.

The four categorical outcome variables were binary. Engaging in leisure physical activity was based on the question of "During the past month, other than your regular job, did you participate in any physical activities or exercise, such as running, calisthenics, golf, gardening, or walking for exercising?" (Yore et al., 2007).
Participants responded with “yes”, “no”, or “don't know”. No participants in the analytic sample responded with don’t know or refused to answer the question. Participants were classified as engaging in > 300 minutes of moderate physical activity vigorous equivalent of physical activity/week (0-300 minutes/week vs. 301+ minutes/week) based on their self-reported physical activity levels. The variable of meeting the aerobic physical activity guidelines was determined by categorizing with respect to at least 150 minutes/week of moderate equivalent physical activity (not meeting: < 150 minutes/week moderate equivalent; meeting: 150+ minutes/week moderate equivalent). Meeting both aerobic and muscle-strengthening physical activity guidelines was calculated by BRFSS using participants' minutes of physical activity and frequency of strengthening physical activity/week based on self-reported data (not meeting: < 150 minutes/week moderate equivalent or < 2 days/week muscle-strengthening activity; meeting: 150+ minutes/week moderate equivalent & 2+ days/week muscle-strengthening activity).

Two primary independent variables were used for analysis, 1) disability status and 2) wearable device usage status. Disability status was based on standard disability-related questions by BRFSS. These questions were part of the BRFSS core module. If the participant responded "yes" to any of the following questions, they were considered to experience at least one form of disability: 1) "Are you blind or do you have serious difficulty seeing, even when wearing glasses?" for vision impairment, 2) "Are you deaf or do you have serious difficulty hearing?" for hearing impairment, 3) "Because of a physical, mental, or emotional condition, do you have serious difficulty concentrating, remembering, or making decisions?" for cognitive
disability, 4) "Because of a physical, mental, or emotional condition, do you have
difficulties doing errands alone such as visiting a doctor's office or shopping?" for
independent living disability, 5) "Do you have difficulty dressing or bathing?" for
self-care disability, and 6) "Do you have serious difficulty walking or climbing
stairs?" for mobility disability. Otherwise, participants were classified as not
experiencing a disability. Wearable device usage was based on the question of "Do
you track your nutrition, sleep, or physical activity using a wearable device or mobile
application (such as Fitbit, Samsung Gear Fit, Apple fitness app or other consumer
application)?". According to BRFSS, wearable devices included wristbands,
biometric clothing, apps or applications (e.g., smartphone tracking apps), or other
devices to monitor general health, nutrition, sleep, or physical activity. Wearable
devices did not include devices prescribed by a healthcare provider or devices that
monitored specific health conditions (such as pacemakers, rehabilitation devices, or
implanted devices). If participants responded with "yes," they were considered to be
wearable device users. If they responded with "no," they were considered to be non-
users.

Multiple demographic and participant characteristics served as potential
covariates for analyses. These variables included: 1) age group (18 to 24, 25 to 34, 35
to 44, 45 to 54, 55 to 64, and 65 years or older), 2) sex (male vs. female), 3) race-
ethnicity (white, black, Hispanic, other races, and multiracial), 4) body mass index
(continuous), 5) education levels (never attended, elementary, some high school, high
school graduate, some college or technical school, and college graduate) and 6)
employment status (yes vs. no). Employment status was coded as to whether
participants were employed at the time of survey administration. If they reported that they were employed for wages or self-employed, they would be considered to be employed. Nevertheless, if they reported that they were any of the following, 1) out of work for one year or more, 2) out of work for less than one year, 3) a homemaker, 4) a student, 5) retired, or 6) unable to work, they were considered unemployed. All of the above participant characteristics were evaluated as potential covariates due to their previously documented associations with physical activity and/or wearable device usage (Al-Isa et al., 2011; Asiamah, 2016; Cheah, 2011; Lämmle et al., 2012; Lim & Taylor, 2005).

**Data Analyses**

Statistical analyses were conducted using R (R Foundation for Statistical Computing, Vienna, Austria) utilizing the "survey" package to model BRFSS complex survey data. Analyses accounted for the complex, multi-stage design of BRFSS by utilizing the examination sampling weights, primary sampling unit indicators, and stratum variables. The level of significance α was set to 0.05 for all analyses.

Descriptive analyses were conducted to summarize the outcome variables and covariates across levels of the primary independent variables of disability status and wearable device usage. Proportions are presented as weighted percentages (% ± SE) while continuous variables are presented as weighted means (M ± SE).

Unadjusted and adjusted linear regression models were fit for each of the continuous outcome variables, while unadjusted and adjusted logistic regression models were fit for each of the categorical outcome variables. The unadjusted model
for each of the regressions included independent variables for wearable device usage (non-user vs. user), disability status (without disabilities vs. with disabilities), and an interaction term between wearable device usage and disability status. Adjusted models were built iteratively using a forward entry procedure with the following potential covariates: 1) age groups (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65 years or older), 2) sex (male vs. female), 3) race-ethnicity (white, black, Hispanic, other races, and multiracial), 4) body mass index (continuous), 5) education levels (never attended, elementary, some high school, high school graduate, some college or technical school, and college graduate) and 6) employment status (yes vs. no). The unadjusted model was used as the base adjusted model and each of the above covariates was entered into the model one-at-a-time in the above order. Covariates were retained in the adjusted model when they significantly reduced the weighted deviance – as evidenced by a significant likelihood ratio test ($p < .10$) from model comparisons. In cases where residual distributions for continuous outcome variables evidenced non-normality or heterogenous variance, a Box-Cox transformation of the outcome variable was performed to better approximate residual normality and homogeneous variance. Model diagnostics utilized graphical techniques including q-q plots and residual vs. fitted plots. Between group comparisons were performed using custom contrasts within the described regression framework. Results from linear regression models were summarized as unstandardized model coefficients and estimated marginal means across factor levels of the independent variables. Logistic models were summarized as odds ratios across factor levels of the independent variables.
Results

Descriptive statistics for participants are displayed in Table 1. 2,661 participants were removed from analysis due to missing data on the usage of wearable devices. Therefore, a total of 8,250 participants were included in analyses due to . Among the sample, 19.6% (95% CI [17.7, 22.0]) were wearable device users. Among wearable device users, 82.2% (95% CI [78.8, 85.0]) were individuals without disabilities. Among non-wearable device users, 74.5% (95% CI [72.3, 76.0]) were participants without disabilities and 25.5% (95% CI [23.5, 28.0]) were participants with disabilities.
Table 1. Characteristics of adults (≥ 18 years) participating in BRFSS 2017 by wearable device and disability status

<table>
<thead>
<tr>
<th>Race &amp; ethnicity (%)</th>
<th>Male</th>
<th>Female</th>
<th>18-24 years old</th>
<th>25-34 years old</th>
<th>35-44 years old</th>
<th>45-54 years old</th>
<th>55-64 years old</th>
<th>≥65 years old</th>
<th>Sex (%)</th>
<th>Age groups (%)</th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
<th>Other races</th>
<th>Multiracial</th>
<th>N</th>
<th>Body mass index (kg/m²)</th>
<th>Education levels (%)</th>
<th>Employment status (%)</th>
<th>Abbreviation</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td>Weighted Value ± SE*</td>
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<td>95% CI</td>
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<tr>
<td>Sex (%)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>524</td>
<td>45.3 ± 3.3</td>
<td>38.8, 51.7</td>
<td>167</td>
<td>40.1 ± 5.2</td>
<td>29.9, 50.2</td>
<td>2028</td>
<td>50.6 ± 1.6</td>
<td>47.5, 53.7</td>
<td>838</td>
<td>44.1 ± 2.3</td>
<td>39.6, 48.6</td>
<td>514</td>
<td>40.4 ± 3.3</td>
<td>36.8, 44.2</td>
<td>1403</td>
<td>18.2 ± 3.0</td>
<td>15.6, 20.8</td>
<td>Yes</td>
<td>426</td>
</tr>
<tr>
<td>Female</td>
<td>611</td>
<td>54.7 ± 3.3</td>
<td>48.3, 61.2</td>
<td>272</td>
<td>59.9 ± 5.2</td>
<td>49.8, 70.1</td>
<td>2565</td>
<td>49.4 ± 1.6</td>
<td>46.3, 52.5</td>
<td>1237</td>
<td>55.9 ± 2.3</td>
<td>51.4, 60.4</td>
<td>644</td>
<td>47.9 ± 3.3</td>
<td>44.6, 51.2</td>
<td>1563</td>
<td>18.2 ± 3.0</td>
<td>15.6, 20.8</td>
<td>No</td>
<td>698</td>
</tr>
</tbody>
</table>
Physical activity outcomes of wearable device users and non-users and individuals with and without disabilities are displayed in Table 2. No significant differences in physical activity outcomes ($p > .05$) were observed between wearable device users with and without disabilities in physical activity/week, vigorous physical activity/week, and METxminutes/week. A higher proportion of wearable device users without disabilities reported engaging in leisure physical activity than users with disabilities ($p = .001$). Also, a higher proportion of users without disabilities met aerobic and combined (aerobic and muscle-strengthening) physical activity guidelines (both $p < .001$).
Table 2. Physical activity outcomes of adults (≥ 18 years) by wearable device and disability status

<table>
<thead>
<tr>
<th></th>
<th>Wearable device users</th>
<th>Non-wearable device users</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without disability</td>
<td>With disability</td>
</tr>
<tr>
<td></td>
<td>n</td>
<td>Weighted Value ± SE*</td>
</tr>
<tr>
<td><strong>Physical activity/week (minutes)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without disability</td>
<td>1136</td>
<td>383.0 ± 25.4</td>
</tr>
<tr>
<td>With disability</td>
<td>1136</td>
<td>63.9 ± 7.4</td>
</tr>
<tr>
<td><strong>Vigorous physical activity/week</strong></td>
<td>1136</td>
<td>1479.0 ± 105.7</td>
</tr>
<tr>
<td><strong>METxminutes/week (minutes)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Without disability</td>
<td>826</td>
<td>76.8 ± 2.7</td>
</tr>
<tr>
<td>With disability</td>
<td>201</td>
<td>12.5 ± 2.7</td>
</tr>
<tr>
<td><strong>Engagement in leisure physical activity (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>510</td>
<td>34.8 ± 3.4</td>
</tr>
<tr>
<td>No</td>
<td>1369</td>
<td>65.2 ± 3.4</td>
</tr>
<tr>
<td><strong>Meeting aerobic physical activity guidelines (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>726</td>
<td>50.8 ± 3.7</td>
</tr>
<tr>
<td>No</td>
<td>1162</td>
<td>42.0 ± 3.7</td>
</tr>
<tr>
<td><strong>Meeting both muscles strengthening &amp; aerobic physical activity guidelines (%)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>222</td>
<td>30.1 ± 3.4</td>
</tr>
<tr>
<td>No</td>
<td>1640</td>
<td>69.9 ± 3.4</td>
</tr>
</tbody>
</table>

*Note.* BRFSS, Behavioral Risk Factor Surveillance System; n, unweighted sample size.

*aEngage in at least 150 minutes of moderate-to-vigorous aerobic physical activity/week.

*Italic* values indicate mean±SE.
Unadjusted and adjusted linear regression models were fitted to compare continuous physical activity outcomes between wearable device users and non-users and individuals with and without disabilities as seen in Table 3. No statistically significant interactions between wearable device usage and disability status were found among all unadjusted and adjusted linear regression models ($p > .05$). Therefore, only the main effects of wearable device usage and disability status were reported from the linear regression models. Statistically significant differences were not found among other continuous physical activity outcomes in unadjusted models except for vigorous physical activity/week between disability status ($p < .001$) as shown in Table 3. For adjusted models, no statistically significant differences were found between levels of wearable device usage status and disability status among the analyzed continuous physical activity outcomes.
### Table 3. Linear models regressing continuous physical activity outcomes on wearable device and disability status

<table>
<thead>
<tr>
<th></th>
<th>Physical Activity/Week (Minutes)</th>
<th>Vigorous Physical Activity/Week (minutes)</th>
<th>METxMinutes/Week</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>b</td>
<td>p</td>
<td>b</td>
</tr>
<tr>
<td><strong>Unadjusted model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>3.82</td>
<td>&lt;0.001*</td>
<td>.82</td>
</tr>
<tr>
<td>Wearable</td>
<td>-.12</td>
<td>.21</td>
<td>.02</td>
</tr>
<tr>
<td>Disability</td>
<td>.04</td>
<td>.78</td>
<td>-.06</td>
</tr>
<tr>
<td>Wearable*Disability</td>
<td>-.25</td>
<td>.37</td>
<td>.02</td>
</tr>
<tr>
<td><strong>Adjusted model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>625.00b</td>
<td>&lt;0.001*</td>
<td>97.05c</td>
</tr>
<tr>
<td>Wearable</td>
<td>-9.30</td>
<td>.75</td>
<td>-2.18</td>
</tr>
<tr>
<td>Disability</td>
<td>47.86</td>
<td>.27</td>
<td>15.15</td>
</tr>
<tr>
<td>Wearable*Disability</td>
<td>-82.58</td>
<td>.23</td>
<td>-5.18</td>
</tr>
</tbody>
</table>

**Note.**  

- **a** Box-cox transformations applied to outcome variables for unadjusted linear models to yield normally distributed and homoscedastic residual distributions.  
- **b** Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m²), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no).  
- **c** Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m²), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no).  
- **d** Model was adjusted for body mass index (kg/m²), race and ethnicity (white, black, Hispanic, other races, multiracial), and education levels (never attend/kindergarten only, elementary school, some high school, high school graduate, some college/technical school, and college graduate), and employment status (yes, no).  

**Abbreviation.**  

- **b**, beta-coefficient of regression model.  
- *, p<0.05.
Logistic regressions were conducted to determine the association between wearable device usage and disability status on binary physical activity outcomes as found in Table 4. Among the unadjusted logistic regression models performed, no significant interactions between wearable device usage and disability status were observed. Therefore, only main effects for wearable device usage and disability status are reported. No statistically significant associations were found between wearable device status and all included binary physical activity outcomes except for engage in leisure physical activity, where wearable device users had a higher unadjusted log odds than non-users for engaging in leisure physical activity. Individuals with disabilities had significantly lower adjusted log and unadjusted log odds than individuals without disabilities for engaging in leisure physical activity accumulating > 300 minutes of moderate physical activity or vigorous equivalent physical activity/week, meeting aerobic physical activity guidelines, and meeting both aerobic and muscle-strengthening physical activity guidelines. These trends generally persisted in adjusted logistic regression models, where the interaction between wearable device usage and disability status was not statistically significant and wearable device usage fell to non-significance.
Table 4. Logistic models regressing binary physical activity outcomes on wearable device and disability status

<table>
<thead>
<tr>
<th>Wearable device</th>
<th>Engage in Leisure Physical Activity</th>
<th>Engage in &gt; 300 Minutes of Physical Activity</th>
<th>Meeting Aerobic Physical Activity Guidelines</th>
<th>Meeting Both Aerobic and Muscle Strengthening Physical Activity Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR(^a) [95% CI]</td>
<td>aOR(^b) [95% CI]</td>
<td>OR(^a) [95% CI]</td>
<td>aOR(^c) [95% CI]</td>
</tr>
<tr>
<td>Yes</td>
<td>1.39 [1.01, 1.90]*</td>
<td>1.38 [.97, 1.96]</td>
<td>1.01 [.77, 1.41]</td>
<td>1.20 [.85, 1.68]</td>
</tr>
<tr>
<td>No(^f)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Disability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>.40 [.29, .55]*</td>
<td>.48 [.34, .69]*</td>
<td>.72 [.53, .97]*</td>
<td>.60 [.42, .87]*</td>
</tr>
<tr>
<td>No(^f)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note. \(^a\)Logistic models included the following independent variables: wearable device utilization (yes, no), disability status (yes, no), and an interaction term between wearable device utilization and disability status. \(^b\)Model was further adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m\(^2\)), race and ethnicity (white, black, Hispanic, other races, multiracial), education level (never attend/kindergarten only, elementary school, some high school, high school graduate, some college/technical school, and college graduate), and employment status (yes, no). \(^c\)Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m\(^2\)), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no). \(^d\)Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m\(^2\)), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no). \(^e\)Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m\(^2\)), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no). \(^f\)“No” is the reference with the odds ratio of 1.0 for each of the regression model.

Abbreviation. OR, odds ratio; aOR, adjusted odds ratio.

\(^*, p<0.05\)
Discussion

The purpose of this study was to compare physical activity levels between wearable device users and non-users with and without disabilities in a free-living setting. Results indicated that individuals using wearable devices had a higher unadjusted log odds (OR = 1.39, 95% CI [1.01, 1.90]) of engaging in leisure physical activity compared to individuals who did not use wearable devices. Non-significant differences between wearable device users and non-users were found among all continuous physical activity outcomes. Individuals with disabilities were less likely to engage in leisure physical activity, > 300 minutes of moderate or vigorous equivalent physical activity, meet aerobic physical activity guidelines, and meet aerobic and muscle-strengthening physical activity guidelines. No significant interactions between wearable device usage and disability status were observed in the any of the evaluated models.

The results showcased that both individuals with and without disabilities were using wearable devices in free-living settings. About 20% of participants reported using wearable devices to track health-related information. The number of participants reporting as wearable devices users was much lower than participants reporting as non-users. While physical activity behaviors may be influenced by wearable devices, other factors could potentially influence physical activity as well. Specific feature sets of a given wearable device could potentially impact physical activity levels. In addition, various participant characteristics, disability status, and disability type could also affect physical activity behaviors.
The potential benefits of wearable devices to promote physical activity are evidenced in those individuals using wearable devices as unadjusted models where it was associated with engaging in leisure physical activity. This suggests that wearable devices may promote greater leisure physical activity in free-living settings (Hickey & Freedson, 2016; Strath & Rowley, 2018). The increased engagement in leisure physical activity could be due to the effect of using wearable devices. One of the features of wearable devices is to remind users to engage in physical activity (Chen et al., 2017; Lyons et al., 2014). Various types of notifications are sent to wearable device users to engage in physical activity, such as text messages, visual messages, and vibration (Chen et al., 2017; Lewis et al., 2020). Sometimes, these notifications are sent to users when the devices detect that the users were engaged in sedentary behaviors or did not engage in physical activity for extended periods of time. Wearable device users could be utilizing this feature of wearable devices to remind themselves to engage in physical activity. One previous study confirmed that wearable device users utilized the notification function of their wearable devices (Lewis et al., 2020). Over 60% of wearable device users identified that the notification function was useful in promoting physical activity and a healthy lifestyle (Lewis et al., 2020). The motivation cues that were included in the notifications were identified as one of the most helpful features of wearable devices for increasing physical activity (Lewis et al., 2020). Additionally, 73.9% of adult wearable device users found that notifications were helpful for promoting engagement in physical activity, with notifications containing motivational cues being identified as most helpful (Lewis et al., 2020). Asimakopoulos et al. (2017) found that dedicated users
would utilize wearable devices to enhance their motivation and willingness to undergo a change in their fitness activities and increase their physical activity. In addition, Kerner and Goodyear (2017) found Fitbit devices were able to increase motivation toward physical activity among teenage adolescents after eight weeks of device usage. The study found that developing physical activity goals using Fitbit devices motivated adolescents to engage in physical activity. Because participants wanted to meet their physical activity goals, they engaged in physical activity to meet said goals (Blackstone & Herrmann, 2020; Chokshi et al., 2018; Kuenze et al., 2021). The social features of the Fitbit device also motivated participants to engage in physical activity (Girginov et al., 2020). Additionally, competition with peers motivated participants in Kerner and Goodyear (2017) to engage in physical activity. Other studies have also identified that social-based features of wearable devices, including between user information sharing, increased user motivation toward engaging in physical activity (Girginov et al., 2020; Stragier et al., 2016; Wu & Liu, 2020).

While results from unadjusted models suggest that wearable device users were more likely to engage in leisure physical activity than non-users, we should not neglect other factors that could influence physical activity as well. This was evidenced by the fall to non-significance of the wearable device user factor in adjusted models. It has been previously demonstrated that individuals interested in health and who tend to try to exercise regularly are more likely to purchase and utilize wearable devices (Lee & Lee, 2018). Additionally, it is believed that various demographic characteristics influence wearable device usage and physical activity
levels. It was found that there was a higher prevalence of wearable device users between the ages of 18 to 34 years old and with higher education (Omura et al., 2017) while the results of this study also found similar trends among adults using wearable devices. Individuals with higher education were more likely to engage in physical activity than individuals with lower education levels (Berrigan & Troiano, 2002; Shaw & Spokane, 2008). Previously, studies have indicated that compared to older adults, younger adults are more likely to engage in physical activity (Johannsen et al., 2008; Krems et al., 2004). Income is another factor that could contribute to the use of wearable devices. Patel et al. (2017) found that individuals with lower incomes were less likely to utilize wearable devices. One of the primary reasons individuals used wearable devices was to hold themselves accountable for being fit and tracking leisure physical activity (Vooris et al., 2019). This suggests that individuals who use wearable devices may have already engaged in regular physical activity prior to wearable device adoption.

While users were more likely to engage in leisure physical activity than non-users, results herein suggest the reported mean weekly duration of physical activity does not significantly differ between wearable device users and non-users. During activities, wearable devices typically do not remind users to continue to engage in that activity. Some wearable devices are capable of tracking time spent in physical activity, such as Fitbit devices which report minutes spent in the various physical activity intensities (i.e., active, and very active) (Chen et al., 2017; Düking et al., 2018; Kaewkannate & Kim, 2016). Providing feedback on the duration of physical activity might promote or motivate wearable device users to spend more time
engaging in physical activity (Liu et al., 2020). Also, setting physical activity goals related to the duration of physical activity with wearable devices might facilitate greater duration of engagement in physical activity as individuals want to meet their goals (Blackstone & Herrmann, 2020). However, more research is needed to better understand the associations between wearable device usage and the duration of physical activity engagement.

This study aligns with previous studies regarding physical activity levels between individuals with and without disabilities. Similar results were found after accounting for wearable device utilization and covariates, where individuals with disabilities were less likely to engage in leisure physical activity and less likely to meet physical activity guidelines. Multiple studies in the past have illustrated that individuals with disabilities are less likely to engage in moderate-to-vigorous physical activity and meet aerobic physical activity guidelines (Hassett et al., 2021; Hollis et al., 2020; Jung et al., 2018; Kamil-Rosenberg et al., 2019). Individuals with disabilities experience barriers that limit their opportunities to engage in physical activity. One barrier that individuals with disabilities face, that wearable devices could potentially overcome, is lower motivation to engage in physical activity (Clemente, 2017; Úbeda-Colomer et al., 2019). The study by Malu and Findlater (2016a) found wearable devices’ motivation strategies helpful to increase users’ motivation toward physical activity and physical activity levels. Another study by Sharan et al. (2016), investigating the use of wearable devices among participants with cerebral palsy, found that the goal-setting features of wearable devices helped motivate participants to engage in physical activity. Even though interventions by
Malu and Findlater (2016a) and Sharan et al. (2016) found increased physical activity among participants with cerebral palsy, results of this study did not align with these intervention studies. This could be because the intervention study was conducted in a controlled setting, whereas the cross-sectional data used in this study were obtained in free-living. Moreover, both intervention studies only focused on individuals with cerebral palsy, while this study included individuals with various disabilities and limitations. Future studies are needed to examine the effect of wearable devices for promoting individuals with disabilities to engage in physical activity across various disability types.

Surprisingly, no statistically significant interaction was found herein between disability status and wearable device usage in regard to physical activity levels. It was hypothesized that physical activity levels would be higher among individuals with disabilities who used wearable devices in comparison to non-users. This suggests that current free-living wearable device usage does not significantly modify physical activity in individuals with disabilities. Different types of disabilities might react differently to physical activity when using wearable devices. For example, individuals using wheelchairs were interested in using wearable devices to track their physical activity levels, but the step count outcome associated with wearables is not particularly useful in most contexts for wheelchair users (Carrington et al., 2015). Different types of disabilities might have different concerns regarding wearable devices in tracking and promoting physical activity. Therefore, further research is needed to examine the feasibility of using wearable devices to promote physical
activity among different types of disabilities and the relationship between physical activity levels, wearable devices, and types and diagnosis of disabilities.

Even though this study was one of the few studies that has examined the association between wearable device utilization, disability status, and physical activity levels, it is not without limitations. This study used cross-sectional data which limited our interpretation of results and participants responded to using wearable devices. BRFSS is a surveillance system based on self-reported information. Therefore, there are potential social and recall biases in participant responses. It is possible that wearable device users reported physical activity levels based on feedback from wearable devices, in comparing to non-users reported from memory or other approaches. Also, all the continuous physical activity variables, and some of the binary variables, were only based on each participant's two most engaged-in physical activities. This was because BRFSS only collected physical activity data related to the two most engaged-in activities. Therefore, physical activity data described herein might not adequately represent the physical activity behaviors of participants. Misclassification of physical activity could occur due to activity categories included in BRFSS might not be applicable to individuals with disabilities. It is important to note that the usage of intensity information (METs) from BRFSS might not be appropriate for individuals with disabilities. Previous study had found that when engaging in the same activities, individuals with Down syndrome expended more energy than individuals without disabilities (Leung et al., 2021). Moreover, physical activity levels could differ between disability types (Manns et al., 2015). However, few studies have examined the association between wearable devices and physical
activity among individuals with and without disabilities in large-scale studies like BRFSS. Therefore, the results of this study provide further insight into the physical activity behaviors of individuals with disabilities, regardless of disability type. Lastly, despite BRFSS being a national surveillance system, cross-sectional data from only eight states were included in this analysis. This could lead to the limited generalizability of the data.

The purpose of this study was to examine the relationship between physical activity levels, utilization of wearable devices, and disability status in free-living settings. Although individuals who used wearable devices were more likely to engage in leisure physical activity than those who did not use wearable devices, time spent in physical activity was not significantly different between the two groups. Also, in alignment with previous studies, individuals with disabilities were less likely to engage in physical activity and meet physical activity guidelines than their counterparts without disabilities. Additional studies are needed to determine the association between physical activity levels and wearable device usage among different disabilities.
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Chapter 3. Manuscript 2

Physical activity levels of wearable device users with and without disabilities who tracked physical activity
Abstract

Wearable devices allow for tracking various health-related information, such as physical activity levels, nutrition, sleep patterns, and chronic health indicators. Typically, wearable device usage is positively associated with physical activity and offers an efficient and cost-effective alternative to other forms of physical activity intervention. Individuals with disabilities face health and physical activity disparities. Using wearable devices to track physical activity could potentially promote activity for individuals with disabilities. Multiple interventions using wearable devices targeting individuals with and without disabilities have showcased their effectiveness in increasing physical activity levels. However, there remains limited information regarding the physical activity levels of wearable device users with and without disabilities who track physical activity in free-living settings. This study, therefore, aims to compare physical activity levels of wearable device users, with and without disabilities, to those who did and did not track physical activity in free-living settings. Wearable device users from the 2017 Behavioral Risk Factor Surveillance System of eight states (N = 2,544) were included in analyses. Multiple continuous and binary physical activity outcomes were used as outcome variables in analyses. Linear and logistic regression was used to compare physical activity outcomes between wearable device users who tracked and did not track physical activity among individuals with and without disabilities. Among participants, 78.8% reported using wearable devices to track physical activity, while 21.2% reported not using wearable devices to track physical activity. Wearable device users who tracked physical activity were more likely to engage in leisure physical activity (OR = 1.74, 95% CI [1.05, 2.88] and to
meet aerobic physical activity guidelines (OR = 1.81, 95% CI [1.12, 2.92]) than those who did not track physical activity with wearable devices. Individuals with disabilities were less likely to engage in physical activity (OR = 0.40, 95% CI [0.24, 0.66]) and to meet both aerobic and muscle-strengthening physical activity guidelines (OR = 0.32, 95% CI [0.17, 0.60]). However, no significant differences between users who tracked physical activity with wearables and those who did not was observed for any of the evaluated continuous physical activity variables. This study highlighted the physical activity disparities between individuals with and without disabilities. Further research is needed to examine the effects of wearable device usage in promoting physical activity among individuals with various disabilities.
Introduction

There is an increasing trend among the general public toward greater usage of wearable devices. Wearables are electromechanical devices worn on the body, which monitor various health-related parameters to provide automated real-time feedback to individuals via smartphone or web-based applications (Brickwood et al., 2019a; Henriksen, Haugen Mikalsen, et al., 2018). According to the 2015 HealthStyle Survey, 12.5% of American adults reported using wearable devices (Omura et al., 2017), which increased to 21.7% in 2018 according to the 2018 Government & Academic Omnibus Survey (Hyde et al., 2020). Recent research has even suggested the adoption of wearable devices could increase further due to changing perspectives on wearables as they become viewed as innovative approaches for improving health (Lee & Lee, 2018).

One primary feature of wearable devices is the ability to track health-related information to promote physical activity and other positive health behaviors (Patel et al., 2015). Wearable devices measure physical activity, such as number of steps, distance traveled, heart rate, energy expenditure, physical activity intensity levels, and/or physical activity duration (Chen et al., 2017; Henriksen, Haugen Mikalsen, et al., 2018). Some of these devices can also be used to monitor caloric intake (Dimitratos et al., 2020), various sleep-related parameters (Haghayegh et al., 2019), and blood sugar levels and blood pressure (Kamei et al., 2020).

Wearable devices can offer a number of health-related benefits for populations with and without disabilities, and multiple studies have demonstrated the ability of wearable devices to promote healthy behaviors. Brickwood et al.’s (2019) meta-
analysis (N = 28 studies) found a significant increase in daily step counts (standardized mean difference = .24, 95% CI [.16, .33], \( p < .001 \)) and moderate and vigorous physical activity (standardized mean differences = .27, 95% CI [.15, .39], \( p < .001 \)) among adults without disabilities using wearable devices. A systematic review (N = 14 studies) by Baron et al. (2021) examined the usage of wearable devices in behavioral sleep medical interventions and found that wearable devices can be a tool to improve sleep quality as well. In addition to physical activity and sleep, a meta-analysis by Kamei et al.’s (2020) found that wearable device usage in monitoring chronic health conditions could not only improve chronic disease management but also enhance adherence to treatment among individuals with chronic obstructive pulmonary disease (COPD), diabetes mellitus, and cardiac disease. Collectively, these studies demonstrate that wearable devices can improve various health-related outcomes, and that wearable devices can be used to successfully track health-related information.

Wearable devices have also been found to play a role in the adoption of healthy physical activity behaviors. That is, since these devices are most commonly used to track physical activity behaviors (Haghi et al., 2017; Tokuçoğlu, 2018), tracking may be used to increase awareness of - and thereby prompt improvements in - users’ physical activity levels. Being aware of one’s physical activity levels could precede positive changes in physical activity. For example, Dale et al. (2016) found that participants who were aware of current physical activity guidelines were more likely to engage in physical activity. Wearable device users who track their physical activity are aware of their physical activity levels through device feedback, which
could potentially lead to a greater likelihood for change in physical activity. At the same time, wearable device users who do not track physical activity might be unaware of their physical activity levels, which would not lead to positive changes in physical activity behaviors (Rooney et al., 2003).

With the rising popularity of wearables, individuals with and without disabilities are utilizing wearable devices to track health-related information (Erdmier et al., 2016; Omura et al., 2017). In regard to individuals with disabilities, however, it is currently unknown whether the types of information people are tracking with their wearable devices are linked to their behaviors. Previous studies have indicated that individuals with disabilities could use wearable devices to monitor their physical activity levels. One study by DasMahapatra et al. (2018) used the Fitbit One (Fitbit Inc., San Francisco), a type of wearable device, to measure physical activity levels of 114 participants with multiple sclerosis in a free-living setting. The study ultimately found that participants using wearables responded positively to tracking physical activity with wearable devices.

Individuals with disabilities are a special population that face numerous health disparities (Pharr & Bungum, 2012), such as higher rates of obesity (Fox et al., 2014), diabetes (Reichard & Stolzle, 2011), cardiovascular disease (Reichard et al., 2011), and a greater likelihood to report fair or poor health (Altman & Bernstein, 2008). Individuals with disabilities are less likely to engage in physical activity and meet the aerobic physical activity guidelines (Jung et al., 2018) and using wearable devices could potentially increase their physical activity levels. Like individuals without disabilities, individuals with disabilities have the option of measuring physical
activity and other health-related information with wearable devices. If individuals with disabilities use wearable devices to track physical activity, it is possible that their physical activity levels may increase.

Currently, there is limited research examining associations between physical activity levels and tracking of physical activity behaviors with wearable devices among individuals with and without disabilities. Both Wang et al. (2017) and Haghi et al. (2017) have examined wearable device usage in measuring physical activity behaviors, vital signs, and medical conditions in different settings. Additionally, multiple studies have examined the validity of wearable devices for measuring physical activity (Leung et al., 2021). The behaviors of wearable device users could be different depending on the information tracked by the wearable device (Lee & Lee, 2020; Rupp et al., 2018). Unfortunately, there are few studies examining the relationship between physical activity behaviors and information tracked by wearable devices among individuals with and without disabilities in free-living settings.

With the increasing trend of using wearable devices to promote health, there is a need to better understand the association between physical activity levels and wearable device usage among individuals with and without disabilities. Therefore, the purpose of this study was to compare physical activity levels of wearable device users with and without disabilities who tracked and did not track physical activity in free-living settings. We hypothesized that users who tracked physical activity with wearable devices will have higher physical activity levels than those who did not track physical activity.
**Method**

**Design**

Data from the Behavioral Risk Factor Surveillance System (BRFSS) were used in the analyses for this study. BRFSS is a national public health surveillance system funded by the Centers for Disease Control and Prevention (CDC) to assess health-related behaviors, chronic health conditions, and preventive health services among non-institutionalized US adult residents. The surveillance system collected data across all 50 states, the District of Columbia, and the three US territories. Each year, over 400,000 US adults participate in BRFSS through interviews conducted using Random Digit Dialing (RDD) methods on both landline and cell phone blocks (Link et al., 2006).

During the 2017 BRFSS cycle, only eight states and the District of Columbia collected the physical activity-related outcome variables of interest. While BRFSS collects data annually, 2017 was the only cycle year thus far that included questions related to wearable devices. Data from the following states were included in analyses: 1) California, 2) Connecticut, 3) Florida, 4) Louisiana, 5) Nebraska, 6) Oregon, 7) Tennessee, and 8) Texas. Due to unspecified quality control issues, wearable device usage data from the District of Columbia have not been released to the public (T. Garner, personal communication, May 13, 2020). For the purpose of this study, data from each state were merged with the larger national 2017 BRFSS data set to facilitate analysis using unique participant identification numbers (N = 10,911). Only participants who reported using wearable devices to track health information (i.e., physical activity, nutrition/calories, sleep, chronic conditions) were included in
analysis. In total, only 23.32% (n = 2,544) reported using wearable devices to track various health information. These participants were included in the current study. Participants of BRFSS provided consent before responding to survey. This secondary analysis of BRFSS data was reviewed by the Oregon State University - Institutional Review Board (IRB) which determined that the data acquisition and analyses were exempt from IRB review.

**Measures**

Physical activity-related variables served as outcome variables for analyses. There were two different types of outcome variables, continuous and categorical, included in this study. Two primary independent variables were also included. Participants’ demographic information and characteristics served as covariates in adjusted analyses.

Three different continuous physical activity outcome variables were included in analyses, 1) physical activity minutes/week (mins), 2) vigorous physical activity/week (mins), and 3) energy expenditure during physical activity/week (metabolic equivalent [MET]xminutes/week). Both physical activity minutes/week and vigorous physical activity/week were provided by BRFSS. These variables were based on the type, intensity, frequency, and duration of the top two most commonly engaged-in leisure physical activities reported by each participant. An allowable upper limit of 2,520 total minutes was set to provide a maximum bound encompassing realistic weekly volume value for physical activity minutes/week and vigorous physical activity/week (Tucker et al., 2011). The difference between these two variables was vigorous physical activity/week (mins) only included time spent in
vigorous intensity (≥ 6 METs). We calculated METxminutes/week using minutes reported in each activity, the frequency of activity/week, and MET levels of each activity based on BRFSS provided data of the top two most engaged-in leisure physical activities reported by each participant.

The four categorical physical activity outcome variables evaluated herein were 1) engagement in leisure physical activity, 2) engagement in > 300 minutes of moderate-to-vigorous physical activity or vigorous equivalent physical activity, 3) meeting aerobic physical activity guidelines of at least 150 minutes of moderate aerobic physical activity or 75 minutes of vigorous equivalence of aerobic physical activity/week, and 4) meeting both aerobic and muscle strengthening (two days/week) physical activity guidelines. Participants were considered as engaging in leisure physical activity if they responded “yes” to the question of "During the past month, other than your regular job, did you participate in any physical activities or exercise, such as running, calisthenics, golf, gardening, or walking for exercising?" (Yore et al., 2007), otherwise, participants were considered as not engaging in leisure physical activity. Participants were classified as engaging in > 300 minutes of moderate-to-vigorous physical activity or vigorous equivalent minutes of physical activity (one vigorous equivalent physical activity minute = two moderate physical activity minutes) or engage in 0-300 minutes of moderate-to-vigorous physical activity or vigorous equivalent minutes of physical activity based on self-reported physical activity levels. Participants were also classified as who met aerobic physical activity guidelines if the weekly duration of their two most commonly engaged-in physical activities exceeded 150 minutes at or above a moderate-intensity and those who did
not met the aerobic physical activity guidelines. Meeting both aerobic and muscle-strengthening physical activity guidelines was calculated by BRFSS using participants’ self-reported physical activity levels (not meeting: < 150 minutes/week moderate equivalent or < 2 days/week muscle-strengthening activity; meeting: 150+ minutes/week moderate equivalent & 2+ days/week muscle-strengthening activity).

The two primary independent variables included in analyses herein were 1) disability status and 2) tracking of physical activity with wearable devices. Disability status was based on participant's self-reports from BRFSS. If the participant responded "yes" to any of the following questions, they were considered to have at least one form of disability: 1) "Are you blind or do you have serious difficulty seeing, even when wearing glasses?" for vision impairment; 2) "Are you deaf or do you have serious difficulty hearing?" for hearing impairment; 3) "Because of a physical, mental, or emotional condition, do you have serious difficulty concentrating, remembering, or making decisions?" for cognitive disability; 4) "Because of a physical, mental, or emotional condition, do you have difficulties doing errands alone such as visiting a doctor's office or shopping?" for independent living disability; 5) "Do you have difficulty dressing or bathing?" for self-care disability; and 6) "Do you have serious difficulty walking or climbing stairs?" for mobility disability. Otherwise, participants were classified as not having a disability. The second primary independent variable focused on tracking physical activity with wearable devices. Tracking physical activity with wearable devices was based on the question of "What type of health information do you track using your mobile app or wearable device?". If participants’ respond included physical activity, they were classified as trackers,
otherwise, they were considered not to be trackers. Participants who reported not tracking physical activity were wearable device users as well but tracking other health information beside physical activity, such as sleeping pattern, nutrition/calories intake, and chronic conditions (e.g., blood pressure, blood sugar levels, etc.).

Participant demographic information and characteristics were used as covariates for adjusted analyses. Potential covariates included: 1) age group (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65 years or older), 2) sex (male vs. female), 3) race-ethnicity (white, black, Hispanic, other races, and multiracial), 4) body mass index (continuous), 5) education levels (never attended, elementary, some high school, high school graduate, some college or technical school, and college graduate) and 6) employment status (yes and no). Employment status was coded as whether participants currently had employment. If participants reported they were employed for wages or self-employed, they were classified as being employed. Nevertheless, if they reported that they were any of the following, 1) out of work for one year or more, 2) out of work for less than one year, 3) a homemaker, 4) a student, 5) retired, or 6) unable to work, they were considered unemployed. These factors were previously found to have associations with physical activity and wearable device usage (Al-Isa et al., 2011; Asiamah, 2016; Cheah, 2011; Lämmle et al., 2012; Lim & Taylor, 2005).

**Data Analyses**

Statistical analyses were conducted using R (R Foundation for Statistical Computing, Vienna, Austria), explicitly utilizing the “survey” package to model BRFSS complex, multi-stage design survey data. Analyses accounted for the complex
design by utilizing appropriate examination sampling weights, primary sampling unit indicators, and stratum variables. The level of significance $\alpha$ was set to 0.05 for all analyses.

Descriptive analyses were conducted to summarize the physical activity outcome variables and covariates by both of the independent variables of disability status and tracker status. Results are presented as weighted proportions ($\% \pm SE$) across categorial variables while continuous variables are presented as weighted means ($M \pm SE$).

Multiple unadjusted and adjusted linear regression models were fit for each of the continuous outcome variables, while multiple unadjusted and adjusted logistic regression models were fit for each of the categorical outcome variables. The unadjusted model for each of the regressions included independent variables for tracker status (tracking physical activity with wearable devices vs. not tracking physical activity with wearable devices), disability status (without disabilities vs. with disabilities), and an interaction term between tracker status and disability status. Adjusted models were built iteratively using a forward entry procedure with the following potential covariates: 1) age groups (18 to 24, 25 to 34, 35 to 44, 45 to 54, 55 to 64, and 65 years or older), 2) sex (male vs. female), 3) race-ethnicity (white, black, Hispanic, other races, and multiracial), 4) body mass index (continuous), 5) education levels (never attended, elementary, some high school, high school graduate, some college or technical school, and college graduate) and 6) employment status (yes vs. no). The unadjusted model was used as the base adjusted model and each of the above covariates was entered into the model one-at-a-time in the above order.
Covariates were retained in the adjusted model when they significantly reduced the weighted deviance – as evidenced by a significant likelihood ratio test ($p < 0.10$) from model comparisons. When residual distributions for continuous dependent variables evidenced non-normality or heterogenous variance, a Box-Cox transformation of the dependent variable was performed to better approximate residual normality and homogenous variance. Model diagnostics utilized graphical techniques including q-q plots and residual vs. fitted plots. Between group comparisons were performed using custom contrasts within the described regression framework. Results from linear regression models were summarized as unstandardized model coefficients and estimated marginal means across factor levels of the independent variables. Logistic models were summarized as odds ratios across factor levels of the independent variables.

**Results**

Descriptive statistics are displayed in Table 1. A total of 2,544 participants from the 2017 BRFSS across the eight states were included in this analysis. A significant majority of participants reported using wearable devices to track their physical activity levels (78.8%; 95% CI [75.3, 82.0], n = 2025). Among participants who did track physical activity with wearable devices, 17.4% (95% CI [14.5, 21.0], n = 546) were individuals with disabilities. Among participants who did not track physical activity with wearable devices, 26.0% (95% CI [20.2, 33.0], n = 158) were individuals with disabilities.
<table>
<thead>
<tr>
<th>Race &amp; ethnicity (%)</th>
<th>Sex (%)</th>
<th>Age groups (%)</th>
<th>Education levels (%)</th>
<th>Body mass index (kg/m²)</th>
<th>Employment status (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>White</td>
<td>Male</td>
<td>18-24 years old</td>
<td>Never attend / kindergarten only</td>
<td>1479</td>
<td>Yes</td>
</tr>
<tr>
<td>Black</td>
<td>Female</td>
<td>25-34 years old</td>
<td>Elementary school</td>
<td>32</td>
<td>862</td>
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<tr>
<td>Hispanic</td>
<td></td>
<td>35-44 years old</td>
<td>Some high school</td>
<td>42</td>
<td>600</td>
</tr>
<tr>
<td>Other races</td>
<td></td>
<td>45-54 years old</td>
<td>High school graduate</td>
<td>329</td>
<td>670</td>
</tr>
<tr>
<td>Multiracial</td>
<td></td>
<td>55-64 years old</td>
<td>Some college / technical school</td>
<td>399</td>
<td>862</td>
</tr>
<tr>
<td></td>
<td></td>
<td>≥65 years old</td>
<td>College graduate</td>
<td>670</td>
<td>600</td>
</tr>
</tbody>
</table>

**Table 1. Characteristics of wearable devices users who tracked physical activity by disability status**

<table>
<thead>
<tr>
<th>Tracked physical activity with wearable devices</th>
<th>Not tracked physical activity with wearable devices</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without disability (n=1479; 82.6%; 95% CI [79.2, 86.0])</td>
<td>Without disability (n=361; 74.0%; 95% CI [67.2, 80.0])</td>
</tr>
<tr>
<td>With disability (n=546; 17.4%; 95% CI [14.5, 21.0])</td>
<td>With disability (n=158; 26.0%; 95% CI [20.2, 33.0])</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>n</th>
<th>Weighted Value ± SE*</th>
<th>95% CI</th>
<th>n</th>
<th>Weighted Value ± SE*</th>
<th>95% CI</th>
<th>n</th>
<th>Weighted Value ± SE*</th>
<th>95% CI</th>
<th>n</th>
<th>Weighted Value ± SE*</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>647</td>
<td>45.7 ± 2.8</td>
<td>40.3, 51.2</td>
<td>222</td>
<td>44.1 ± 4.8</td>
<td>34.6, 53.5</td>
<td>159</td>
<td>48.3 ± 5.5</td>
<td>37.6, 59.0</td>
<td>66</td>
<td>45.0 ± 6.7</td>
</tr>
<tr>
<td>Female</td>
<td>831</td>
<td>54.3 ± 2.8</td>
<td>48.8, 59.7</td>
<td>324</td>
<td>55.9 ± 4.8</td>
<td>46.5, 65.4</td>
<td>202</td>
<td>51.7 ± 5.5</td>
<td>41.0, 62.4</td>
<td>92</td>
<td>55.0 ± 6.7</td>
</tr>
<tr>
<td>18-24 years old</td>
<td>93</td>
<td>11.5 ± 1.9</td>
<td>7.9, 15.1</td>
<td>20</td>
<td>13.5 ± 4.3</td>
<td>5.1, 21.9</td>
<td>19</td>
<td>13.2 ± 4.6</td>
<td>4.2, 22.2</td>
<td>3</td>
<td>3.5 ± 2.4</td>
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<tr>
<td>25-34 years old</td>
<td>295</td>
<td>25.0 ± 2.6</td>
<td>19.9, 30.0</td>
<td>21</td>
<td>9.3 ± 2.7</td>
<td>4.0, 14.7</td>
<td>58</td>
<td>24.4 ± 4.8</td>
<td>14.9, 33.9</td>
<td>10</td>
<td>10.7 ± 4.6</td>
</tr>
<tr>
<td>35-44 years old</td>
<td>216</td>
<td>17.8 ± 2.2</td>
<td>13.5, 22.1</td>
<td>45</td>
<td>17.6 ± 4.7</td>
<td>8.4, 26.8</td>
<td>56</td>
<td>21.8 ± 4.9</td>
<td>12.1, 31.5</td>
<td>13</td>
<td>13.3 ± 5.5</td>
</tr>
<tr>
<td>45-54 years old</td>
<td>229</td>
<td>18.8 ± 2.4</td>
<td>14.2, 23.5</td>
<td>57</td>
<td>7.2 ± 1.7</td>
<td>4.0, 10.5</td>
<td>63</td>
<td>15.4 ± 3.6</td>
<td>8.3, 22.4</td>
<td>24</td>
<td>19.9 ± 4.0</td>
</tr>
<tr>
<td>55-64 years old</td>
<td>321</td>
<td>14.8 ± 2.0</td>
<td>10.9, 18.7</td>
<td>124</td>
<td>22.2 ± 3.4</td>
<td>15.5, 29.0</td>
<td>74</td>
<td>14.8 ± 2.9</td>
<td>9.1, 20.6</td>
<td>35</td>
<td>19.0 ± 6.4</td>
</tr>
<tr>
<td>≥65 years old</td>
<td>425</td>
<td>12.1 ± 1.2</td>
<td>9.7, 14.5</td>
<td>279</td>
<td>30.1 ± 3.8</td>
<td>22.5, 37.6</td>
<td>91</td>
<td>10.5 ± 2.1</td>
<td>6.3, 14.7</td>
<td>73</td>
<td>33.6 ± 3.8</td>
</tr>
</tbody>
</table>

**Abbreviation.** BRFSS, Behavioral Risk Factor Surveillance System.

*Italic values indicate mean±SE.*
Generally, users without disabilities spent less time in physical activity/week and vigorous physical activity/week than those with disabilities. Additionally, among users with and without disabilities, those who tracked physical activity engaged in leisure physical activity at a substantially higher proportion than those who did not track physical activity (see Table 2).
<table>
<thead>
<tr>
<th>Physical activity outcomes of wearable device users who tracked physical activity by disability status</th>
<th>Track physical activity with wearable device (n=2025)</th>
<th>Not track physical activity with wearable device (n=519)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without disability (n=1479)</td>
<td>With disability (n=546)</td>
</tr>
<tr>
<td>n</td>
<td>Weighted Value ± SE*</td>
<td>95% CI</td>
</tr>
<tr>
<td>Physical activity/week (minutes)</td>
<td>1064</td>
<td>389.2 ± 20.7</td>
</tr>
<tr>
<td>Vigorous physical activity/week (minutes)</td>
<td>1066</td>
<td>74.5 ± 7.5</td>
</tr>
<tr>
<td>METxminutes/week</td>
<td>1040</td>
<td>1471.1 ± 84.8</td>
</tr>
<tr>
<td>Engagement in leisure physical activity (%)</td>
<td>Yes</td>
<td>1090</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>246</td>
</tr>
<tr>
<td>Engagement in &gt; 300 minutes of physical activity or vigorous equivalent minutes/week (%)</td>
<td>Yes</td>
<td>782</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>503</td>
</tr>
<tr>
<td>Meeting aerobic physical activity guidelines (%)</td>
<td>Yes</td>
<td>777</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>513</td>
</tr>
<tr>
<td>Meeting both aerobic and muscles strengthening physical activity guidelines (%)</td>
<td>Yes</td>
<td>315</td>
</tr>
<tr>
<td></td>
<td>No</td>
<td>961</td>
</tr>
</tbody>
</table>

*Italic values indicate mean±SE.

Note. BRFSS, Behavioral Risk Factor Surveillance System; n, unweighted sample size.
No significant differences ($p > .05$) in continuous outcome variables were observed between wearable device users who tracked their activity and those who did not (see Table 3). Additionally, no significant differences ($p > .05$) were observed between those with disabilities and those without. Moreover, no significant interactions between wearable device tracking and disability statuses were observed ($p > .05$).
Table 3. Linear models regressing continuous physical activity outcomes on tracking physical activity with wearable devices and disability status

<table>
<thead>
<tr>
<th>Physical Activity/Week (mins)</th>
<th>Vigorous Physical Activity/Week (mins)</th>
<th>METxMinutes/week</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Unadjusted model&lt;sup&gt;a&lt;/sup&gt;</td>
<td>Adjusted model</td>
</tr>
<tr>
<td><strong>Intercept</strong></td>
<td>3.57</td>
<td>447.75b</td>
</tr>
<tr>
<td></td>
<td>&lt;0.001*</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td><strong>Trackers</strong></td>
<td>.24</td>
<td>-6.04</td>
</tr>
<tr>
<td></td>
<td>0.27</td>
<td>0.90</td>
</tr>
<tr>
<td><strong>Disability</strong></td>
<td>.11</td>
<td>24.82</td>
</tr>
<tr>
<td></td>
<td>0.74</td>
<td>0.81</td>
</tr>
<tr>
<td><strong>Trackers*Disability</strong></td>
<td>-.32</td>
<td>-65.67</td>
</tr>
<tr>
<td></td>
<td>0.41</td>
<td>0.56</td>
</tr>
<tr>
<td></td>
<td><strong>p</strong></td>
<td><strong>p</strong></td>
</tr>
<tr>
<td></td>
<td>.84</td>
<td>.88&lt;sup&gt;c&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td>&lt;0.001*</td>
<td>&lt;0.001*</td>
</tr>
<tr>
<td></td>
<td>-.02</td>
<td>-.005</td>
</tr>
<tr>
<td></td>
<td>0.51</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>-.10</td>
<td>.02</td>
</tr>
<tr>
<td></td>
<td>0.08</td>
<td>0.73</td>
</tr>
<tr>
<td></td>
<td>.07</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td>.03</td>
<td>-.49</td>
</tr>
<tr>
<td></td>
<td>0.31</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>0.51</td>
<td>0.62</td>
</tr>
<tr>
<td></td>
<td>0.51</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Note. <sup>a</sup>Box-cox transformations applied to dependent variables for unadjusted linear models to yield normally distributed and homoscedastic residual distributions. <sup>b</sup>Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m<sup>2</sup>), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no). <sup>c</sup>Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), body mass index (kg/m<sup>2</sup>), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no). <sup>d</sup>Model was adjusted for body mass index (kg/m<sup>2</sup>), race and ethnicity (white, black, Hispanic, other races, multiracial), and employment status (yes, no).

Abbreviation. b, beta-coefficient of regression model.

*, p<.05.
Unadjusted and adjusted logistic regression models were fitted to evaluate the associations between tracker status and disability status with various categorical physical activity outcomes. No significant interactions \((p > .05)\) were found between tracker status and disability status across all unadjusted and adjusted models (see Table 4). Therefore, only main effects from the logistic models are reported. Trackers had a higher log odds of engaging in leisure physical activity than non-trackers in unadjusted and adjusted models \((all \ p < .05)\). Across the unadjusted and adjusted models, wearable device users with disabilities had a lower log odds of engaging in leisure physical activity, engaging in > 300 minutes of physical activity, meeting aerobic physical activity guidelines, and meeting both aerobic and muscle-strengthening physical activity guidelines than wearable device users without disabilities \((all \ p < .05)\).
Table 4. Logistic models regressing binary physical activity outcomes on tracking physical activity outcomes with wearable devices and disability status

<table>
<thead>
<tr>
<th>Trackers</th>
<th>Engage in Leisure Physical Activity</th>
<th>Engage in &gt; 300 Minutes of Physical Activity</th>
<th>Meeting Aerobic Physical Activity Guidelines</th>
<th>Meeting Both Aerobic and Muscle Strengthen Physical Activity Guidelines</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR(^a) [95% CI]</td>
<td>aOR(^b) [95% CI]</td>
<td>OR(^a) [95% CI]</td>
<td>aOR(^c) [95% CI]</td>
</tr>
<tr>
<td>Yes</td>
<td>1.74 [1.05, 2.88](^*)</td>
<td>1.85 [1.08, 3.19](^*)</td>
<td>1.48 [.91, 2.40]</td>
<td>1.59 [.97, 2.60]</td>
</tr>
<tr>
<td>No(^f)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Disability</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>.40 [.24, .66](^*)</td>
<td>.50 [.29, .88](^*)</td>
<td>.62 [.38, 1.00]</td>
<td>.54 [.32, .89] (^*)</td>
</tr>
<tr>
<td>No(^f)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Note. \(^a\)Logistic models included the following independent variables: wearable device utilization (yes, no), tracking physical activity with wearable devices (yes, no), and an interaction term between wearable device utilization and disability status. \(^b\)Model was adjusted for body mass index (kg/m\(^2\)), race and ethnicity (white, black, Hispanic, other races, multiracial), education levels (never attend/kindergarten only, elementary school, some high school, high school graduate, some college/technical school, and college graduate), and employment status (yes, no). \(^c\)Model was adjusted for age group (18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55-64 years old, and ≥65 years old), and body mass index (kg/m\(^2\)). \(^d\)Model was adjusted for body mass index (kg/m\(^2\)). \(^e\)Model was adjusted for body mass index (kg/m\(^2\)), and education levels (never attend/kindergarten only, elementary school, some high school, high school graduate, some college/technical school, and college graduate). \(^f\)“No” is the reference with the odds ratio of 1.0 for each of the regression model.

Abbreviation. OR, odds ratio; aOR, adjusted odds ratio.

\(^*\), \(p<0.05\).
Discussion

This study compared physical activity levels of wearable device users with and without disabilities who did and did not track physical activity using wearables in free-living. Over 50% of participants with and without disabilities reported using wearable devices to track their physical activity. However, no statistically significant effects were observed among the linear regression models with continuous physical activity variables (i.e., physical activity/week, vigorous physical activity/week, and METxminutes/week). Results indicated that users who tracked physical activity had a higher log odds of engaging in leisure physical activity (OR = 1.74, 95% CI [1.05, 2.88]) and meeting aerobic physical activity guidelines (OR = 1.81, 95% CI [1.12, 2.92]) when compared to non-trackers. Consistent with previous studies, individuals with disabilities had a lower log odds of engaging in leisure physical activity (OR = 0.40, 95% CI [0.24, 0.66]), engaging in > 300 minutes of physical activity (aOR = .54, 95% CI [.32, .89]), and meeting both aerobic and muscle-strengthening physical activity guidelines (OR = .32, 95% CI [.17, .60]). Significant associations were observed between disability status and meeting aerobic physical activity guidelines in the logistic regressions after accounting for tracking physical activity status and covariates. Among all linear and logistic regression models, no statistically significant interactions were observed between disability status and physical activity tracker status ($p > .05$).

Study participants in this survey were all wearable device users and results indicated that tracking physical activity with wearable devices was associated with greater engagement in physical activity. Also, physical activity trackers were
associated with meeting aerobic physical activity guidelines. These findings suggest that being aware of one’s own physical activity might increase the motivation of users to engage in physical activity – a finding consistent with previous literature (Jin et al., 2020; O’Loughlin et al., 2021). In an intervention by Bice et al. (2016), adults were given a wearable device with the goal of increasing physical activity motivation. They found that participants had a statistically significant increase in motivation related to physical activity. Thus, the facilitation of motivation toward physical activity from wearable devices could increase physical activity among users.

One of the features of wearable devices is goal setting and gamification (Sullivan & Lachman, 2017). Previous studies have found that individuals who tracked physical activity with wearable devices might set personal physical activity goals or the default physical activity goal of 10,000 steps per day. Furthermore, wearable device users could earn badges or rewards, components of gamification, from the wearable devices when they meet their physical activity goals (Lunney et al., 2016; Sullivan & Lachman, 2017). Sullivan and Lachman also found that the goal settings and gamification features of wearable devices could increase motivation toward physical activity (Sullivan & Lachman, 2017). Overall, the determination of meeting physical activity goals could potentially explain why wearable device users who tracked physical activity levels were more likely to meet aerobic physical activity guidelines herein.

Unlike wearable device interventions, our results found tracking physical activity with wearable devices were not associated with greater time spend in physical activity. The intervention by Martin et al. (2015), among participants without
disabilities, examined the effectiveness of blinding tracked physical activity information from wearable devices in promoting physical activity. That is, participants were not aware of or knew their physical activity levels as tracked by the wearable devices they used. The study found that participants who were not blind to their physical activity levels from wearable devices had significantly higher physical activity levels compared to participants who were blinded to their tracked physical activity levels (Martin et al., 2015). The difference in results herein and by Martin et al. (2015) could be due to the settings. With Martin et al. (2015), participants were given wearable devices to use, and participants provided consent to participate in the intervention. Knowing that someone was tracking their physical activity levels could lead to reactivity, where participants react to the intervention by engaging in more physical activity than their typical everyday life. It was previously found that individuals displayed reactivity to tracking of physical activity by engaging in more physical activity (Stiglbauer et al., 2019). In the current study, participants were not part of an intervention study, and simply engaged in physical activity as part of their daily life and/or routine. Thus, the free-living settings in this study may limit the reactivity that can occur in intervention studies.

Few studies have examined the use of wearable devices and self-monitoring for promoting physical activity among individuals with disabilities. It was previously found that self-monitoring of physical activity among secondary students with autism led to an increase in physical activity (Todd & Reid, 2006). Todd and Reid used a self-monitoring board/grid to promote physical activity instead of using wearable devices. The results showcased that the act of tracking physical activity could
increase physical activity among individuals with autism. A more recent intervention conducted by Kraiss (2017) used a wearable device to promote physical activity through goal-setting and self-monitoring of physical activity among college students with intellectual and developmental disabilities. Four college students between the ages of 18 – 23 years-old with intellectual and developmental disabilities participated in the intervention and increased their daily step counts after setting goals and monitoring their number of steps using wearable devices for 22 days. In this study herein, we found that tracking physical activity with wearable devices was not associated with greater durations spent in physical activity. The difference between this cross-sectional study and other intervention studies could be due to the difference in settings. Participants with disabilities reacted to the interventions when they were told to monitor their own physical activity levels (Hilgenkamp et al., 2012; Zhu & Haegele, 2019). Additionally, participants with disabilities included in this study were based on self-reported disability and functionality associated with disability, rather than a specific diagnosis, such as autism and Down syndrome. The difference in disability diagnoses and types could potentially lead to differences in results between types of disabilities. Further research is needed to examine whether tracking physical activity with wearable devices could increase physical activity among different types of disabilities, per diagnosis.

Results herein align with previous investigations among individuals with disabilities, specifically finding that individuals with disabilities are less likely to engage in leisure physical activity and meet physical activity guidelines than those without disabilities (Hilgenkamp et al., 2012; Jung et al., 2018; McKeon et al., 2013;
Ezeugwu et al. (2015) found that individuals with multiple sclerosis spent more time in sedentary behaviors and less time in light physical activity when measured with accelerometers. It was also found that there was a low prevalence of adults with intellectual disability (10.7%) meeting the aerobic physical activity guidelines (Oviedo et al., 2017). Using the accelerometer data from the National Health and Nutrition Examination Survey (NHANES) from 2003 to 2006, Manns et al. (2015) found that adults with mobility disability had more sedentary time and less active time than those without mobility disability. This study, therefore, contributes to the current literature that highlights the physical activity disparities between individuals with and without disabilities.

It was hypothesized that physical activity levels would differ between disability status across wearable device to track status. It was unexpected that the interaction term between disability status and using wearable devices to track physical activity was not statistically significant. This could be due to the classification of disability status since physical activity levels could be different among different types and diagnoses of disabilities (de Hollander & Proper, 2018; Nordstrøm et al., 2013), documented herein, thereby adding to model error and uncertainty. The experiences of using wearable devices may be different between types and diagnosis of disability as well. Individuals with wheelchairs had more concern using wearable devices due to accessibility and accuracy in tracking their physical activity levels (Carrington et al., 2015). In comparison, individuals with multiple sclerosis had a high acceptability in using wearable devices to track their physical activity and daily step counts in free-living settings (DasMahapatra et al.,
In other words, different types and diagnoses of disability had different levels of physical activity and reacted to wearable devices in tracking physical activity differently. Therefore, more studies are needed to examine the feasibility and reactivity of wearable devices in tracking physical activity among different types and diagnoses of disabilities.

Even though this study is one of the few large-sample studies that examined associations between physical activity behaviors, disability status, and usage of wearable devices in tracking physical activity in a free-living setting it is not without limitations. Since BRFSS utilized self-reported responses on the classification of disability and physical activity levels, there may be social and recall biases reflected in the underlying data summarized here. This could have potentially led to the somewhat common overestimation of physical activity via self-report. It was possible that those who tracked physical activity with wearable devices reported their physical activity levels based on wearable devices in comparing to other approaches, such as memory recall. Therefore, influencing the result of this study. These biases could also be included the variable of using wearable devices to track physical activity.

Unfortunately, the questions used to determine if participants used wearable devices to track physical activity and other health-related indicators were quite broad and likely made it difficult to accurately represent the usage of wearable devices among survey participants. Additionally, there was no operational definition of using wearable devices to track physical activity, sleep patterns, nutrition, calories burned, and health indicators. The physical activity outcomes used in this study were based on self-reported physical activities of the two most frequent activities by each participant.
rather than participants' full range of physical activities engaged in. Therefore, the results of the analysis may not fully represent the physical activity behaviors for each participant. Also, misclassification could occur for determining the intensity of physical activity among participants with disabilities. Previously study by Leung et al. (2021) found that individuals with Down syndrome exhausted more energy when engaging in the same physical activity as individuals without disabilities. Using the provided MET levels from BRFSS could potentially limited the interpretation of the results.

This study showed that individuals who used wearable devices to track physical activity were more likely to engage in leisure physical activity and meet the aerobic physical activity guidelines than were individuals who did not track physical activity with wearable devices. However, individuals with disabilities were less likely to engage in physical activity and meet the aerobic and muscle strengthening physical activity guidelines. This study aligns with other investigations providing significant evidence that individuals with and without disabilities are using wearable devices in an effort to promote physical activity and health. Because wearable devices remain one of the most promising physical activity and health intervention avenues yet to be robustly explored, more research is needed to better understand the associations between wearable devices in tracking physical activity, disability status, and physical activity levels, especially examining the effectiveness of wearable devices in promoting physical activity among different types and diagnoses of disabilities.
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Chapter 4. General Conclusion
This study investigated the association between wearable device usage and physical activity levels of individuals with and without disabilities in free-living settings. This study had two aims: 1) to compare physical activity levels between wearable device users with and without disabilities and non-users with and without disabilities and 2) to compare physical activity levels between wearable device users who tracked physical activity with and without disabilities and wearable device users who did not track physical activity levels with and without disabilities. Self-reported data from the Behavioral Risk Factors Surveillance System (BRFSS) of eight different states (California, Connecticut, Florida, Louisiana, Nebraska, Oregon, Tennessee, and Texas) were utilized in analyses. Numerous linear and logistic regression models were fitted using examination sampling weights, primary sampling unit indicators and stratum variables to account for the complex survey design inherent in BRFSS. Overall, this study suggests that individuals using wearable devices were more likely to engage in leisure physical activity. However, duration in physical activity was not significantly different between wearable device users and non-users. Similar to previous studies, individuals with disabilities were less likely to engage in physical activity and meet physical activity guidelines than those without disabilities.

Across both studies, using wearable devices or tracking physical activity with wearable devices was not associated with increased time spent in physical activity, including physical activity/week (mins), vigorous physical activity/week (mins), and METxminutes/week. However, tracking of physical activity levels was associated
with an increased likelihood of engagement in physical activity despite not being associated with any greater mean amount of time spent in physical activity. A previous systematic review examined the effectiveness of wearable devices for promoting physical activity and found that the majority of interventions (> 50%) used total step counts as the outcome of interest when using wearable devices (Coughlin & Stewart, 2016). While step counts are a standard output of wearable devices, an increase in step counts might not be equivalent to increased time spent in physical activity, or vigorous physical activity specifically, as daily step totals provide no context for the manner in which those steps are accumulated throughout the day. Considering that there is a time component associated with aerobic physical activity guidelines, further research is needed to examine the effectiveness of wearable devices for increasing the duration of physical activity among individuals with and without disabilities.

In this investigation, individuals with disabilities were less likely to engage in physical activity and meet physical activity guidelines. Individuals with disabilities are known to suffer from a number of physical activity-related disparities, where they are less likely to engage in leisure physical activity, higher intensity activities, and meet physical activity guidelines (Hilgenkamp, Reis, et al., 2012; Jung et al., 2018; McKeon et al., 2013; Temple & Walkley, 2003; Wouters et al., 2019). Wearable devices serve as a promising technology that could be useful for promoting physical activity among individuals with disabilities. Multiple interventions found improved physical activity levels among individuals with disabilities using wearable devices (Cai et al., 2017; Olson et al., 2019; Ptomey et al., 2017; Sharan et al., 2016). The
difference in settings, intervention settings, and free-living settings might contribute to the difference in results between this cross-sectional study and other interventions. Therefore, there is a need to continue examinations of the feasibility and the effectiveness of wearable devices for promoting physical activity among individuals with disabilities.

The interaction term between wearable device usage or using wearable devices to track physical activity and disability status was non-significant across all regression models evaluated herein. This suggests that the outcome of physical activity was not moderated by disability status and usage of wearable devices. This could be due to the classification of disability in the current study. The classification of disability was based on participants' self-reported functionality, visual impairments, hearing impairments, cognitive disability, independent living disability, self-care disability, and mobility disability. Different types of disabilities could potentially react to wearable devices differently and hence the combined variable herein may be leaving a significant amount of variance yet to be properly explained. The acceptance of using wearable devices in tracking physical activity and various health information could be different among different disability types as well. Examining the feasibility of using wearable devices to track physical activity and promote physical activity is continuously needed to understand better the effectiveness of wearable devices for promoting physical activity among individuals with various types of disabilities.

The results of this study demonstrate the positive association between wearable devices and promoting certain aspects of physical activity. However, to
fully understand the association between usage of wearable devices, disability status, and physical activity behaviors, more research in free-living settings is needed. Future studies should further examine the association between wearable device usage and different disability types and diagnoses. Various factors could influence individuals with and without disabilities using wearable devices and their association with physical activity behaviors in free-living settings. Identifying these factors can aid in promoting physical activity using wearable devices among individuals with and without disabilities. The goal of using wearable devices is to promote positive health behaviors. A better understanding of the relationship between wearable devices and physical activity could lead to identifying a better approach in promoting physical activity for individuals with and without disabilities.
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Appendix
Appendix A: Literature Review

The purpose of this literature review is to provide the reader with information on the areas of physical activity, physical activity and individuals with disabilities, wearables devices, wearable device interventions of physical activity, self-determination theory and wearable devices, and wearable devices and individuals with disabilities.

Physical Activity

Physical activity is defined as any bodily movement resulting in energy expenditure (Caspersen et al., 1985). Engagement in physical activity can lead to positive health-related benefits, including decreasing the risk for specific type of cancers, metabolic syndrome (e.g., type 2 diabetes), cardiorespiratory disorders and conditions (e.g., heart attack), managing weight, lowering blood pressure and blood cholesterol, lowering the risk of falls, building stronger bones, muscles, and joints, decreasing the risk of osteoporosis, and increasing mood (Haskell et al., 2009b; McReynolds & Rossen, 2004; Steinbeck, 2001; Warburton et al., 2006). It is important to note that these health benefits are more positively associated with higher intensity levels of physical activity (Antero Kesaniemi et al., 2001; Kohl, 2001; Lee & Skerrett, 2001) and physical inactivity is the fourth leading cause of mortality, surpassed by hypertension, tobacco use, and high blood glucose (Blair & Brodney, 1999; Kokkinos et al., 2011; Mokdad et al., 2004; World Health Organization, 2010).

Physical activity can be categorized into three intensity levels: 1) light, 2) moderate, and 3) vigorous levels (Ainsworth et al., 2012; Caspersen et al., 1985). Higher levels of physical activity result from higher levels of energy expenditure,
measured in the unit of MET or metabolic equivalent (Ainsworth et al., 2000, 2011).

One MET could be represented by the amount of energy used sitting quietly (Ainsworth et al., 2011), while higher MET levels indicate higher energy expenditure, thus higher physical activity intensity levels. Physical activity levels are classified into different intensity levels based on the energy expenditure levels or MET levels, as shown in Table 1, according to Ainsworth et al. (2000, 2011) and the 2018 Physical Activity Guidelines Advisory Committee Scientific Report (2018 Physical Activity Guidelines Advisory Committee, 2018). The Compendium of Physical Activities by Ainsworth and colleagues (2000, 2011) can be used as a reference guide for identifying various physical activity at each intensity level.

Table 1. Physical activity intensity levels based on MET levels

<table>
<thead>
<tr>
<th>MET levels</th>
<th>Intensity Levels</th>
<th>Example Activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.5 – &lt; 3</td>
<td>Light</td>
<td>walking slowly, dishwashing, making beds, fishing, playing darts, billiards</td>
</tr>
<tr>
<td>3 – 6</td>
<td>Moderator</td>
<td>brisk pace, washing windows, golfing, light bicycling, light swimming running, basketball, skiing, playing tennis, boxing</td>
</tr>
<tr>
<td>&gt; 6</td>
<td>Vigorous</td>
<td>skiing, playing tennis, boxing</td>
</tr>
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</table>

Note. MET, metabolic equivalent.

According to the recently published physical activity guidelines, adults should engage in at least 150 minutes of accumulated moderate physical activity or 75 minutes of vigorous physical activity per week (2018 Physical Activity Guidelines Advisory Committee, 2018). It is recommended that individuals follow the recommended guidelines to obtain the minimum benefits of physical activity. Even though there are minimum recommendations, many individuals are not meeting the
physical activity guidance, where these individuals have failed to obtain at least 150 minutes of moderate physical activity or 75 minutes of vigorous physical activity per week as measured by self-reported questionnaire (Carlson et al., 2010). Due to the benefits of physical activity and the lack of adults meeting physical activity guidelines, physical activity has become a public health concern, primarily due to the obesity epidemic experiences in the US (Hales et al., 2020; Mokdad et al., 1999; Morrill & Chinn, 2004) relating to physical activity inactivity (Pietiläinen et al., 2008) and physical activity is one of the primary behaviors that can combat the health concerns associated with obesity (Crawford & Ball, 2002; Keim et al., 2004).

**Physical Activity and Individuals with Disabilities**

Compared to individuals without disabilities, individuals with disabilities are less likely to meet the physical activity guidelines (Carroll et al., 2014; Hsieh et al., 2017; Temple & Walkley, 2003). Individuals with disabilities might spend a similar amount of time in light physical activity compared to people without disabilities, however this group is less likely to engage in equivalent amounts of moderate physical activity (Jung et al., 2018). Individuals with disabilities encounter more barriers in promoting physical activity compared to their peers without disabilities (Rimmer et al., 2004; Rimmer et al., 2008). Individuals with disabilities experience personal, social, and environmental barriers when engaging in physical activity, such as lack of motivation, lack of time, negative attitude and stigma toward individuals with disabilities, lack of support system for physical activity, lack of accessible inclusive facilities, lack of trained professionals, and lack of transportation (Rimmer et al., 2004). The barriers that individuals with disabilities face increase the
difficulties for them to engage in physical activity and meet the physical activity guidelines.

Personal factors influence physical activity behaviors of individuals with disabilities. This includes, but is not limited to, lack of motivation, lower self-efficacy, and lower confidence relating to physical activity affect individuals with disabilities' ability to engage in physical activity (McGarty & Melville, 2018; Shields & Synnot, 2016; Temple, 2007). It was found that lack of self-confidence was one of the many barriers that prevent older adults with mild and moderate intellectual disabilities to engage in physical activity (van Schijndel-Speet et al., 2014b).

Additionally, it was found that individuals with intellectual disabilities may feel that without the appropriate assistance from their caregivers, peers, families, or trained professionals, they cannot engage in physical activity (Bodde & Seo, 2009).

Motivation plays an important role in physical activity behaviors, Saebu and Sørensen (2011), using a self-reported questionnaire found that personal factors, such as intrinsic motivation and identifying as an active person, were strongly associated with physical activity behaviors compared to environmental factors in individuals with disabilities. Identifying strategies that increase confidence, motivation, and self-efficacy levels could increase the physical activity levels of individuals with disabilities (Saebu & Sørensen, 2011; van Schijndel-Speet et al., 2014b).

Individuals with disabilities face social and societal barriers to participation in physical activity. This might include stigma and discrimination in physical activity settings (Bodde & Seo, 2009; J. J. Martin, 2013b) and negative attitudes toward disability (Bodde & Seo, 2009; Rimmer et al., 2004). These negative social
environments prevent individuals with disabilities from participating in physical activity due to feelings of being unwanted and uncomfortableness (Bodde & Seo, 2009). It has been found that some parents, caregivers, and families of individuals with disabilities are often worried about individuals with disabilities getting injured during physical activity (Bodde & Seo, 2009). Their concern for individuals with disabilities limit individuals with disabilities from participating in physical activity (Bodde & Seo, 2009). As described by Bodde and Seo (2009), the seemingly negative support hindered individuals with intellectual disabilities from participating in physical activity. This barrier is related to other social barriers of believing individuals with disabilities do not engage in physical activity (Bodde & Seo, 2009; Rimmer et al., 2004; Shields & Synnot, 2014). Believing individuals with disabilities are unable to engage in physical activity negatively reinforces the inactivity of individuals with disabilities. Further, lack of professionals having knowledge and skills working with individuals with disabilities in physical activity settings prevents individuals with disabilities from engaging in physical activity (Rimmer et al., 2004).

Physical accessibility is one of the biggest challenges for individuals with disabilities for engagement in physical activity (Bodde & Seo, 2009; Rimmer et al., 2004; Shields & Synnot, 2014). There is often a lack of appropriate physical activity facilities and environments for individuals with disabilities to safely engage in physical activity (Bodde & Seo, 2009; Buffart et al., 2009; Rimmer et al., 2004). When there are appropriate physical activity facilities for individuals with disabilities, these locations are often found to be inconvenient to individuals with disabilities, such as facilities too far and lack of transportation and time to travel to the facilities (Bodde &
Seo, 2009). Limited transportation prevents participation in physical activity for individuals with disabilities (Bodde & Seo, 2009). Individuals with disabilities often rely on public transit or their caregivers to provide transportation for them (Bodde & Seo, 2009; Rimmer et al., 2004). Sometimes, outdoor physical activity facilities might not be suitable for individuals with disabilities. Outdoor and neighborhoods are often not disability friendly, where individuals with disabilities might not be physically able to access these facilities for physical activity (Rosenberg et al., 2013). For example, for individuals using a wheelchair, a particular surface is not suitable for individuals using wheelchairs (Menzies et al., 2020; Nilsson et al., 2015; Rosenberg et al., 2013). Therefore, it prevents individuals from using a wheelchair in engaging physical activity at a park. Also, specialized equipment is sometimes needed for individuals with disabilities to engage in physical activity at any physical activity facilities, both indoor and outdoor (Brawley et al., 2003; Murphy & Carbone, 2008; Rimmer & Rowland, 2008; Rimmer et al., 2004). Without this equipment, individuals with disabilities might not be able to engage in physical activity fully. Many physical activity facilities might lack specialized equipment at their facilities for individuals to use. This further limited the opportunity of individuals with disabilities to engage in physical activity.

**Wearable Devices**

Wearable devices is one approach to overcome the personal barriers of individuals with disabilities regarding lack of motivation in physical activity. For the past several years, wearable devices have been the top trend in the physical activity and fitness industry for the past several years (Thompson, 2019) and it is popular among the general public (Erdmier et al., 2016; Omura et al., 2017). Wearable devices are a
noninvasive type of technology in the form of small hardware that includes an application with tracking and monitoring fitness metrics such as distance walked, calories consumed, and in some devices, heart rate and sleep pattern tracking (Düking et al., 2018; Kaewkannate & Kim, 2016). The general public and consumers had used wearable devices to monitor their own or other people's fitness and health (Lunney et al., 2016). These devices are viewed as a low-cost alternative to resource-intensive traditional physical activity interventions, such as personal trainers, group exercise classes, and gym membership, that can be used to track various health-related information (Chen et al., 2017). Within recent years, many wearable devices can wirelessly sync information recorded to the smartphone application associated with the device (Erdmier et al., 2016; Kaewkannate & Kim, 2016). This feature allows users to access their information in real-time, which is an advantage of wearable devices because users can receive feedback directly and immediately after certain physical activity and/or movements. Wearable devices are part of the more significant movement of "quantified self," which refers to the cultural phenomenon of self-tracking with technology (Chen et al., 2017; Patel et al., 2015; Stragier et al., 2016). Wearable devices can be used in different populations, such as children, older adults, individuals with disabilities, etc. Many individuals are using these wearable devices to track and monitor their physical well-being.

Providing information in real-time has practical application (Del Rosario et al., 2014). Wearable devices, including smartphone tracking applications, can be used as an intervention targeting physical activity behavior change and weight management through self-monitoring of personal physical activity levels and eating behaviors.
The ability to access information in real-time is a comfortable and convenient method for tracking information compared to the older methods of exercise diaries and retrospective questionnaires, which required users to calculate the information themselves (Kaewkannate & Kim, 2016). Feedback is another aspect of wearable devices where users can track if they have been adherent to the behavior or their goals (Patel et al., 2015). This feedback acts as a tangible record for users in their personal engagement of physical activity (Naslund et al., 2016).

Wearable devices use multiple sensors to record data, including physical activity related-data (Düking et al., 2018; Lunney et al., 2016). Accelerometers are sensors used in almost all wearable devices (Mercer et al., 2016). Other sensors include electrochemical, optical, acoustic, pressure-sensitive, inertial measurement units, and global navigation satellite systems (Düking et al., 2018). Thus, devices allow users to track steps, calorie intake, calories burned, heartrate, exercise frequency, and more (Coughlin & Stewart, 2016; Stragier et al., 2016). Heartrate is a common physical activity metric and can be used to measure physical activity and physical activity intensity levels. Wearable device users favor wearable devices with heartrate monitoring capacity (Kaewkannate & Kim, 2016), possibly because heartrate is an easily understandable metric and device users are more prone to information that is understandable to them (Goodyear et al., 2019).

Another feature of wearable devices is the ability to share information with other people. This social feature is a big part of wearable devices. Individuals can share their information with family, friends, and other wearable device users. It has been found that this social feature increases motivation for physical activity among users.
Using survey data from 394 participants, Stragier et al. (2016) found the online fitness communities associated with wearable devices are highly associated with positive physical activity engagement. Wearable users positively respond to the social feature of wearable devices (Kaewkannate & Kim, 2016). In the online fitness community, the social function of wearable devices, is a big part of wearable devices (Stragier et al., 2016). Wearable device users can share their experiences and records on these online communities that increase their perceived usefulness of these online communities and wearable devices (Stragier et al., 2016). Wearable devices' social features are one feature of wearable devices that can facilitate users' physical activity.

Overall, wearable device users typically have high satisfaction with wearable devices' features and properties, particularly on design and how it fits comfortably on the body (Kaewkannate & Kim, 2016; Naslund et al., 2016). Consumers are more likely to use wearable devices in tracking physical activity if they perceive wearable devices as a benefit and easy to use (Chen et al., 2017; Lunney et al., 2016). Many wearable device users find wearable devices, such as Fitbit devices, fun, motivating, and easy to use (Chen et al., 2017; Naslund et al., 2016). Additionally, wearable device users feel a sense of accomplishment in receiving their feedback and being more active, thus continue using the devices to monitor physical activity levels (Naslund et al., 2016).

Wearable devices can facilitate behavior change, such as increasing physical activity among users (Patel et al., 2015). Having access to physical activity information in real-time could educate and increase users' awareness of their current physical activity levels (Naslund et al., 2016; Patel et al., 2015). Wearable devices could
motivate individuals for behavior change (Patel et al., 2015). For wearable devices to be effective in facilitating behavior changes, the features of wearable devices need to be motivating enough to make changes, users need to remember to use the devices, the devices need to be able to track the targeted behaviors accurately, and feedback from the devices is being delivered to users (Patel et al., 2015). Wearable devices also have the feature of goal setting and reminders and prompt that promote physical activity and help users meet their respective physical activity goals (Naslund et al., 2016; Patel et al., 2015).

Based on the Coventry, Aberdeen, and London-Refined taxonomy on behavior change theory techniques, wearable devices usually contain the various techniques as shown in Table 2. (Lyons et al., 2014; Mercer et al., 2016). Although these techniques might be present in wearable devices, most devices tend to focus on techniques for goal settings, where participants can develop their own physical activity goals; self-regulation, where users can self-monitor their physical activity levels; and social support, where users can share their physical activity levels data with others (Mercer et al., 2016). But features such as goal setting, social comparison, online communities, gamification (e.g., rewards), and providing prompts for habit-forming are designs that promote behavior change (Chen et al., 2017). These techniques presented in wearable devices increase the likelihood of wearable devices being used as an intervention for promoting physical activity levels (Lyons et al., 2014). Because of these techniques being utilized by wearable devices, it is able to promote the behavior change of physical activity among users. For example, the techniques of goal setting on outcomes for physical activity levels are commonly found in many wearable devices. Allowing users to
develop their goals provide a platform for the users to review their goals and determine whether they have met their goals. The wide variety of features of wearable devices can increase physical activity levels of users.

Table 2. Behavior change theory techniques found in wearable devices

<table>
<thead>
<tr>
<th>Behavior change theory techniques</th>
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<tbody>
<tr>
<td>Provides information regarding approval from other people</td>
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<tr>
<td>Provide normative information about others' behaviors</td>
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<tr>
<td>Prompt review of behavioral goals</td>
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<tr>
<td>Provide reward contingent on successful behaviors</td>
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<tr>
<td>Prompt self-monitoring of behaviors</td>
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<tr>
<td>Prompt focus on past successes</td>
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<tr>
<td>Provide feedback on performances</td>
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<tr>
<td>Facilitate social comparison</td>
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<tr>
<td>Plan social support/social change</td>
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<tr>
<td>Goal setting on behaviors</td>
</tr>
<tr>
<td>Stimulate anticipation of future rewards</td>
</tr>
<tr>
<td>Goal setting on outcomes</td>
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<tr>
<td>Prompt review of outcome goals</td>
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<tr>
<td>Prompt rewards contingent on the effort or progress towards behaviors</td>
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<tr>
<td>Prompt self-monitoring of behavioral outcomes</td>
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<tr>
<td>Provide instruction on how to perform the behaviors</td>
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<tr>
<td>Teach to use prompts and cues</td>
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<tr>
<td>Provide information on the consequences of behaviors in general</td>
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<tr>
<td>Shaping</td>
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<tr>
<td>Provide information on the consequences of behaviors to the individuals</td>
</tr>
<tr>
<td>Provide information on where and when to perform the behaviors</td>
</tr>
<tr>
<td>Prompt practices</td>
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<tr>
<td>Time management</td>
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<tr>
<td>Action planning</td>
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<td>Model and demonstrate the behaviors</td>
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Wearable Device Interventions for Physical Activity

Wearable devices can be easily used within physical activity interventions to increase physical activity levels (Mercer et al., 2016). Many interventions have utilized wearable devices in promoting physical activity among individuals without disabilities. For example, Pope et al. (2019) administered a 12-week randomized trial pilot intervention using Polar M400 devices among 38 college students with the mean age
of 21.5±3.4 years. The purpose of the intervention was to promote physical activity and dietary behaviors among college students. The intervention utilized both wearable devices (i.e., Polar M400) and health education classes based on the behavioral change theory of social cognitive theory (Pope et al., 2019). The intervention results found that wearable devices facilitated and increased physical activity among college students when used along with the health education classes. Gordon and Bloxham (2017) compared the effect of Fitbit Charge HR and pedometers in increasing physical activity among 17 non-chronic lower back pain individuals (9 in the Fitbit Charge HR group and 8 in the pedometer group). They found an increase in physical activity in both groups after three months, but there were no significant differences in the increased steps between the two groups. Kim et al. (2018) examined the effect of using Misfit Flash in promoting 87 college students' physical activity for a 15 weeks intervention. The intervention results indicated that the control group (non-wearable device group) had a significant decrease in moderate-to-vigorous physical activity (MVPA). In contrast, the intervention group (wearable device group) had a nonsignificant change in MVPA after 15 weeks (Kim et al., 2018). Both groups showed a decrease in MVPA and increased sedentary behaviors after the intervention ended (Kim et al., 2018). The intervention results found that without additional behavior change techniques and intervention among college students, using wearable devices alone might not increase physical activity levels (Kim et al., 2018). The results from the study demonstrate that using wearable devices alone might not increase physical activity after a period of using. Also individuals differences regarding motivation, trust in devices, and useability of devices influences how wearable device users are using the device for
increasing physical activity levels (Rupp et al., 2018a). In another study, Jauho et al. (2015) found that using the wearable device of Polar Active increased daily activity among Finnish young men. The experimental group decreased sedentary behaviors in the short-term when compared to the control group. However, there were no significant physical activity differences in the long term (e.g., three months) (Jauho et al., 2015). Also, Kurti and Dallery (2013) conducted a non-randomized trial of Fitbit-based physical activity intervention among 12 adults over 50 years and found a positive increase in step counts after two months by 182%. A similar intervention by Washington et al. (2014) used a Fitbit-based physical activity intervention among 11 healthy adults between 18 and 26 years and found an increase of overall step counts of 23% after three weeks. In a randomized controlled trial of a six weeks Fitbit intervention, Wang et al. (2015) found a positive increase in moderate to vigorous physical activity within the intervention group of using wearable devices. Still, there were no group differences when compared to the control group. Despite the weakness found among these interventions, interventions using wearable devices demonstrated their ability to promote physical activity among individuals without disabilities.

In the systematic review by Coughlin and Stewart (2016), including six pre- and post-test trials and seven randomized control trials, found wearable devices can be used for physical activity promotion. Various brands of consumer wearable devices, such as Fitbit, Dynamo Activity Tracker, and IDEA, were found to be among the included studies included to promote physical activity behavior. The review found that it was feasible to use wearable devices to promote physical activity. However, it did find that many of these studies were limited by small sample size, short study duration,
and uncertain generalizability (Coughlin & Stewart, 2016). It is important to note that many of these interventions provided the participants' wearable devices, rather than participants already owning a wearable device. Brickwood et al.'s (2019b) meta-analysis investigated wearable devices' effectiveness in increasing physical activity among interventions that included components of wearable devices. A total of studies of 26 articles were included in the meta-analysis. The results of the meta-analysis found there was a significant increase in steps among wearable device users (SMD = .23, 95% CI [.15, .32], p < .001) and control group with an approximate increase of 627 steps (95% CI [417, 862]) per day (Brickwood et al., 2019b). The meta-analysis found that wearable device users had increased in minutes per day present in MVPA compared to the control group (SMD = .28, 95% CI [.14, 41], p < .001) (Brickwood et al., 2019b). Increase in energy expenditure were also observed among wearable device users in compared to the control group (SMD = .32, 95% CI [.05, .58], p = .02) (Brickwood et al., 2019b). However, there were nonsignificant decreases in sedentary behavior between wearable device users and control (SMD = -.21, 95% CI [-.46, .03], p = .09) (Brickwood et al., 2019b). One interesting finding of the meta-analysis was the combination of wearable devices and other behavior changes techniques will yield larger effects in promoting physical activity compared to using wearable devices alone (Brickwood et al., 2019b). In the meta-analysis by Fanning et al. (2012) examining the effect of using mobile devices in promoting physical activity levels found similar results. A total of 13 studies were included in the meta-analysis and found that a positive mean effect of using mobile phones and mobile phone application in increasing physical activity (g = .54, 95% CI [.17, .91], p = .01) (Fanning et al., 2012). Regardless
of differences in intervention protocols, wearable devices can increase the participants' physical activity levels in the intervention. The overall effect of wearable devices on physical activity is positive.

There are interventions aimed to identify the feasibility of using wearable devices in promoting physical activity, as seen in the systematic review by Hu et al. (2020). A total of 19 studies with five randomized controlled trials, six non-randomized studies, five qualitative studies, and three reviews were included in the systematic review by Hu et al. (2020). The systematic review investigated the perspective of overweight and obese individuals in using wearable devices for weight management. It found that wearable device users like wearable devices. Device users increased their awareness of their physical activity levels while feedback from devices promoted their physical activity levels. The review also identified that wearable devices increased users' self-efficacy related to physical activity. In a non-randomized study of 6 months with Fitbit devices for 11 individuals with serious mental illness and obesity conducted by Naslund et al. (2016) found individuals agreeing with the results of the systematic review by Hu et al. (2020). Participants in Naslund et al. (2016) were highly satisfied with the devices and stated that they might continue using the devices for physical activity promotion (Naslund et al., 2016). However, in the study by Goodyear, Kerner, and Quennerstedt (2019), findings indicated that children and adolescents had inconclusive attitudes toward wearable devices in promoting physical activity. The study found that the children and adolescents found that Fitbit devices helped increase their physical activity levels, especially feedback from the devices. Some expressed that the feedback made them feel bad about themselves for not meeting the physical
activity goals. Also, the competition caused by peer surveillance with Fitbit devices discouraged them from enjoying being physically active. They expressed that they engaged in physical activity to "best" their peers, which created an unhealthy environment for them. This study also found that many wearable device users only felt comfortable monitoring behaviors (physical activity metrics) that they understand. These interventions demonstrated that there are high acceptance and feasibility of using wearable devices in promoting physical activity, where wearable device users found these devices to be useful in increasing their physical activity levels.

**Self-Determination Theory and Wearable Devices**

Many users of wearable devices aim to increase or maintain their physical activity levels. The increase in physical activity levels found among wearable devices users can be explained through self-determination theory. Self-determination theory focuses on the idea that an increase in motivation toward the desired behavior will lead to behavior change (Kerner & Goodyear, 2017; Ryan & Deci, 2000). If someone increases their motivation in participating in physical activity, they are more likely to engage in physical activity. However, physical activity motivation needs to be voluntary or self-determined (Kerner & Goodyear, 2017).

Three primary psychological needs need to be met in the self-determination theory, 1) autonomy, 2) competence, and 3) relatedness (Ryan & Deci, 2000). When individuals are satisfied with these three psychological needs, they are more motivated, leading to behavior change. The need for autonomy is related to an individual's locus of control—in other words, it is about their own choices in their behaviors (DeCharms, 1968). In terms of physical activity, it can be about the individuals' choice of activity
and their choice of participating in physical activity. When individuals control their own activity choice, they are more likely to engage in physical activity. This is also related to the individuals having control of their physical activity behaviors, where they originate from their behaviors. The need for competence is related to the desire to feel capable and confident when executing a behavior (Skinner & Belmont, 1993). In relation to physical activity, when someone is confident in their ability to engage in physical activity, they are more likely to engage in physical activity. This can be related to their self-efficacy levels. For example, when someone is confident in their skill in shooting a basketball, they are more likely to shoot the basketball as physical activity. The last psychological need is the need for relatedness. This psychological need is associated with connecting with other people (Baumeister & Leary, 1995). Under the self-determination theory, relatedness is about making a social connection with other people. When individuals have peers that engage in physical activity with them, they are more likely to participate in physical activity.

It is hypothesized that using wearable devices could increase motivation in physical activity based on the self-determination theory (Friel & Garber, 2020; Nuss et al., 2020; Schaben & Furness, 2018). Wearable devices' features can fulfill the psychological needs of autonomy, competence, and relatedness (Kerner & Goodyear, 2017; Rupp et al., 2018a; Ryan & Deci, 2000). Many wearable devices allow users to personalize goals that meet their ability levels (Kerner & Goodyear, 2017). Also, wearable devices do not prescribe or restrict the type of activity a user engages in (Kerner & Goodyear, 2017). Wearable devices can fulfill the autonomy needs as it allows users to make their own decision regarding their physical activity levels (Friel
Wearable devices also meet competence needs by providing feedback on physical activity levels (Gualtieri et al., 2016; Kerner & Goodyear, 2017). Providing feedback could increase users' confidence regarding physical activity (Gualtieri et al., 2016). Also, wearable devices use badges, alerts, and prompts, all feedback, to increase users' competence levels in physical activity (Kerner & Goodyear, 2017). By tracking user's physical activity levels and providing feedback, it allows users to know whether they meet their physical activity goals or not. Feedback from wearable devices can help motivated users to engage in physical activity. When the users discover that they did not meet their physical activity goals from the feedback provided from their wearable devices, it might motivate them to increase their physical activity to meet their goals (Gualtieri et al., 2016; Rupp et al., 2016). The ability to set personalized physical activity-related goals can increase competence levels because the wearable users can better meet the goal (Rupp et al., 2016). The dashboard of providing feedback allows users to access their competency level and autonomy to better engage in physical activity (Friel & Garber, 2020). It is found that wearable devices using multiple competency supportive strategies such as affording users with the required skills, differentiation of exercise sequences, encouraging self-reflection, giving opportunities for receiving constructive feedback (Friel & Garber, 2020). The social features of wearable devices and their associated smartphone applications and online forums/communities allow users to form meaningful relationships with other users (Kerner & Goodyear, 2017). Wearable device users can further share their data with their family and friends and challenge each other in friendly competitions (Kerner & Goodyear, 2017; Rupp et al., 2016). Using Wearable devices can impact users'
motivation in engagement in physical activity (Friel & Garber, 2020; Kerner & Goodyear, 2017; Nuss et al., 2020). By incorporating the psychological needs from self-determination theory into the features of wearable devices can increase users' autonomy, competence, and relatedness and are more likely to utilize the devices (Lee et al., 2015). Wearable device users increase motivation in physical activity (Friel & Garber, 2020; Nuss et al., 2020). Increased physical activity motivation will lead to an increase in physical activity (Friel & Garber, 2020).

**Wearable Devices and Individuals with Disabilities**

Individuals with disabilities are interested in using wearable devices in tracking their physical activity levels. It was found that wheelchair athletes are interested in using wearable devices in tracking their physical activity (Carrington et al., 2015). But the wheelchair athletes in the study were worried about the accessibility of the devices and the accuracy of the devices (Carrington et al., 2015). A standard unit among wearable devices is steps, and the number of steps is often used in the algorithm in estimating energy expenditure and calorie burn. Therefore, it might not be appropriate for individuals who use a wheelchair to use wearable devices to track their physical activity levels. It was found that individuals with mobility impairments are interested in using wearable devices and have a positive perception of wearable devices (Malu & Findlater, 2016b). Like individuals using a wheelchair, individuals with mobility impairments worry that wearable devices are not being inclusive enough (Malu & Findlater, 2016b). Many of these individuals perceived wearable devices not being accurate in measuring their movements and physical activity levels (Malu & Findlater, 2016b). In the same study, individuals with cerebral palsy found wearable devices of
Fitbit Flex are challenging to keep on their wrist (Malu & Findlater, 2016b). The study also found some of the Fitbit devices' motivation strategies used to meet their ability levels (Malu & Findlater, 2016b). Rather than steps, individuals using wheelchair found the information of calories burned to be more useful than steps and stairs climbed from Fitbit devices (Malu & Findlater, 2016b). Despite the limitation of wearable devices as perceived by individuals with mobility, many of them view wearable devices to be positive and could facilitate their physical activity behaviors (Malu & Findlater, 2016b). In addition to individuals with wheelchair and mobility impairments, individuals with multiple sclerosis are also using wearable devices to track their physical activity levels (Block et al., 2017). Wearable device users with multiple sclerosis found the devices to be less expensive, more fashion-friendly, and could potentially allow for longer-term step count monitoring (Block et al., 2017). A study by Ptomey et al. (2017) examined the feasibility of wearable devices such as pedometer and accelerometer in measuring physical activity in adults with intellectual and developmental disabilities (IDD) and found that individuals with IDD can use pedometer but not accelerometer to self-monitor physical activity. Individuals with IDD have high compliance with wearing pedometers but often need reminders from other people to remind them (Ptomey et al., 2017). Like individuals with mobility impairments and multiple sclerosis, there is less accuracy in measuring individuals with IDD's physical activity levels with wearable devices (i.e., pedometer) (Ptomey et al., 2017). In addition to adults with IDD, children with IDD also have a high compliance rate with wearable devices such as Fitbit Charge HR (Brazendale et al., 2019). Overall,
evidence suggests that individuals with disabilities are using wearable devices and perceive wearable devices can positively influence their physical activity behaviors.

There was evidence suggesting that individuals with disabilities can increase their physical activity levels through wearable devices. It was found that among 27 young adults with Down syndrome (mean age of 27.9 years old) increased their physical activity levels using Fitbit, online exercise sessions, individual support and education, and homework (Ptomey et al., 2019). In the intervention, adults with Down syndrome found Fitbit devices useful in motivating them to increase their physical activity levels and enjoyed using them during the 12 weeks intervention (Ptomey et al., 2019). In another intervention for individuals with cerebral palsy found the feedback from wearable devices to be useful in increasing physical activity (Sharan et al., 2016). In a randomized controlled trial of 20 individuals with cerebral palsy aged 10 to 20 years received exercise training form physical therapists and wearable devices around their neck to have higher step counts and distance walked in compared to the control group that did not receive wearable device (Sharan et al., 2016). The intervention allowed participants with cerebral palsy with the wearable devices to set their own step goals and found that goal-setting help motivated the participants with cerebral palsy (Sharan et al., 2016).
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###2017 BRFSS
###200705

###directory
setwd("~/Documents/2017 BRFSS/Data Only")
dir()

###package
library(rio)
library(foreign)
library(haven)
library(dplyr)
library(survey)
library(MASS)
library(jtools)

###cdc
llcp2017 <- import("LLCP2017.XPT")
dat_all <- read.xport("LLCP2017.XPT")
colnames(dat_all)

###oregon
dat_or <- read_sas("or_brfss2017.sas7bdat", NULL)
dat_or$WDUSENOW_or <- dat_or$WDUSENOW
dat_or$WDSHARE_or <- dat_or$WDSHARE
dat_or$typeinfo_or <- coalesce(dat_or$WDINFTKR1, dat_or$WDINFTKR2,
dat_or$WDINFTKR3, dat_or$WDINFTKR4, dat_or$WDINFTKR5)
or <- subset(dat_or, select=c("SEQNO_OREGON",
                          WDUSENOW_or, WDSHARE_or, typeinfo_or
                      ))
dat_all_or <- merge(x=dat_all, y=or, by.x='SEQNO', by.y='SEQNO_OREGON',
                      all.x=T)
remove(list=c('dat_or', 'or'))

###california
dat_ca <- read_sas("ca_brfss_17pr2.sas7bdat", NULL)
ca <- subset(dat_ca, select=c("SEQNO",
                           WEAR1, WEAR2, WEAR3, WEAR4
                       ))
dat_all_or_ca <- merge(x=dat_all_or, y=ca, by.x='SEQNO', by.y='SEQNO', all.x=T)
dat_all_or_ca$wearable <- coalesce(dat_all_or_ca$WDUSENOW_or, 
    dat_all_or_ca$WEAR1)

dat_all_or_ca$shareinfo <- coalesce(dat_all_or_ca$WDSHARE_or, 
    dat_all_or_ca$WEAR4)

dat_all_or_ca$typeinfo <- coalesce(dat_all_or_ca$typeinfo_or, 
    dat_all_or_ca$WEAR2)

remove(list=c('dat_ca', 'ca'))

###florida

dat_fl <- read_sas("fl_brfss17_public.sas7bdat", NULL)

dat_fl$WDUSENOW_fl <- dat_fl$WDUSENOW

dat_fl$WDSHARE_fl <- dat_fl$WDSHARE

dat_fl$WDINFTRK_fl <- as.numeric(dat_fl$WDINFTRK)

g <- subset(dat_fl, select=c(
    SEQNO, 
    WDUSENOW_fl, WDSHARE_fl, WDINFTRK_fl
))

dat_all_or_ca_fl <- merge(x=dat_all_or_ca, y=g, by.x='SEQNO', by.y='SEQNO',
    all.x=T)

dat_all_or_ca_fl$wearable <- coalesce(dat_all_or_ca_fl$wearable, 
    dat_all_or_ca_fl$WDUSENOW_fl)

dat_all_or_ca_fl$shareinfo <- coalesce(dat_all_or_ca_fl$shareinfo, 
    dat_all_or_ca_fl$WDSHARE_fl)

dat_all_or_ca_fl$typeinfo <- coalesce(dat_all_or_ca_fl$typeinfo, 
    dat_all_or_ca_fl$WDINFTRK_fl)

remove(list=c('dat_fl', 'fl'))

###texas


dat_tx <- read_sas("tx_state_17_working_pudf.sas7bdat", NULL)

dat_tx$typeinfo_tx <- coalesce(dat_tx$tx13q02a, dat_tx$tx13q02b, dat_tx$tx13q02c, 
    dat_tx$tx13q02d, dat_tx$tx13q02e)

g <- subset(dat_tx, select=c(
    seqno, 
    tx13q01, typeinfo_tx, tx13q04
))

dat_all_or_ca_fl_tx <- merge(x=dat_all_or_ca_fl, y=g, by.x='SEQNO', by.y='seqno',
    all.x=T)

remove(list=c('dat_fl', 'fl'))
dat_all_or_ca_fl_tx$typeinfo <- coalesce(dat_all_or_ca_fl_tx$typeinfo, 
dat_all_or_ca_fl_tx$typeinfo tx)

remove(list=c('dat_tx', 'tx'))

### tennessee
dat_tn <- read_sas("tn_wearable2.sas7bdat", NULL)
dat_tn$WDUSENOW_tn <- dat_tn$WDUSENOW
dat_tn$WDSHARE_tn <- dat_tn$WDSHARE
dat_tn$WDINFTRK_tn <- as.numeric(dat_tn$WDINFTRK)

tn <- subset(dat_tn, select=c(  
SEQNO,  
WDUSENOW_tn, WDSHARE_tn, WDINFTRK_tn  
))

dat_all_or_ca_fl_tx_tn <- merge(x=dat_all_or_ca_fl_tx, y=tn, by.x='SEQNO',  
by.y='SEQNO', all.x=T)

dat_all_or_ca_fl_tx_tn$wearable <- coalesce(dat_all_or_ca_fl_tx_tn$wearable,  
dat_all_or_ca_fl_tx_tn$WDUSENOW_tn)
dat_all_or_ca_fl_tx_tn$shareinfo <- coalesce(dat_all_or_ca_fl_tx_tn$shareinfo,  
dat_all_or_ca_fl_tx_tn$WDSHARE_tn)
dat_all_or_ca_fl_tx_tn$typeinfo <- coalesce(dat_all_or_ca_fl_tx_tn$typeinfo,  
dat_all_or_ca_fl_tx_tn$WDINFTRK_tn)

remove(list=c('dat_tn', 'tn'))

### connecticut
dat_ct <- read_sas("ct_brfssct_2017_notwn_stadd_chld.sas7bdat", NULL)
dat_ct$WDUSENOW_ct <- dat_ct$WDUSENOW
dat_ct$WDINFTRK_ct <- as.numeric(dat_ct$WDINFTRK)
dat_ct$WDSHARE_ct <- dat_ct$WDSHARE
c <- subset(dat_ct, select=c(  
SEQNO,  
WDUSENOW_ct, WDINFTRK_ct, WDSHARE_ct  
))

dat_all_or_ca_fl_tx_tn_ct <- merge(x=dat_all_or_ca_fl_tx, y=ct, by.x='SEQNO',  
by.y='SEQNO', all.x=T)

dat_all_or_ca_fl_tx_tn_ct$wearable <- coalesce(dat_all_or_ca_fl_tx_tn_ct$wearable,  
dat_all_or_ca_fl_tx_tn_ct$WDUSENOW_ct)
dat_all_or_ca_fl_tx_tn_ct$shareinfo <- coalesce(dat_all_or_ca_fl_tx_tn_ct$shareinfo,  
dat_all_or_ca_fl_tx_tn_ct$WDSHARE_ct)
dat_all_or_ca_fl_tx_tn_ct$typeinfo <- coalesce(dat_all_or_ca_fl_tx_tn_ct$typeinfo,  
dat_all_or_ca_fl_tx_tn_ct$WDINFTRK_ct)
remove(list=c('dat_ct', 'ct'))

### louisiana
dat_la <- read_sas("LABRFSSDATASET2017.sas7bdat", NULL)
dat_la$WDUSENOW_la <- dat_la$WDUSENOW
dat_la$WDINFTRK_la <- as.numeric(dat_la$WDINFTRK)
dat_la$WDSHARE_la <- dat_la$WDSHARE
la <- subset(dat_la, select=c(
    SEQNO,
    WDUSENOW_la, WDINFTRK_la, WDSHARE_la
))
dat_all_or_ca_fl_tx_tn_ct_la <- merge(x=dat_all_or_ca_fl_tx_tn_ct, y=la,
    by.x='SEQNO', b.y='SEQNO', all.x=T)
dat_all_or_ca_fl_tx_tn_ct_la$wearable <-
    coalesce(dat_all_or_ca_fl_tx_tn_ct_la$wearable,
        dat_all_or_ca_fl_tx_tn_ct_la$WDUSENOW_la)
dat_all_or_ca_fl_tx_tn_ct_la$shareinfo <-
    coalesce(dat_all_or_ca_fl_tx_tn_ct_la$shareinfo,
        dat_all_or_ca_fl_tx_tn_ct_la$WDSHARE_la)
dat_all_or_ca_fl_tx_tn_ct_la$typeinfo <-
    coalesce(dat_all_or_ca_fl_tx_tn_ct_la$typeinfo,
        dat_all_or_ca_fl_tx_tn_ct_la$WDINFTRK_la)
remove(list=c('dat_l', 'la'))

### nebraska
dat_ne <- read_sas("nebrfss_2017_osu_request.sas7bdat", NULL)
dat_ne$WDUSENOW_ne <- dat_ne$WDUSENOW
dat_ne$WDINFTRK_ne <- as.numeric(dat_ne$WDINFTRK)
dat_ne$WDSHARE_ne <- dat_ne$WDSHARE
ne <- subset(dat_ne, select=c(
    SEQNO,
    WDUSENOW_ne, WDINFTRK_ne, WDSHARE_ne))
dat_all_or_ca_fl_tx_tn_ct_la_ne <- merge(x=dat_all_or_ca_fl_tx_tn_ct, y=ne,
    by.x='SEQNO', b.y='SEQNO', all.x=T)
dat_all_or_ca_fl_tx_tn_ct_la_ne$wearable <-
    coalesce(dat_all_or_ca_fl_tx_tn_ct_la_ne$wearable,
        dat_all_or_ca_fl_tx_tn_ct_la_ne$WDUSENOW_ne)
dat_all_or_ca_fl_tx_tn_ct_la_ne$shareinfo <-
coalesce(dat_all_or_ca_fl_tx_tn_ct_la_ne$shareinfo,
          dat_all_or_ca_fl_tx_tn_ct_la_ne$WDSHARE_ne)

dat_all_or_ca_fl_tx_tn_ct_la_ne$typeinfo <-
coalesce(dat_all_or_ca_fl_tx_tn_ct_la_ne$typeinfo,
          dat_all_or_ca_fl_tx_tn_ct_la_ne$WDINFTTRK_ne)

remove(list=c('dat_ne', 'ne'))

###subset state data

dat <- subset(dat_all_or_ca_fl_tx_tn_ct_la,
                dat_all_or_ca_fl_tx_tn_ct_la$X_STATE==c(6, 41, 48, 9, 22, 31))
colnames(dat)

remove(list=c('dat_all', 'dat_all_or', 'dat_all_or_ca', 'dat_all_or_ca_fl',
             'dat_all_or_ca_fl_tx', 'dat_all_or_ca_fl_tx_tn',
             'dat_all_or_ca_fl_tx_tn_ct', 'dat_all_or_ca_fl_tx_tn_ct_la',
             'dat_all_or_ca_fl_tx_tn_ct_la_ne'))

###7 & 9 & 99 = NA

dat$wearable <- ifelse(dat$wearable %in% c(7, 9, 99), NA, dat$wearable)
dat$wearable <- ifelse(dat$wearable==2, 0, dat$wearable)
dat$shareinfo <- ifelse(dat$shareinfo %in% c(7, 9, 99), NA, dat$shareinfo)
dat$shareinfo <- ifelse(dat$shareinfo==2, 0, dat$shareinfo)
dat$typeinfo <- ifelse(dat$typeinfo %in% c(7, 9, 99), NA, dat$typeinfo)

###type of infor measure

###physical activity

dat$trackpa <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(12, 1, 135,
                                                                     1235, 13, 123, 1234, 134, 31, 215, 145, 125, 3125, 132, 241, 14, 312, 124, 3142, 213,
                                                                     15, 13452, 321, 12345, 1345, 241, 21, 231, 1342, 142, 415, 41, 2134, 1423, 451, 314,
                                                                     3214, 315, 13245, 51, 1325, 3512, 143, 1243, 152, 1245), 1, 0))
dat$trackpa5 <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(12, 1,
                                                                      135, 1235, 13, 123, 1234, 134, 31, 215, 145, 125, 3125, 132, 241, 14, 312, 124, 3142,
                                                                      213, 15, 13452, 321, 12345, 1345, 241, 21, 231, 1342, 142, 415, 41, 2134, 1423, 451,
                                                                      314, 3214, 315, 13245, 51, 1325, 3512, 143, 1243, 152, 1245, 5, 35, 45, 25,235, 245),
                                                                      1, 0))

###nutrition/calories

dat$tracknut <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(12, 2,
                                                                         1235, 123, 1234, 215, 125, 3125, 24, 132, 241, 312, 124, 3142, 213, 13452, 321,
                                                                         12345, 25, 23, 214, 21, 231, 235, 1342, 142, 32, 2134, 1423, 245, 3214, 13245, 1325,
                                                                         3512, 42, 1243, 152, 1245), 1, 0))
dat$tracknut5 <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(12, 2,
                                                                          1235, 123, 1234, 215, 125, 3125, 24, 132, 241, 312, 124, 3142, 213, 13452, 321,
### Sleep

```r
dat$tracksleep <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(135, 1235, 34, 13, 123, 1234, 3, 134, 31, 3125, 132, 35, 312, 3142, 213, 13452, 321, 12345, 1345, 23, 231, 235, 1342, 32, 2134, 1423, 3142, 3214, 315, 13245, 1325, 1345, 23, 231, 235, 1342, 32, 2134, 1423, 3142, 3214, 315, 13245, 1325, 1352, 143, 1243, 152, 1245, 5, 25, 235, 245), 1, 0))
dat$tracksleep5 <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(135, 1235, 34, 13, 123, 1234, 3, 134, 31, 3125, 132, 35, 312, 3142, 213, 13452, 321, 12345, 1345, 23, 231, 235, 1342, 32, 2134, 1423, 3142, 3214, 315, 13245, 1325, 1352, 143, 1243, 5, 35, 235), 1, 0))
```

### Chronic indicator (blood sugar, blood pressure)

```r
dat$trackcond <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(34, 4, 1234, 134, 145, 24, 241, 14, 124, 3142, 13452, 45, 12345, 1345, 23, 214, 142, 415, 41, 2134, 1423, 451, 314, 245, 3214, 13245, 1432, 1423, 1243, 2143, 1245, 5, 45, 245), 1, 0))
dat$trackcond5 <- ifelse(is.na(dat$typeinfo), NA, ifelse(dat$typeinfo %in% c(34, 4, 1234, 134, 145, 24, 241, 14, 124, 3142, 13452, 45, 12345, 1345, 23, 214, 142, 415, 41, 2134, 1423, 451, 314, 245, 3214, 13245, 1432, 1423, 1243, 2143, 1245, 5, 45, 245), 1, 0))
```

### Disability status

```r
### 7 & 9 & 99 = NA
dat$blind <- ifelse(dat$BLIND %in% c(7, 9, 99), NA, dat$BLIND)
dat$deaf <- ifelse(dat$DEAF %in% c(7, 9, 99), NA, dat$DEAF)
dat$decide <- ifelse(dat$DECIDE %in% c(7, 9, 99), NA, dat$DECIDE)
dat$diffalon <- ifelse(dat$DIFFALON %in% c(7, 9, 99), NA, dat$DIFFALON)
dat$diffdres <- ifelse(dat$DIFFDRES %in% c(7, 9, 99), NA, dat$DIFFDRES)
dat$diffwalk <- ifelse(dat$DIFFWALK %in% c(7, 9, 99), NA, dat$DIFFWALK)
```

### Disability variable

```r
dat$dis <- ifelse(dat$blind==1 & !is.na(dat$blind) | dat$deaf==1 & !is.na(dat$deaf) | dat$decide==1 & !is.na(dat$decide) | dat$diffalon==1 & !is.na(dat$diffalon) | dat$diffdres==1 & !is.na(dat$diffdres) | dat$diffwalk==1 & !is.na(dat$diffwalk), 1, 0)
```

### Physical activity variable

```r
###EXERANY2 During the past month, other than your regular job, did you participate in any physical activity
###binary (yes/no)
dat$EXERANY2 [dat$EXERANY2==" "] <- NA
dat$pa <- ifelse(dat$EXERANY2 %in% c(7, 9), NA, dat$EXERANY2)
```

```r
dat$pa <- ifelse(dat$pa == 2, 0, dat$pa)
```

```r
###PA1MIN_ Minutes of total physical activity per week
###continuous
dat$PA1MIN_ [dat$PA1MIN_==" "] <- NA
dat$spamin_week <- dat$PA1MIN_
### PA1VIGM Minutes of total vigorous physical activity per week
### continuous
dat$PA1VIGM_[dat$PA1VIGM_==" "] <- NA
### PA150R2 150 Minute Physical Activity Calculated
### binary
dat$X_PA150R2 [dat$X_PA150R2==" "] <- NA
dat$pa150min <- ifelse(dat$X_PA150R2 %in% 9, NA, dat$X_PA150R2)
dat$pa150min <- ifelse(dat$pa150min %in% c(2, 3), 0, dat$pa150min)
### PAINDX1 Physical Activity Index (meeting aerobic recommendations)
dat$X_PAINDX1 [dat$X_PAINDX1==" "] <- NA
dat$paguide <- ifelse(dat$X_PAINDX1 %in% 9, NA, dat$X_PAINDX1)
dat$paguide <- ifelse(dat$paguide == 2, 0, dat$paguide)
### _PAINDX1 Physical Activity Index (meeting aerobic recommendations)
### categorical
dat$paactivecat <- ifelse(dat$paactive %in% 4, 0, dat$paactive)
### vigorous mins per week
dat$PA1VIGM_[dat$PA1VIGM_==" "] <- NA
dat$vigmin <- dat$PA1VIGM_
### strength activities frequency per week (times)
dat$STRFREQ_[dat$STRFREQ_==" "] <- NA
dat$strengthact <- ifelse(dat$STRFREQ_ >= 99000, NA, dat$STRFREQ_)
dat$strengthact <- dat$strengthact/1000
### 300 mins of MVPA (1 = 301+ and 0 = 0-300)
dat$pa300 <- ifelse(dat$X_PA30021 %in% 9, NA, dat$X_PA30021)
dat$pa300 <- ifelse(dat$pa300 == 2, 0, dat$pa300)
### meeting both aerobic and strengthening guidelines
dat$bothpaguide <- ifelse(dat$X_PAREC1 %in% 9, NA, dat$X_PAREC1)
dat$bothpaguide <- ifelse(dat$bothpaguide >= 2, 0, dat$bothpaguide)
### meeting strengthening guidelines
dat$strengguide <- ifelse(dat$X_PASTRNG %in% 9, NA, dat$X_PASTRNG)
dat$strengguide <- ifelse(dat$strengguide == 2, 0, dat$strengguide)

### demographic data
### sex
dat$sex <- ifelse(dat$SEX == 9, NA, dat$SEX)
dat$sex <- ifelse(dat$sex == 2, 0, dat$sex)
dat$sex <- as.factor(dat$sex)
### age category
dat$agegroup <- dat$X_AGE_G
### race
dat$race <- ifelse(dat$X_RACE == 9, NA, dat$X_RACE)
dat$X_RACE_G1[dat$X_RACE_G1 == ""] <- NA
dat$race5 <- dat$X_RACE_G1
### housing
dat$housing <- ifelse(dat$RENTHOM1 >= 7, NA, dat$RENTHOM1)
dat$housing_n <- ifelse(dat$housing == 1, 1, 0)
### marital
dat$marry <- ifelse(dat$MARITAL == 9, NA, dat$MARITAL)
dat$marry_n <- ifelse(dat$marry %in% c(1, 6), 1, 0)
### education
dat$edu <- ifelse(dat$EDUCA == 9, NA, dat$EDUCA)
### asthma
dat$asthma <- ifelse(dat$ASTHMA3 >= 7, NA, dat$ASTHMA3)
### employment
dat$EMPLOY1[dat$EMPLOY1 == ""] <- NA
dat$employ <- ifelse(dat$EMPLOY1 >= 9, NA, dat$EMPLOY1)
dat$employ <- ifelse(dat$employ == 2, 1, dat$employ)
dat$employ <- ifelse(dat$employ == 3, 0, dat$employ)
dat$employ <- ifelse(dat$employ == 4, 0, dat$employ)
dat$employ <- ifelse(dat$employ == 5, 0, dat$employ)
dat$employ <- ifelse(dat$employ == 6, 0, dat$employ)
dat$employ <- ifelse(dat$employ == 7, 0, dat$employ)
dat$employ <- ifelse(dat$employ == 8, 0, dat$employ)
dat$employ <- factor(dat$employ)
### BMI
dat$bmi <- dat$X_BMI5
dat$bmi <- dat$bmi/100
### type of phone
dat$phone <- ifelse(dat$CELLFON4 == 2, 0, dat$CELLFON4)
### geographic location
dat$georegion <- dat$MSCODE
dat$georegion_n <- ifelse(dat$georegion >= 2, 0, dat$georegion)
### variable cleaning
dat$EXEROFT1_n <- ifelse(dat$EXEROFT1 >= 777, NA, dat$EXEROFT1)
dat$EXEROFT2_n <- ifelse(dat$EXEROFT2 >= 777, NA, dat$EXEROFT2)
dat$PAFREQ1_n <- ifelse(dat$PAFREQ1_ >= 99000, NA, dat$PAFREQ1_)
dat$PAFREQ2_n <- ifelse(dat$PAFREQ2_ >= 99000, NA, dat$PAFREQ2_)
dat$EXERHMM1_n <- ifelse(dat$EXERHMM1 >= 777, NA, dat$EXERHMM1)
dat$EXERHMM2_n <- ifelse(dat$EXERHMM2 >= 777, NA, dat$EXERHMM2)
### 109-199 & 201-299 dilemma
dat$EXROFT1_week <- ifelse(dat$EXEROFT1_n %in% c(101:199), dat$EXEROFT1_n, NA)
dat$EXROFT1_month <- ifelse(dat$EXEROFT1_n %in% c(201:299),
dat$EXEROFT1_n, NA)
dat$EXROFT2_week <- ifelse(dat$EXEROFT2_n %in% c(101:199),
dat$EXEROFT2_n, NA)
dat$EXROFT2_month <- ifelse(dat$EXEROFT2_n %in% c(201:299),
dat$EXEROFT2_n, NA)

###MET minute for activity 1
dat$metmin1 <- dat$X_MINA1 * (dat$METVL1_ /10)
dat$metmin1_n <- dat$PADUR1_ * (dat$PAFREQ1_ /1000) * (dat$METVL1_ /10)

###MET minute for activity 2
dat$metmin2 <- dat$X_MINAC21 * (dat$METVL2_ /10)
dat$metmin2_n <- dat$PADUR2_ * (dat$PAFREQ2_ /1000) * (dat$METVL2_ /10)

###total MET min per week
dat$metmin <- dat$metmin1 + dat$metmin2
dat$metmin_n <- dat$metmin1_n + dat$metmin2_n

###engage in pa
dat$engagepa <- dat$EXERANY2

###pa min per week
dat$pamin_week

###missing data variable category
dat$missing_wearable <- ifelse(!is.na(dat$wearable), 1, 0)
dat$missing_wearable <- as.factor(dat$missing_wearable)

###missing variable for dis
dat$missing_dis <- ifelse(!is.na(dat$blind) |
  !is.na(dat$deaf) |
  !is.na(dat$decide) |
  !is.na(dat$diffalon) |
  !is.na(dat$diffdres) |
  !is.na(dat$diffwalk), 1, 0)
dat$missing_dis <- as.character(dat$missing_dis)

###survey model
mydesign <- svydesign(
  data = dat,
  ids = ~X_PSU,
  weights = ~X_LLCPWT,
  strata = ~X_STSTR,
  nest = T
  )
options(survey.lonely.psu = 'adjust')

### checking different between missing and non-missing data of wearable devices
dat$missing_wearable <- as.character(dat$missing_wearable)
### sex
dat$sex <- as.character(dat$sex)
svychisq(~missing_wearable+sex, mydesign, survey.lonely.psu = "remove")
### age group
dat$agegroup <- as.character(dat$agegroup)
svychisq(~missing_wearable+agegroup, mydesign, survey.lonely.psu="remove")
### race
dat$race <- as.character(dat$race)
svychisq(~missing_wearable+race, mydesign, survey.longely.psu="remove")
### housing
dat$housing <- as.character(dat$housing)
svychisq(~missing_wearable+housing, mydesign, survey.longely.psu="remove")
### martial status
dat$marry <- as.character(dat$marry)
svychisq(~missing_wearable+marry, mydesign, survey.longley.psu="remove")
### education
dat$ed <- as.character(dat$ed)
svychisq(~missing_wearable+ed, mydesign, survey.longley.psu="remove")

### checking different between missing and non-missing data of disability
### sex
svychisq(~missing_dis+sex, mydesign, survey.lonely.psu="remove")
### age group
svychisq(~missing_dis+agegroup, mydesign, survey.lonely.psu="remove")
### race
svychisq(~missing_dis+race, mydesign, survey.longely.psu="remove")
svychisq(~missing_dis+X_RACE_G1, mydesign, survey.longely.psu="remove")
### might be more appropriate due to larger sample size within levels
### housing
svychisq(~missing_dis+housing, mydesign, survey.longely.psu="remove")
### martial status
svychisq(~missing_dis+marry, mydesign, survey.longley.psu="remove")
### education
svychisq(~missing_dis+ed, mydesign, survey.longley.psu="remove")

### output CSV
write.csv(dat, "2017 BRFSS 200908.csv")
### reading data
dat <- read.csv('2017 BRFSS 200908.csv', header = T)

### output CSV
write.csv(dat, "2017 BRFSS 200909.csv")
###reading data
dat <- read.csv('2017 BRFSS 200909.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 200910.csv")
###data
dat <- read.csv('2017 BRFSS 200910.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 200927.csv")
###data
dat <- read.csv('2017 BRFSS 200927.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201007.csv")
###data
dat <- read.csv('2017 BRFSS 201007.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201024.csv")
###data
dat <- read.csv('2017 BRFSS 201024.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201029.csv")
###data
dat <- read.csv('2017 BRFSS 201029.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201214.csv")
###data
dat <- read.csv('2017 BRFSS 201214.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201215.csv")
###data
dat <- read.csv('2017 BRFSS 201215.csv', header = T)

###output CSV
write.csv(dat, "2017 BRFSS 201222.csv")
###data
dat <- read.csv('2017 BRFSS 201222.csv', header = T)

###2 factors descriptive analysis
###descriptive analysis
###210107

###directory
setwd("~/Documents/2017 BRFSS/Data Only")

###package
library(rio)
library(foreign)
library(haven)
library(dplyr)
library(survey)
library(MASS)
library(emmeans)

###data
dat <- read.csv('2017 BRFSS 201222.csv', header=T)
dat_sub <- dat[complete.cases(dat$dis), ] ###data without missing data
dat_sub <- dat[complete.cases(dat_sub$wearable), ] ###data without missing data
dat <- dat_sub

###factor
dat$dis <- factor(dat$dis)
dat$wearable <- factor(dat$wearable)
dat$trackpa <- factor(dat$trackpa)
dat$trackpa5 <- factor(dat$trackpa5)
dat$sex <- factor(dat$sex)
dat$agegroup <- factor(dat$agegroup)
dat$race5 <- factor(dat$race5)
dat$ed <- factor(dat$ed)
dat$employ <- factor(dat$employ)

###Add Intercept for Calculating Various Quantities
dat$INT <- rep(1, nrow(dat))

###survey models
brfss <- svydesign(ids = ~X_PSU, strata = ~ X_STSTR, data = dat, nest = TRUE,
weights = ~X_LLCPWT)
options(survey.lonely.psu = "remove")

###Helper Functions####
###Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){
  ###Extract Data From svyglm model###
dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$sallprob))), use.names=F)
mcall <- eval(x$call[[2]])
### Re-fit Model ###

```r
lm.mod <- lm(mcall, weights=wts, data=dat)
```

### Overwrite Model Components ###

```r
rf1 <- ref_grid(lm.mod)
rf1@bhat <- as.numeric(x$coefficients)
rf1@V <- vcov(x)
rf1@dfargs$df <- degf(x$survey.design)
rf1@misc$sigma <- sqrt(deviance(x))
```

### Final Function ###

```r
emmeans(rf1, ...)
```

### Overwrite Model Components ###

```r
contrast.svy <- function(x, ...){
  ### Extract Data From svyglm model ###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob)), use.names=F)
  mcall <- eval(x$call[[2]])
  ### Re-fit Model ###
  lm.mod <- lm(mcall, weights=wts, data=dat)
  ### Overwrite Model Components ###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ### Final Function ###
  emmeans::contrast(rf1, ...)
}
```

### Degree of Freedom ###

#### sex

```r
sexdfframe <- subset(brfss$variables, !is.na(sex))
sexnpsu <- nlevels(factor(sexdfframe$X_PSU)); sexnstr <- nlevels(factor(sexdfframe$X_STSTR))
dfsex <- sexnpsu - sexnstr
```

#### age group

```r
agedfframe <- subset(brfss$variables, !is.na(agegroup))
agenpsu <- nlevels(factor(agedfframe$X_PSU)); agenstr <- nlevels(factor(agedfframe$X_STSTR))
dfage <- agenpsu - agenstr
```

#### race & ethnicity

```r
racedfframe <- subset(brfss$variables, !is.na(race5))
racenpsu <- nlevels(factor(racedfframe$X_PSU)); racenstr <- nlevels(factor(racedfframe$X_STSTR))
dfrace <- racenpsu - racenstr
```

#### bmi
bmidfframe <- subset(brfss$variables, !is.na(bmi))
bminpsu <- nlevels(factor(bmidfframe$X_PSU)); bminstr <-
nlevels(factor(bmidfframe$X_STSTR))
dfbmi <- bminpsu - bminstr
###education
eddfframe <- subset(brfss$variables, !is.na(ed))
ednpsu <- nlevels(factor(eddfframe$X_PSU)); ednstr <-
nlevels(factor(eddfframe$X_STSTR))
dfed <- ednpsu - ednstr
###employment
employdfframe <- subset(brfss$variables, !is.na(employ))
employnpsu <- nlevels(factor(employdfframe$X_PSU)); employnstr <-
nlevels(factor(employdfframe$X_STSTR))
dfemploy <- employnpsu - employnstr
###mean by 2 factors
###bmi
summarise(group_by(dat, wearable, dis), count=n())
bmi_mean_mod <- svyglm(bmi ~ wearable + dis + wearable*dis, design=brfss,
family='gaussian')
bmi_mean_obj <- invisible(print(svyby(~bmi, ~wearable+dis, design=brfss,
svymean, na.rm=T, keep.vars=T)))
bmi_mean_95 <- invisible(print(emmeans.svy(bmi_mean_mod, ~wearable*dis,
df=dfbmi, level=0.95)))
###proportion by 2 factors
###sex
summarise(group_by(dat, wearable, dis, sex), count=n())
sex_mod <- svyby(~sex, ~wearable+dis, design=brfss, svymean, na.rm=T,
keep.vars=T)
sex_95 <- confint(sex_mod, level=0.95, df=dfsex)
sex_mod
sex_95
###age group
agecount <- summarise(group_by(dat, wearable, dis, agegroup), count=n())
View(agecount)
age_mod <- svyby(~agegroup, ~wearable+dis, design=brfss, svymean, na.rm=T,
keep.vars=T)
age_95 <- confint(age_mod, level=0.95, df=dfage)
age_mod
View(age_mod)
View(age_95)
###race
racecount <- summarise(group_by(dat, wearable, dis, race5), count=n())
View(racecount)
race_mod <- svyby(~race5, ~wearable+dis, design=brfss, svymean, na.rm=T, keep.vars=T)
View(race_mod)
race_95 <- confint(race_mod, level=0.95, df=dfrace)
View(race_95)
### education level
edcount <- summarise(group_by(dat, wearable, dis, ed), count=n())
View(edcount)
ed_mod <- svyby(~ed, ~wearable+dis, design=brfss, svymean, na.rm=T, keep.vars=T)
View(ed_mod)
ed_95 <- confint(ed_mod, level=0.95, df=dfed)*100
View(ed_95)
### employment
employcount <- summarise(group_by(dat, wearable, dis, employ), count=n())
employcount
employ_mod <- svyby(~employ, ~wearable+dis, design=brfss, svymean, na.rm=T, keep.vars=T)
employ_mod
employ_95 <- confint(employ_mod, level=0.95, df=dfemploy)*100
employ_95

### 2 factors descriptive analysis
### descriptive analysis on physical activity outcomes
### 210108

### directory
setwd("~/Documents/2017 BRFSS/Data Only")

### package
library(rio)
library(foreign)
library(haven)
library(dplyr)
library(survey)
library(MASS)
library(emmeans)

### data
dat <- read.csv('2017 BRFSS 210130.csv', header=T)
dat_sub <- dat[complete.cases(dat$dis), ] ### data without missing data
dat_sub <- dat[complete.cases(dat_sub$wearable), ] ### data without missing data
dat <- dat_sub

### factor
dat$pa <- factor(dat$pa)
dat$pa300 <- factor(dat$pa300)
dat$paguide <- factor(dat$paguide)
dat$strengguide <- factor(dat$strengguide)
dat$bothpaguide <- factor(dat$bothpaguide)

### Add Intercept for Calculating Various Quantities
dat$INT <- rep(1, nrow(dat))

### Survey models
brfss <- svydesign(ids = ~X_PSU, strata = ~ X_STSTR, data = dat, nest = TRUE,
weights = ~X_LLCPWT)
options(survey.lonely.psu = "remove")

### Helper Functions####
### Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){
  ### Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
mcall <- eval(x$call[[2]])
  ### Re-fit Model###
  lm.mod <- lm(mcall, weights=wts, data=dat)
  ### Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ### Final Function###
  emmeans(rf1, ...)
}

contrast.svy <- function(x, ...){
  ### Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
mcall <- eval(x$call[[2]])
  ### Re-fit Model###
  lm.mod <- lm(mcall, weights=wts, data=dat)
  ### Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ### Final Function###
```r
emmeans::contrast(rf1, ...)
}

### degree of freedom
### leisure pa
padfframe <- subset(brfss$variables, !is.na(pa))
panpsu <- nlevels(factor(padfframe$X_PSU)); panstr <- nlevels(factor(padfframe$X_STSTR))
dfpa <- panpsu - panstr
### pa min/wk
pamindfframe <- subset(brfss$variables, !is.na(pamin_week))
paminnpsu <- nlevels(factor(pamindfframe$X_PSU)); paminnstr <- nlevels(factor(pamindfframe$X_STSTR))
dfpamin <- paminnpsu - paminnstr
### vigorous min
vigmindfframe <- subset(brfss$variables, !is.na(vigmin))
vigminnpsu <- nlevels(factor(vigmindfframe$X_PSU)); vigminnstr <- nlevels(factor(vigmindfframe$X_STSTR))
dfvigmin <- vigminnpsu - vigminnstr
### 300 mins of pa
pa300dfframe <- subset(brfss$variables, !is.na(pa300))
pa300npsu <- nlevels(factor(pa300dfframe$X_PSU)); pa300nstr <- nlevels(factor(pa300dfframe$X_STSTR))
dfpa300 <- pa300npsu - pa300nstr
### aerobic guide
aerobicdfframe <- subset(brfss$variables, !is.na(paguide))
aerobicnpsu <- nlevels(factor(aerobicdfframe$X_PSU)); aerobicnstr <- nlevels(factor(aerobicdfframe$X_STSTR))
aerobicdf <- aerobicnpsu - aerobicnstr
### strength guide
strengthdfframe <- subset(brfss$variables, !is.na(strengguide))
strengthnpsu <- nlevels(factor(strengthdfframe$X_PSU)); strengthnstr <- nlevels(factor(strengthdfframe$X_STSTR))
dfstrength <- strengthnpsu - strengthnstr
### both guidelines
bothdfframe <- subset(brfss$variables, !is.na(bothpaguide))
bothonpsu <- nlevels(factor(bothdfframe$X_PSU)); bothonstr <- nlevels(factor(bothdfframe$X_STSTR))
dfboth <- bothonpsu - bothonstr
### met*min/wk
metdfframe <- subset(brfss$variables, !is.na(metmin))
metnpsu <- nlevels(factor(metdfframe$X_PSU)); metnstr <- nlevels(factor(metdfframe$X_STSTR))
dfmet <- metnpsu - metnstr
### strength activites
stact <- subset(brfss$variables, !is.na(strengthact))
```
stactnpsu <- nlevels(factor(stact$X_PSU)); stactnstr <-
nlevels(factor(stact$X_STSTR))
dfstact <- stactnpsu - stactnstr

###mean by 2 factors
###pa min/week
pamin_mod <- svyglm(pamin_week ~ wearable + dis + wearable*dis, design=brfss,
  family='gaussian')
pamin_obj <- invisible(print(svyby(~pamin_week, ~wearable+dis, design=brfss,
  svymean, na.rm=T, keep.vars=T)))
pamin_95 <- invisible(print(emmeans.svy(pamin_mod, ~wearable*dis, level=0.95)))
###vig min/week
vigmin_mod <- svyglm(vigmin ~ wearable+dis+wearable*dis, brfss,
  family='gaussian')
vigmin_obj <- invisible(print(svyby(~vigmin, ~wearable+dis, brfss, svymean,
  na.rm=T, keep.vars=T)))
vigmin_95 <- invisible(print(emmeans.svy(vigmin_mod, ~wearable*dis,
  level=0.95)))
###met min/week
metmin_mod <- svyglm(metmin~wearable+dis+wearable*dis, brfss,
  family='gaussian')
metmin_obj <- invisible(print(svyby(~metmin, ~wearable+dis, brfss, svymean,
  na.rm=T, keep.vars=T)))
metmin_95 <- invisible(print(emmeans.svy(metmin_mod, ~wearable*dis,
  level=0.95)))
###strength activity/week
stact_mod <- svyglm(strengthact ~ wearable+dis+wearable*dis, brfss,
  family='gaussian')
stact_obj <- invisible(print(svyby(~strengthact, ~wearable+dis, brfss, svymean,
  na.rm=T, keep.vars=T)))
stact_95 <- invisible(print(emmeans.svy(stact_mod, ~wearable*dis,
  level=0.95)))

###proportion by 2 factors
###leisure pa
summarise(group_by(dat, wearable, dis, pa), count=n())
pa_mod <- svyby(~factor(pa), ~wearable+dis, brfss, svymean, na.rm=T, keep.vars=T)
pa_mod
pa_95 <- confint(pa_mod, level=0.95)
pa_95
###300 min of pa
summarise(group_by(dat, wearable, dis, pa300), count=n())
pa3_mod <- svyby(~factor(pa300), ~wearable+dis, brfss, svymean, na.rm=T,
  keep.vars=T)
pa3_mod
pa3_95 <- confint(pa3_mod, level=0.95)
pa3_95
### aerobic guideline

```r
summarise(group_by(dat, wearable, dis, paguide), count=n())
aerobic_mod <- svyby(~factor(paguide), ~wearable+dis, brfss, svymean, na.rm=T, keep.vars=T)
aerobic_mod
aerobic_95 <- confint(aerobic_mod, level=0.95)
aerobic_95
```

### both guidelines

```r
summarise(group_by(dat, wearable, dis, bothpaguide), count=n())
both_mod <- svyby(~factor(bothpaguide), ~wearable+dis, brfss, svymean, na.rm=T, keep.vars=T)
both_mod
confint(both_mod, level=0.95)
```

### strength guide

```r
summarise(group_by(dat, wearable, dis, strengguide), count=n())
stguide_mod <- svyby(~factor(strengguide), ~wearable+dis, brfss, svymean, na.rm=T, keep.vars=T)
stguide_mod
confint(stguide_mod, level=0.95)
```

### logistic regression

### crude model

### directory

```r
setwd("~/Documents/2017 BRFSS/Data Only")
```

### data

```r
dat <- read.csv('2017 BRFSS 210130.csv', header=T)
```

### package

```r
library(survey)
library(emmeans)
library(car)
```

### factor

```r
dat$sex <- factor(dat$sex)
dat$sagegroup <- factor(dat$sagegroup)
dat$race5 <- factor(dat$race5)
dat$ed <- factor(dat$ed)
dat$employ <- factor(dat$employ)
dat$pa <- as.numeric(dat$pa)
dat$pa300 <- factor(dat$pa300)
dat$paguide1 <- dat$paguide
dat$paguide <- factor(dat$paguide)
dat$strengguide <- factor(dat$strengguide)
```
dat$bothpaguide <- factor(dat$bothpaguide)
dat$wearable <- factor(dat$wearable)
dat$dis <- factor(dat$dis)

###survey model
brfss <- svydesign(ids=~X_PSU, strata=~X_STSTR, data=dat, nest=TRUE,
weights=~X_LLCPWT)
options(survey.lonely.psu="adjust")

###Helper Functions####
###Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){ ###Change these for working with logits####
###Extract Data From svyglm model###
dat <- x$data
wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
mcall <- eval(x$call[[2]])
###Re-fit Model###
lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
###Overwrite Model Components###
rf1 <- ref_grid(lm.mod)
rf1@bhat <- as.numeric(x$coefficients)
rf1@V <- vcov(x)
rf1@dfargs$df <- degf(x$survey.design)
rf1@misc$sigma <- sqrt(deviance(x))
###Final Function###
emmeans(rf1, ...)
}

contrast.svy <- function(x, ...){ ###Change these for working with logits####
###Extract Data From svyglm model###
dat <- x$data
wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
mcall <- eval(x$call[[2]])
###Re-fit Model###
lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
###Overwrite Model Components###
rf1 <- ref_grid(lm.mod)
rf1@bhat <- as.numeric(x$coefficients)
rf1@V <- vcov(x)
rf1@dfargs$df <- degf(x$survey.design)
rf1@misc$sigma <- sqrt(deviance(x))
###Final Function###
emmeans::contrast(rf1, ...)
}

###engagement in leisure physical activity
### no adjustment
modpa <- svyglm(pa~wearable+dis+wearable*dis, brfss, family='binomial')
summary(modpa)
Anova(modpa, type=3) ## In this example the interaction is non-significant so we could ignore or remove it.
   ## However, we'll compute the relevant odds ratios anyways
   ## Realize significance tests on the logit (log odds) and odds ratio scales may disagree
   ## this is due to differences in the geometry of 2-dimensional logit space vs. 2-dimensional odds space

### Setup the Contrasts We're Interesting In####
c1 <- c(1, 0, 0, 0) ### wearable 1 vs. wearable 0 at dis = 1
c2 <- c(0, 1, 0, 0) ### wearable 1 vs. wearable 0 at dis = 0
c3 <- c(0, 0, 1, 0) ### dis 1 vs dis 0 at wearable = 1
c4 <- c(0, 0, 0, 1) ### dis 1 vs. dis 0 at wearable = 0

### Get the Marginal Means####
mod.em <- emmeans.svy(modpa, ~wearable*dis, df=(6.586*10^4)) ### Throw a ton of df at this to approximate a z-distribution
mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c
mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1), adjust="bonferonni")); mod.cadj

### Unadjusted for Multiple Comparisons####
mod.c.odds <- mod.c[,c(1,2,5,6)]
mod.c.odds$estimate <- exp(mod.c.odds$estimate)
mod.c.odds$lower.CL <- exp(mod.c.odds$lower.CL)
mod.c.odds$upper.CL <- exp(mod.c.odds$upper.CL)
names(mod.c.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.c.odds

# contrast   odds.ratio   lower.CL   upper.CL
#1 c(0, 0, -1, 1) 1.38626483200535477 0.85140077280528348
2.25713934710549902 ### wearable 1 vs. wearable 0 at dis = 1
#2 c(-1, 1, 0, 0) 1.38733853980045385 0.9306928591660425
2.06803802734251052 ### wearable 1 vs. wearable 0 at dis = 0
#3 c(0, -1, 0, 1) 0.40096573552539655 0.22576768907256356
0.71211926616190113 ### dis 1 vs dis 0 at wearable = 1
#4 c(-1, 0, 1, 0) 0.4012762967090153 0.31213893090617489
0.51586857758027815 ### dis 1 vs. dis 0 at wearable = 0

### Sample interpretation for first term in this table...
### Among those with disabilities, wearable devices users have a higher odds (non-significant) of meeting pa than non-wearable device users
### Adjusted for Multiple Comparisons###
mod.c.odds2 <- mod.cadj[,c(1,2,5,6)] ### This is an adjusted variant where the interaction tests of interest are p-value corrected
### for multiple testing. This would generally be the preferred approach.
### Notice the wider confidence intervals below when compared to above
### This is because the Bonferroni correction effectively sets alpha to 0.05/4 = 0.0125
mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)
mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)
mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)
names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.c.odds2

# contrast odds.ratio lower.CL upper.CL
#1 c(0, 0, -1, 1) 1.38626483200535477 0.74481019365984868
2.5801696021972530 ### wearable 1 vs. wearable 0 at dis = 1
#2 c(-1, 1, 0, 0) 1.38733853980045385 0.8341351118709571
2.30742981347052423 ### wearable 1 vs. wearable 0 at dis = 0
#3 c(0, -1, 0, 1) 0.40096573552539655 0.19285029181199009
0.83367009484310506 ### dis 1 vs dis 0 at wearable = 1
#4 c(-1, 0, 1, 0) 0.40127629670091053 0.29134991261193138
0.55267792892210044 ### dis 1 vs. dis 0 at wearable = 0

### As interaction was non-significant - revealed by ANOVA above just compute main effect odds ratios for significant terms in the model ###
### Get the Marginal Means###
mod.wear <- emmeans.svy(modpa, ~wearable, df=(6.586*10^4)) ### wearable was not actually statistically significant so you could skip this
### However, I'm illustrating here so you can see the approach.
mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise"))

### Unadjusted for Multiple Comparisons###
mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]
mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)
mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)
mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)
names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.wc3.odds

# contrast odds.ratio lower.CL upper.CL
#1 1 - 0 1.3868015819903834 1.0124430405986644 1.8995820512271171 ###
Notice 95% confidence interval for odds ratio fully > than 0
### However, p-value for original logit model is $p = 0.10802$
### Important to interpret the significance of model effects on the logit scale first
### Then compute the odds ratios of interest after significant model components are found.

### Get the Marginal Means
```r
mod.dis <- emmeans.svy(modpa, ~dis, df=(6.586*10^4)) ### dis was highly significant
mod.di <- confint(contrast(mod.dis, method = "revpairwise"))
```

### Unadjusted for Multiple Comparisons
```r
mod.di.odds <- mod.di[,c(1,2,5,6)]
mod.di.odds$estimate <- exp(mod.di.odds$estimate)
mod.di.odds$lower.CL <- exp(mod.di.odds$lower.CL)
mod.di.odds$upper.CL <- exp(mod.di.odds$upper.CL)
names(mod.di.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.di.odds
```

```
# contrast      odds.ratio                  lower.CL          upper.CL
#1 1 - 0 0.401120986057309 0.29378028891462754 0.54768155498119475
```

### Disabled individuals have a significantly lower odds of achieving the pa variable (value of 1) than do non-disabled individuals.

### model diagnostic
```r
resid0<- resid(modpa)
fitted0 <- fitted(modpa)
max(resid0); min(resid0)
hist(resid0, breaks=seq(-10, 10, 1), xlim=c(-15, 15))
qqnorm(resid0); qqline(resid0)
plot(fitted0, resid0)
```

### dissertation
### crude logistic model
###210222

### package
library(rio)
library(foreign)
library(haven)
library(dplyr)
library(survey)
library(MASS)
library(emmeans)
###directory
setwd("~/Documents/2017 BRFSS/Data Only")

###data
dat <- read.csv('2017 BRFSS 210130.csv', header=T)
dat <- dat[complete.cases(dat$dis), ] ###data without missing data
dat <- dat[complete.cases(dat$trackpa), ] ###data without missing data

###factor
dat$sex <- factor(dat$sex)
dat$agegroup <- factor(dat$agegroup)
dat$race5 <- factor(dat$race5)
dat$ed <- factor(dat$ed)
dat$employ <- factor(dat$employ)
dat$pa <- as.numeric(dat$pa)
dat$pa300 <- factor(dat$pa300)
dat$paguide1 <- dat$paguide
dat$paguide <- factor(dat$paguide)
dat$strengguide <- factor(dat$strengguide)
dat$bothpaguide <- factor(dat$bothpaguide)
dat$wearable <- factor(dat$wearable)
dat$trackpa <- factor(dat$trackpa)
dat$dis <- factor(dat$dis)

###survey model
brfss <- svydesign(ids=~X_PSU, strata=~X_STSTR, data=dat, nest=TRUE,
weights=~X_LLCPWT)
options(survey.lonely.psu="adjust")

###Helper Functions#####
###Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){ ###Change these for working with logits#####
###Extract Data From svyglm model###
dat <- x$data
wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
mcall <- eval(x$call[[2]])
###Re-fit Model###
lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
###Overwrite Model Components###
rf1 <- ref_grid(lm.mod)
rf1@bhat <- as.numeric(x$coefficients)
rf1@V <- vcov(x)
rf1@dargs$df <- degf(x$survey.design)
rf1@misc$sigma <- sqrt(deviance(x))
###Final Function###
emmeans(rf1, ...)

contrast.svy <- function(x, ...){
###Change these for working with logits####
###Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
  mcall <- eval(x$call[[2]])
###Re-fit Model###
  lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
###Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
###Final Function###
  emmeans::contrast(rf1, ...)
}

###Setup the Contrasts We're Interesting In###
  c1 <- c(1, 0, 0, 0) ### trackpa 1 vs. trackpa 0 at dis = 1
  c2 <- c(0, 1, 0, 0) ### trackpa 1 vs. trackpa 0 at dis = 0
  c3 <- c(0, 0, 1, 0) ### dis 1 vs dis 0 at trackpa = 1
  c4 <- c(0, 0, 0, 1) ### dis 1 vs. dis 0 at trackpa = 0

###engagement in leisure physical activity###
  modpa <- svyglm(pa~trackpa+dis+trackpa*dis, brfss, family='binomial')
  summary(modpa)
  Anova(modpa, type=3)
  mod.em <- emmeans.svy(modpa, ~trackpa*dis, df=(6.586*10^4)) ###Throw a ton of
df at this to approximate a z-distribution
  mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c
  mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1),
    adjust="bonferroni")); mod.cadj
  mod.c.odds2 <- mod.cadj[,c(1,2,5,6)]
  mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)
  mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)
  mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)
  names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")
  mod.c.odds2
  mod.wear <- emmeans.svy(modpa, ~trackpa, df=(6.586*10^4))
  mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise"))
  mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]
  mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)
  mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)
mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)
names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.wc3.odds
mod.dis <- emmeans.svy(modpa, ~dis, df=(6.586*10^4)) ### dis was highly significant
mod.di <- confint(contrast(mod.dis, method = "revpairwise"))
mod.di.odds <- mod.di[,c(1,2,5,6)]
mod.di.odds$estimate <- exp(mod.di.odds$estimate)
mod.di.odds$lower.CL <- exp(mod.di.odds$lower.CL)
mod.di.odds$upper.CL <- exp(mod.di.odds$upper.CL)
names(mod.di.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.di.odds

###engagement in at least 301 minutes of physical activity per week
modpa300 <- svyglm(pa300~trackpa+dis+trackpa*dis, brfss, family='binomial')
summary(modpa300)
Anova(modpa300, type=3)
mod.em <- emmeans.svy(modpa300, ~trackpa*dis, df=(6.586*10^4)) ###Throw a ton of df at this to approximate a z-distribution
mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c
mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1), adjust="bonferonni")); mod.cadj
mod.c.odds2 <- mod.cadj[,c(1,2,5,6)]
mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)
mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)
mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)
names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.c.odds2
mod.wear <- emmeans.svy(modpa300, ~trackpa, df=(6.586*10^4))
mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise"))
mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]
mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)
mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)
mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)
names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.wc3.odds
mod.dis <- emmeans.svy(modpa300, ~dis, df=(6.586*10^4)) ### dis was highly significant
mod.di <- confint(contrast(mod.dis, method = "revpairwise"))
mod.di.odds <- mod.di[,c(1,2,5,6)]
mod.di.odds$estimate <- exp(mod.di.odds$estimate)
mod.di.odds$lower.CL <- exp(mod.di.odds$lower.CL)
mod.di.odds$upper.CL <- exp(mod.di.odds$upper.CL)
names(mod.di.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.di.odds
###meeting aerobic physical activity guidelines

modpaguide <- svyglm(paguide~trackpa+dis+trackpa*dis, brfss, family="binomial")

summary(modpaguide)

Anova(modpaguide, type=3)

mod.em <- emmeans.svy(modpaguide, ~trackpa*dis, df=(6.586*10^4)) ###Throw a ton of df at this to approximate a z-distribution

mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c

mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1), adjust="bonferonni"); mod.cadj

mod.c.odds2 <- mod.cadj[,c(1,2,5,6)]

mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)

mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)

mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)

names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.c.odds2

mod.wear <- emmeans.svy(modpaguide, ~trackpa, df=(6.586*10^4))

mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise")

mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]

mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)

mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)

mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)

names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.wc3.odds

mod.dis <- emmeans.svy(modpaguide, ~dis, df=(6.586*10^4)) ### dis was highly significant

mod.di <- confint(contrast(mod.dis, method = "revpairwise")

mod.di.odds <- mod.di[,c(1,2,5,6)]

mod.di.odds$estimate <- exp(mod.di.odds$estimate)

mod.di.odds$lower.CL <- exp(mod.di.odds$lower.CL)

mod.di.odds$upper.CL <- exp(mod.di.odds$upper.CL)

names(mod.di.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.di.odds

###meeting strength physical activity guidelines

modstrengguide <- svyglm(strengguide~trackpa+dis+trackpa*dis, brfss, family="binomial")

summary(modstrengguide)

Anova(modstrengguide, type=3)

mod.em <- emmeans.svy(modstrengguide, ~trackpa*dis, df=(6.586*10^4)) ###Throw a ton of df at this to approximate a z-distribution

mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c

mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1), adjust="bonferonni"); mod.cadj

mod.c.odds2 <- mod.cadj[,c(1,2,5,6)]

mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)

mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)
mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)
names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.wear <- emmeans.svy(modstrengguide, ~trackpa, df=(6.586*10^4))
mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise"))
mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]
mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)
mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)
mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)
names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.wc3.odds

###meeting both aerobic and strength physical activity guidelines

modbothsaguide <- svyglm(bothpaguide~trackpa+dis+trackpa*dis, brfss, family="binomial")
summary(modbothsaguide)

Anova(modbothsaguide, type=3)

mod.em <- emmeans.svy(modbothsaguide, ~trackpa*dis, df=(6.586*10^4))

##Throw a ton of df at this to approximate a z-distribution
mod.c <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1))); mod.c
mod.cadj <- confint(contrast(mod.em, method = list(c4-c3,c2-c1,c4-c2,c3-c1), adjust="bonferonni")); mod.cadj

mod.c.odds2 <- mod.cadj[,c(1,2,5,6)]
mod.c.odds2$estimate <- exp(mod.c.odds2$estimate)
mod.c.odds2$lower.CL <- exp(mod.c.odds2$lower.CL)
mod.c.odds2$upper.CL <- exp(mod.c.odds2$upper.CL)
names(mod.c.odds2) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.c.odds2

mod.wear <- emmeans.svy(modbothsaguide, ~trackpa, df=(6.586*10^4))
mod.wc3 <- confint(contrast(mod.wear, method = "revpairwise"))
mod.wc3.odds <- mod.wc3[,c(1,2,5,6)]
mod.wc3.odds$estimate <- exp(mod.wc3.odds$estimate)
mod.wc3.odds$lower.CL <- exp(mod.wc3.odds$lower.CL)
mod.wc3.odds$upper.CL <- exp(mod.wc3.odds$upper.CL)
names(mod.wc3.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")

mod.wc3.odds
mod.dis <- emmeans.svy(modbothpaguide, ~dis, df=(6.586*10^4)) ### dis was highly significant
mod.di <- confint(contrast(mod.dis, method = "revpairwise"))
mod.di.odds <- mod.di[,c(1,2,5,6)]
mod.di.odds$estimate <- exp(mod.di.odds$estimate)
mod.di.odds$lower.CL <- exp(mod.di.odds$lower.CL)
mod.di.odds$upper.CL <- exp(mod.di.odds$upper.CL)
names(mod.di.odds) <- c("contrast","odds.ratio","lower.CL","upper.CL")
mod.di.odds

###logisitc regression
###adjusted model
###210301

###directory
setwd("~/Documents/2017 BRFSS/Data Only")

###data
dat <- read.csv('2017 BRFSS 210130.csv', header=T)
dat <- dat[complete.cases(dat$dis), ] ###data without missing data
dat <- dat[complete.cases(dat$trackpa), ]

###package
library(survey)
library(emmeans)
library(car)

###factor
dat$sex <- factor(dat$sex)
dat$agegroup <- factor(dat$agegroup)
dat$race5 <- factor(dat$race5)
dat$ed <- factor(dat$ed)
dat$employ <- factor(dat$employ)
dat$pa <- factor(dat$pa)
dat$pa300 <- factor(dat$pa300)
dat$paguide1 <- dat$paguide
dat$paguide <- factor(dat$paguide)
dat$strengguide <- factor(dat$strengguide)
dat$bothpaguide <- factor(dat$bothpaguide)
dat$trackpa <- factor(dat$trackpa)
dat$wearable <- factor(dat$wearable)
dat$dis <- factor(dat$dis)
dat <- within(dat, wearable <- relevel(wearable, ref="0"))
dat <- within(dat, dis <- relevel(dis, ref="0"))

###survey model
brfss <- svydesign(ids=~X_PSU, strata=~X_STSTR, data=dat, nest=TRUE, weights=~X_LLCPWT)
options(survey.lonely.psu="adjust")

###Helper Functions####
###Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){ ###Change these for working with logits####
  ###Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
  mcall <- eval(x$call[[2]])
  ###Re-fit Model###
  lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
  ###Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ###Final Function###
  emmeans(rf1, ...)
}

contrast.svy <- function(x, ...){ ###Change these for working with logits####
  ###Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
  mcall <- eval(x$call[[2]])
  ###Re-fit Model###
  lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
  ###Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ###Final Function###
  emmeans::contrast(rf1, ...)
}

###Setup the Contrasts We're Interesting In#####
c1 <- c(1, 0, 0, 0) ### trackpa 1 vs. trackpa 0 at dis = 1
c2 <- c(0, 1, 0, 0) ### trackpa 1 vs. trackpa 0 at dis = 0
c3 <- c(0, 0, 1, 0) ### dis 1 vs dis 0 at trackpa = 1
c4 <- c(0, 0, 0, 1) ### dis 1 vs. dis 0 at trackpa = 0
### Engagement in leisure physical activity

### No adjustment

modpa0 <- svyglm(pa~trackpa+dis+trackpa*dis, brfss, family='binomial')
modpa1 <- svyglm(pa~trackpa+dis+trackpa*dis+agegroup, brfss, family='binomial')
anova(modpa0, modpa1)
modpa2 <- svyglm(pa~trackpa+dis+trackpa*dis+sex, brfss, family='binomial')
anova(modpa0, modpa2)
modpa3 <- svyglm(pa~trackpa+dis+trackpa*dis+bmi, brfss, family='binomial')
anova(modpa0, modpa3)
modpa4 <- svyglm(pa~trackpa+dis+trackpa*dis+bmi+race5, brfss, family='binomial')
anova(modpa3, modpa4)
modpa5 <- svyglm(pa~trackpa+dis+trackpa*dis+bmi+race5+ed, brfss, family='binomial')
anova(modpa4, modpa5)
modpa6 <- svyglm(pa~trackpa+dis+trackpa*dis+bmi+race5+ed+employ, brfss, family='binomial')
anova(modpa5, modpa6)

### Engagement in at least 300 minutes of PA

mod3000 <- svyglm(pa300~trackpa+dis+trackpa*dis, brfss, family='binomial')
mod3001 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup, brfss, family='binomial')
anova(mod3000, mod3001)
mod3002 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup+sex, brfss, family='binomial')
anova(mod3001, mod3002)
mod3003 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup+bmi, brfss, family='binomial')
anova(mod3001, mod3003)
mod3004 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup+bmi+race5, brfss, family='binomial')
anova(mod3003, mod3004)
mod3005 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup+bmi+ed, brfss, family='binomial')
anova(mod3003, mod3005)
mod3006 <- svyglm(pa300~trackpa+dis+trackpa*dis+agegroup+bmi+employ, brfss, family='binomial')
anova(mod3003, mod3006)

### Meeting aerobic guidelines

modaerobic0 <- svyglm(paguide~trackpa+dis+trackpa*dis, brfss, family='binomial')
modaerobic1 <- svyglm(paguide~trackpa+dis+trackpa*dis+agegroup, brfss, family='binomial')
anova(modaerobic0, modaerobic1)
modaerobic2 <- svyglm(paguide~trackpa+dis+trackpa*dis+sex, brfss, family='binomial')
anova(modaerobic0, modaerobic2)
modaerobic3 <- svyglm(paguide~trackpa+dis+trackpa*dis+bmi, brfss, family='binomial')
anova(modaerobic0, modaerobic3)
modaerobic4 <- svyglm(paguide~trackpa+dis+trackpa*dis+bmi+race5, brfss, family='binomial')
anova(modaerobic3, modaerobic4)
modaerobic5 <- svyglm(paguide~trackpa+dis+trackpa*dis+bmi+ed, brfss, family='binomial')
anova(modaerobic3, modaerobic5)
modaerobic6 <- svyglm(paguide~trackpa+dis+trackpa*dis+bmi+employ, brfss, family='binomial')
anova(modaerobic3, modaerobic6)

### meeting strength guidelines
modstrength0 <- svyglm(strengguide~trackpa+dis+trackpa*dis, brfss, family='binomial')
modstrength1 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup, brfss, family='binomial')
anova(modstrength0, modstrength1)
modstrength2 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup+sex, brfss, family='binomial')
anova(modstrength1, modstrength2)
modstrength3 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup+bmi, brfss, family='binomial')
anova(modstrength1, modstrength3)
modstrength4 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup+bmi+race5, brfss, family='binomial')
anova(modstrength3, modstrength4)
modstrength5 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup+bmi+ed, brfss, family='binomial')
anova(modstrength3, modstrength5)
modstrength6 <- svyglm(strengguide~trackpa+dis+trackpa*dis+agegroup+bmi+ed+employ, brfss, family='binomial')
anova(modstrength5, modstrength6)

### meeting both aerobic and strength guidelines
modboth0 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis, brfss, family='binomial')
modboth1 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+agegroup, brfss, family='binomial')
anova(modboth0, modboth1)
modboth2 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+sex, brfss, family='binomial')
anova(modboth0, modboth2)
modboth3 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+bmi, brfss, family="binomial")
anova(modboth0, modboth3)
modboth4 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+bmi+race5, brfss, family="binomial")
anova(modboth3, modboth4)
modboth5 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+bmi+ed, brfss, family="binomial")
anova(modboth3, modboth5)
modboth6 <- svyglm(bothpaguide~trackpa+dis+trackpa*dis+bmi+ed+employ, brfss, family="binomial")
anova(modboth5, modboth6)

###logistic regression
###adjusted model
###210301

###directory
setwd("~/Documents/2017 BRFSS/Data Only")

###data
dat <- read.csv('2017 BRFSS 210130.csv', header=T)

###package
library(survey)
library(emmeans)
library(car)

###factor
dat$sex <- factor(dat$sex)
dat$agegroup <- factor(dat$agegroup)
dat$race5 <- factor(dat$race5)
dat$ed <- factor(dat$ed)
dat$employ <- factor(dat$employ)
dat$pa <- factor(dat$pa)
dat$pa300 <- factor(dat$pa300)
dat$paguide1 <- dat$paguide
dat$paguide <- factor(dat$paguide)
dat$strengguide <- factor(dat$strengguide)
dat$bothpaguide <- factor(dat$bothpaguide)
dat$wearable <- factor(dat$wearable)
dat$dis <- factor(dat$dis)
dat <- within(dat, wearable <- relevel(wearable, ref="0"))
dat <- within(dat, dis <- relevel(dis, ref="0"))

###survey model
brfss <- svydesign(ids=~X_PSU, strata=~X_STSTR, data=dat, nest=TRUE, weights=~X_LLCPWT)
options(survey.lonely.psu="adjust")

###Helper Functions###
###Create EM-Means Functions for Survey Data###
emmeans.svy <- function(x, ...){
  ###Change these for working with logits###
  ###Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
  mcall <- eval(x$call[[2]])
  ###Re-fit Model###
  lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
  ###Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ###Final Function###
  emmeans(rf1, ...)
}

contrast.svy <- function(x, ...){
  ###Change these for working with logits###
  ###Extract Data From svyglm model###
  dat <- x$data
  wts <- unlist(subset(dat, select=c(names(x$survey.design$allprob))), use.names=F)
  mcall <- eval(x$call[[2]])
  ###Re-fit Model###
  lm.mod <- glm(mcall, weights=wts, data=dat, family="binomial")
  ###Overwrite Model Components###
  rf1 <- ref_grid(lm.mod)
  rf1@bhat <- as.numeric(x$coefficients)
  rf1@V <- vcov(x)
  rf1@dfargs$df <- degf(x$survey.design)
  rf1@misc$sigma <- sqrt(deviance(x))
  ###Final Function###
  emmeans::contrast(rf1, ...)
}

###Setup the Contrasts We're Interesting In###
c1 <- c(1, 0, 0, 0) ### wearable 1 vs. wearable 0 at dis = 1
c2 <- c(0, 1, 0, 0) ### wearable 1 vs. wearable 0 at dis = 0
c3 <- c(0, 0, 1, 0) ### dis 1 vs dis 0 at wearable = 1
c4 <- c(0, 0, 0, 1) ### dis 1 vs. dis 0 at wearable = 0
### Engagement in leisure physical activity

#### No adjustment

```r
modpa0 <- svyglm(pa ~ wearable + dis + wearable*dis, brfss, family='binomial')
modpa1 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup, brfss, family='binomial')
anova(modpa0, modpa1)
modpa2 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup + sex, brfss, family='binomial')
anova(modpa1, modpa2)
modpa3 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup + bmi, brfss, family='binomial')
anova(modpa1, modpa3)
modpa4 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup + bmi + race5, brfss, family='binomial')
anova(modpa3, modpa4)
modpa5 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup + bmi + race5 + ed, brfss, family='binomial')
anova(modpa4, modpa5)
modpa6 <- svyglm(pa ~ wearable + dis + wearable*dis + agegroup + bmi + race5 + ed + employ, brfss, family='binomial')
anova(modpa5, modpa6)
```

### Engagement in at least 300 minutes of PA

```r
mod3000 <- svyglm(pa300 ~ wearable + dis + wearable*dis, brfss, family='binomial')
mod3001 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup, brfss, family='binomial')
anova(mod3000, mod3001)
mod3002 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup + sex, brfss, family='binomial')
anova(mod3001, mod3002)
mod3003 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup + bmi, brfss, family='binomial')
anova(mod3001, mod3003)
mod3004 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup + bmi + race5, brfss, family='binomial')
anova(mod3003, mod3004)
mod3005 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup + bmi + race5 + ed, brfss, family='binomial')
anova(mod3004, mod3005)
mod3006 <- svyglm(pa300 ~ wearable + dis + wearable*dis + agegroup + bmi + race5 + employ, brfss, family='binomial')
anova(mod3004, mod3006)
```

### Meeting aerobic guidelines
modaerobic0 <- svyglm(paguide~wearable+dis+wearable*dis, brfss, family="binomial")
modaerobic1 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup, brfss, family="binomial")
anova(modaerobic0, modaerobic1)
modaerobic2 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup+sex, brfss, family="binomial")
anova(modaerobic1, modaerobic2)
modaerobic3 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup+bmi, brfss, family="binomial")
anova(modaerobic2, modaerobic3)
modaerobic4 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup+bmi+race5, brfss, family="binomial")
anova(modaerobic3, modaerobic4)
modaerobic5 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup+bmi+race5+ed, brfss, family="binomial")
anova(modaerobic4, modaerobic5)
modaerobic6 <- svyglm(paguide~wearable+dis+wearable*dis+agegroup+bmi+race5+ed+employ, brfss, family="binomial")
anova(modaerobic5, modaerobic6)

###meeting strength guidelines
modstrength0 <- svyglm(strengguide~wearable+dis+wearable*dis, brfss, family="binomial")
modstrength1 <- svyglm(strengguide~wearable+dis+wearable*dis+agegroup, brfss, family="binomial")
anova(modstrength0, modstrength1)
modstrength2 <- svyglm(strengguide~wearable+dis+wearable*dis+agegroup+sex, brfss, family="binomial")
anova(modstrength1, modstrength2)
modstrength3 <- svyglm(strengguide~wearable+dis+wearable*dis+agegroup+sex+bmi, brfss, family="binomial")
anova(modstrength2, modstrength3)
modstrength4 <- svyglm(strengguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5, brfss, family="binomial")
anova(modstrength3, modstrength4)
modstrength5 <- svyglm(strengguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5+ed, brfss, family="binomial")
anova(modstrength4, modstrength5)
modstrength6 <- svyglm(strengthguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5+ed+employment, brfss, family='binomial')
aov(modstrength5, modstrength6)

### meeting both aerobic and strength guidelines
modboth0 <- svyglm(bothpguide~wearable+dis+wearable*dis, brfss, family='binomial')
modboth1 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup, brfss, family='binomial')
aov(modboth0, modboth1)
modboth2 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup+sex, brfss, family='binomial')
aov(modboth1, modboth2)
modboth3 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup+sex+bmi, brfss, family='binomial')
aov(modboth2, modboth3)
modboth4 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5, brfss, family='binomial')
aov(modboth3, modboth4)
modboth5 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5+ed, brfss, family='binomial')
aov(modboth4, modboth5)
modboth6 <- svyglm(bothpguide~wearable+dis+wearable*dis+agegroup+sex+bmi+race5+ed+employment, brfss, family='binomial')
aov(modboth5, modboth6)