Validation of a pressure sensing walkway for obstacle crossing measures.

ESRM 6990V: Intro to R - Final Project.

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INTRODUCTION

Functional activity assessments, such as walking gait, can play an important role in the clinic (Vries, Roy, and Chester 2009; Ricci et al. 2019; Sawacha et al. 2009), and in everyday life (Papadopoulos et al. 2015). Traditionally, clinical gait assessments were accomplished using visual observations (Nutt 2001), however outcomes are limited by the clinician's experience and the ability to detect small changes over time (Kressig and Beauchet 2006). Although technological advances such as optical motion capture or inertial measurement units (IMUs) allow for the capture of objective, three-dimensional movement, these systems are often costly and require trained technicians to analyze the data, making them an unrealistic option for most clinics (Fatone and Stine 2015; Paul et al. 2015; Kanko et al. 2021). Therefore, alternative, more cost and time effective methods for collecting movement data have been sought (Michelini, Eshraghi, and Andrysek 2020).

Alternative methods that are valid and reliable for collection of gait measures include both two-dimensional video and the use of a pressure sensing walkway (Fatone and Stine 2015; Michelini, Eshraghi, and Andrysek 2020; Sanders, Wang, and Kontson 2024). As falls are the second leading cause of unintentional injury among both young and older adults (World Health Organization 2024), many gait assessments evaluate functional abilities and its relationship to falls. One of the leading causes of falls among young adults are trips, which account for approximately 25% of unintentional fall events (Michel Johannes Hubertus Heijnen and Rietdyk 2016). Trips often occur due to a physical obstruction along the path of locomotion. The Occupational Safety and Health Administration Occupational Safety a (2024) defines a trip as "whenever your foot hits an object and you are moving with enough momentum to be thrown off balance". Likewise, recently Avalos and Rosenblatt Avalos and Rosenblatt (2024) defined trips as "an unexpected obstruction of the swinging limb by an obstacle". To gain insights into why we trip, many researchers have examined ways individuals cross, or step over, obstacles and what alters their crossing strategies.

In the literature, obstacle crossing is generally considered a balance task that requires negotiation of your center of mass over an obstacle, from one limb to the other (Liao et al. 2014). Whether we think about it or not, humans negotiate obstacles daily. Obstacles in sport can include things like hurdles in track and field events, but more commonly, obstacles present in our everyday life such as toys or shoes left on the floor, parking curbs in a parking lot, or branches on the sidewalk after a storm. Successful obstacle crossings (i.e., crossing the obstacle without contacting it) require sufficient horizontal and vertical clearance to avoid contacting the obstacle (Chou and Draganich 1998; Michel J. H. Heijnen, Muir, and Rietdyk 2012; Michel J. H. Heijnen et al. 2014). Horizontal clearance measures are often examined for their insights into the base of support while obstacle crossing (Chen et al. 1991; Chou and Draganich 1998) and include approach and landing distances, and crossing step length. Approach distance is the horizontal distance between the obstacle and the trailing toe (Chen et al. 1991; Chou and Draganich 1998; Patla and Rietdyk 1993; Vitório et al. 2010), whereas landing distance is the horizontal distance between the obstacle and the leading heel after crossing the obstacle when the foot is on the ground. Crossing step length is defined as the horizontal distance between the heel of the trailing foot to the heel of the contralateral leading foot when in double support over the obstacle. Where the leading limb is the limb that crosses over the obstacle first, and the trailing limb is the limb that crosses over the obstacle second.

Unfortunately, although obstacle crossing behavior has been studied extensively (Michel J. H. Heijnen, Muir, and Rietdyk 2012; Patla and Rietdyk 1993; Rietdyk and Rhea 2011; Spaulding and Patla 1991), most obstacle crossing studies present obstacles to participants in laboratory environments, which may not reflect obstacle crossing behaviors in the real world (Sharma et al. 2023; Sparrow et al. 1996). Laboratory studies have been crucial for gaining a general understanding of obstacle crossing behaviors, however, there is a growing body of literature suggesting the sterile, highly controlled environments presented in a laboratory may not replicate the complex outdoor environment that humans live in day-to-day (Sharma et al. 2023; Shumway-Cook and Woollacott 1995; Simon 2004). Several studies have examined how gait measures differ while indoors and outdoors, and have found differences in measures such as gait velocity (Hollander et al. 2022; Kuntapun et al. 2020; Schmitt et al. 2021) and minimum toe clearance (Hollander et al. 2022; Scanlon III 2014). Unfortunately, these studies only examined walking gait and not specifically obstacle crossing so there is much to be learned. In fact, only one study has been identified that collected obstacle crossing measures in an outdoor, real-world environment (Kuntapun et al. 2020). However, this study only examined spatiotemporal gait parameters, therefore was not telling of how obstacle crossing measures such as horizontal or vertical clearance changed with environment.

The lack of obstacle crossing literature in real-world environments can likely be attributed to the collection difficulty of these measures while outdoors. Although modern technology has allowed for more real-world biomechanical data capture while using modalities such as markerless kinematic tracking systems or IMUs, these systems currently cannot track stationary objects in space without intensive mathematical equations. Even when accomplished using intensive mathematical equations, measures such as toe clearance then tend to be inflated due to the cumulative integrations that need to happen over the time of the collection (Lai et al. 2008). Therefore, in order to expand the knowledge of how individuals cross obstacles in the real world, we need to consider other collection methods. In line with the push to provide clinics with "simpler and more cost effective gait analysis methods" (Michelini, Eshraghi, and Andrysek 2020), the overarching purpose of this study is to compare the accuracy and reliability of a well-established methodology for examining walking gait (i.e., a pressure sensing walkway), in a novel application of assessing obstacle crossing measures. Since this pressure sensing walkway has been shown to be valid and reliable for capturing spatiotemporal gait measures (Vallabhajosula et al. 2019), I hypothesize that the pressure sensing walkway will perform "good" or "excellent" for accuracy through evaluation of percent error, for reliability through evaluation of intra-class correlation coefficients, and have acceptable agreement when examining validity through a Bland-Altman analysis.

METHODS

DATA COLLECTION

Fifty adult participants (31 females; 24 ± 6 years; height: 1.72 ± 0.10 m; weight: 76.1± 20.9 kg), who can ambulate unassisted participated in this study. Participants were recruited through word of mouth at the University of Arkansas. Participants were excluded if they had an uncontrolled neurological or orthopedic condition that could impair walking function, if they reported a recent musculoskeletal injury that could preclude their ability to safely participate in study procedures or alter their normal gait, or if they uncorrected vision loss. Uncontrolled neurological or orthopedic conditions, any recent musculoskeletal injury, and uncorrected vision loss were self-reported via a demographic/health history questionnaire. Participants with uncontrolled neurological or orthopedic conditions were excluded due to disease processes or injury commonly affecting gait parameters (Mirelman et al. 2019; Nonnekes et al. 2018; Stolze et al. 2005). Whereas, participants with uncorrected vision loss were excluded out of an abundance of safety and due to gait characteristics and obstacle crossing measures changing with altered visual conditions (Cloutier and DeLucia 2022; Jansen, Toet, and Werkhoven 2010; Mohagheghi, Moraes, and Patla 2004; Novak and Deshpande 2014). The study was approved by the University's Institutional Review Board (protocol #: 2105335358).

Experimental Set-Up

Prior to participant arrival, Vicon motion capture cameras (Vicon Motion Systems, Oxford, UK) and a pressure sensing walkway (Zeno Electronic Walkway; ZenoMetrics, Peekskill, New York, USA) were set up in the MOVE laboratory at the University of Arkansas. Motion capture cameras are mounted near the ceiling around the laboratory space, where the Zeno

Electronic Walkway (Zeno Walkway) was set up in the middle of the capture volume (Figure 1).

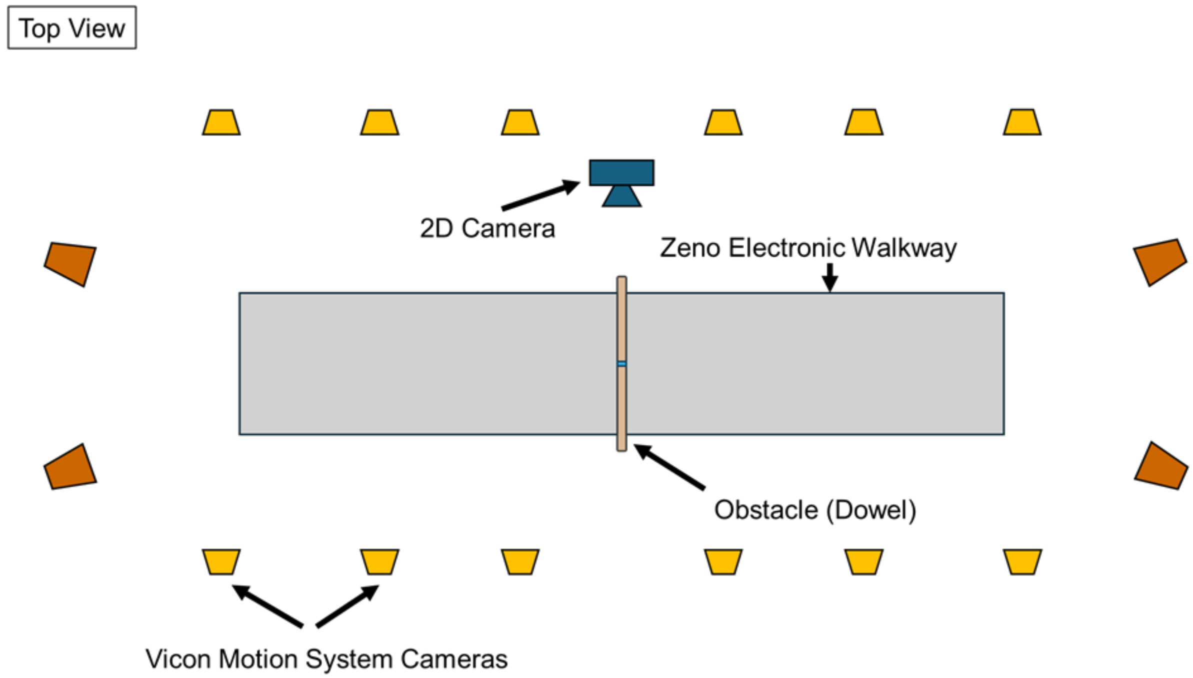

Figure 1: Figure 1. Top View of the Indoor Laboratory Set Up

Note. Vicon Motion System cameras consist of 4 Vantage (denoted as dark orange) and 12 Vero cameras denoted in light orange).

Once the laboratory space was set up, the Vicon motion capture cameras were calibrated within the Nexus Software (Version 2.16, Vicon Motion Systems, Oxford, UK) in accordance with Vicon Motion Systems documentation (Vicon Motion Systems, n.d.) using Vicon's Active Wand 2 (Vicon Motion Systems, Oxford, UK). In the "calibrate cameras" section of Nexus, the Active Wand was waved around an intended 2m x 2m x 1m three-dimensional (3D) capture volume to ensure the cameras are adequately identifying the wand and to collect information on where the wand is in space, and relative to each camera. Once the software had registered at least 1,000 valid frames of wand data, it calibrated the cameras by computing the residual mean squared error between each frame of data for every camera and calculated the global agreement. After cameras are calibrated, the volume origin was set using the "Set Volume Origin" section within Nexus. The Active Wand was set in a pre-determined origin (0, 0, 0; x, y, z) point within the laboratory space. Following origin positioning, the floor plane was manually set to ensure the digital floor plane is consistent with the physical floor plane of the laboratory.

The Zeno Walkway was calibrated within ProtoKinetics Movement Analysis Software (PKMAS, Version 600c3e, ProtoKinetics LLC, Havertown, PA, USA). To calibrate, upon starting the software PKMAS queried if the walkway is clear of any obstacles. Once cleared, the software registered the incoming voltage from the weight of the protectant mat and identified this as an unloaded voltage condition. This voltage was then filtered out as "noise" when analyzing future step data. The obstacle used in this study was a cuboid, wooden dowel rod (height: 120mm; depth: 25mm) that was placed upon wooden stands on the Zeno Walkway. The stands were placed in pre-determined, outlined locations to ensure similar obstacle placement across all participants and that the obstacle base was not moved within participants if contact was made. The dowel was marked with a piece of colored tape down the center of the obstacle (parallel to the direction of the walkway) and was presented with three reflective markers; one on each distal end and one on a flat surface of the dowel rod to enable post-processing analysis (Figure 2).

Figure 2: Figure 2. Obstacle (Dowel) Used for Obstructed Walking Assessment

Obstacle Crossing Protocol

Figure 3 provides a simplistic overview of the participant study flow. Upon arrival and prior to any data collection, all participants completed an electronic informed consent. Once consented, participants were asked to complete a demographic/health history questionnaire on REDCap to collect basic demographic information and confirm inclusion/exclusion criteria. Following questionnaire completion, eligible participants had their height and weight taken using a standard stadiometer and scale, respectively. At this point, all areas with reflectors on the shoes or clothing will be covered with black non-reflective tape.

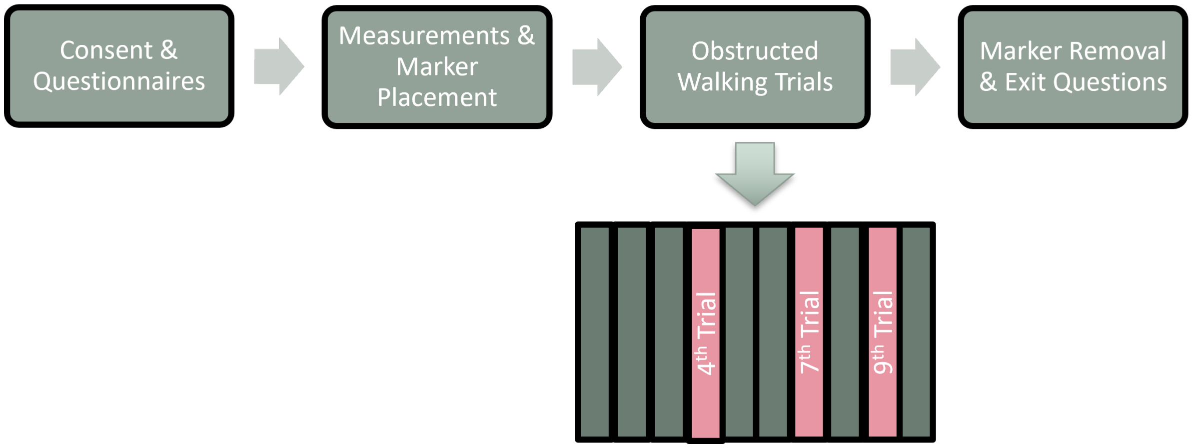

Figure 3: Figure 3. Participant Study Flow

After all reflectors were covered with tape, participants were then fitted with five optical-passive, retroreflective identifying markers on each of their normal, comfortable walking shoes. Reflective markers (14mm) were adhered to the participant using double-sided toupee tape. A "toe" marker was placed on the most anterior aspect of the shoe (anterior of the hallux or index toe) and a "heel" marker on the most posterior side of the shoe (over the posterior aspect of the calcaneus) in line with the anterior marker. Additional markers were placed on the shoe over the 2nd and 5th metatarsal head and on the lateral malleolus. Although all calculations occurred at the toe and heel markers, the 5th metatarsal head, and the lateral malleolus markers will assist in leg identification and gap filling during the post-processing steps within Nexus software. The placement of the "toe" and "heel" markers were decided based on Loverro and colleagues Loverro, Mueske, and Hamel (2013) publication, which identified the location of minimum foot clearance on the shoe when crossing obstacles. They identified that the minimal foot clearance in the lead limb typically occurs in the most posterior or posterolateral area of the shoe, whereas in the trailing limb, the minimal foot clearance occurs at the most anterior point of the shoe (Loverro, Mueske, and Hamel 2013).

Next, participants were asked to complete a series of obstructed walking trials. Participants completed at least 10 trials in total, and these trials were captured simultaneously via Vicon motion capture and the use of a pressure sensing walkway. Three-dimensional trajectory data were captured with the sixteen Vicon motion capture cameras and footfall pressure data were recorded via the Zeno Walkway. All systems captured at 120Hz and data from the shared 2m x 2m x 1m capture volume will be analyzed. At this point, a research assistant pressed down on the Zeno Walkway directly below the dowel to activate the walkway's pressure sensors. By activating the walkway's pressure sensors below the dowel, assisted in identification of dowel location.

All participants were given standardized instructions before the 10 obstructed walking trials as *"Starting here (point to the starting line off the Zeno Walkway), I'd like you to walk across the* *walkway at a comfortable pace, stepping over the obstacle along the way. Once you are off the mat on the other side, I would like you to stop and turn around, then wait until I tell you to go again. Do you have any questions?"* Once any questions have been answered, Vicon motion systems was initiated to collect data ensuring simultaneous collection through all collection instruments. Participants completed at least 10 trials of stepping over the dowel (height: 120mm; depth: 25mm) at their preferred pace and crossed the obstacle with their self-selected limb. If a participant contacted the obstacle in any way (deeming it an "unsuccessful trial"), they were asked to complete one additional trial for every "unsuccessful" trial made within the first 10 crossings. That is, if they had 2 unsuccessful trials within the first 10 crossings, then they would complete 12 crossings in total. Trials in which the equipment produced unusable data (e.g., the participant started walking before the equipment was recording) were additionally repeated.

After completing the obstructed walking trials, participants had the reflective markers removed, were asked if they would like to be entered into a gift card raffle (25 gift cards total, worth $15 each). If they wanted to be entered into the raffle, additional information was gathered (e.g., email address and contact information) from the participant prior to participant departure.

ANALYSIS PLAN

Post-processing of dependent variables occurred separately for the pressure sensing walkway, with Vicon Motion Systems serving as the "gold standard". All dependent variables were obtained through Vicon Motion Systems. Pressure data from the Zeno Walkway will be processed via the PKMAS software to calculate approach distance and landing distance. Approach distance was calculated as the horizontal distance between the trailing limb toe marker and the obstacle when the leading limb is directly over the obstacle (i.e., during single support). Landing distance was calculated as the horizontal distance between the leading limb heel marker and the obstacle when the trailing limb is directly over the obstacle (i.e., during single support).

Trial Processing

As this study aims to compare the accuracy and reliability of a pressure sensing walkway against a gold standard, to ensure a wide variety of crossing strategies are assessed, three trials per participant will be randomly selected and processed for final analysis.

Vicon Motion Capture Analysis

Marker trajectory data from the three-dimensional (3D) motion capture system were processed within Nexus (Vicon Motion Systems) and MATLAB (MathWorks, Natick, MA, USA) software as previously done in our laboratory (Jendro, Raffegeau, and Schmitt 2025). The 3D motion capture obtained "X, Y, Z" coordinates for each marker throughout the trials. The "X" coordinate refers to the medio-lateral direction as the participant walks down the walkway, the “Y” coordinate indicates the antero-posterior direction as the participant walks down the walkway, and the “Z” coordinate indicates the vertical distance above the ground. For the remainder of this document and across methodologies, I will reference antero-posterior direction as the horizontal measure, and the vertical direction as such. Marker trajectories were gap-filled using the rigid body gap fill, then filtered within Nexus using a Butterworth low-pass, fourth-order, zero-lag filter with a cut-off frequency set to 6 Hz. Data was then exported through a custom MATLAB code to extract all dependent variables based on the position of the toe and heel markers in relation to the reflective markers placed on the obstacle.

Stance phase of each foot was identified via the minimum vertical position of the toe and heel markers around the obstacle. Toe-off was defined as the minimum vertical position of the marker that precedes the crossing step, where heel-strike was defined as the minimum vertical position of the trajectory after crossing.

Pressure Sensing Walkway (Zeno Electronic Walkway) Analysis

Pressure data from the Zeno Electronic Walkway was analyzed using ProtoKinetics Movement Analysis Software (PKMAS) and MATLAB software. Data was cleaned (e.g., removing any half steps off the mat and reidentifying any mislabeled steps), and the obstacle was identified and labeled within PKMAS. Time series pressure sensor data was processed and exported through PKMAS and run through a custom MATLAB code to extract dependent variables.

Footfalls (steps) of interest were identified, via searching for the nearest footfalls around the obstacle. Exported PKMAS data of those footfalls included the location of the sensors that were compressed during that step. The antero-posterior difference in the number of pressure sensors compressed was used to calculate the dependent variables. As each sensor has a dimension of 0.5in x 0.5in (12.7mm x 12.7mm), to calculate distance using this method, the number of sensors between toe/heel and the obstacle was identified and then multiplied by 12.7mm to calculate distance. For example, in Figure 4 the trailing toe would be activating pressure sensors in column 4, when the dowel is presented in column 9. To calculate approach distance, the two column numbers were used to perform exclusive subtraction to calculate the number of sensors between the two points of interest, and then multiplied by a factor of 12.7mm as it is the horizontal distance of each sensor. Landing distance measurements occurred in this same fashion.

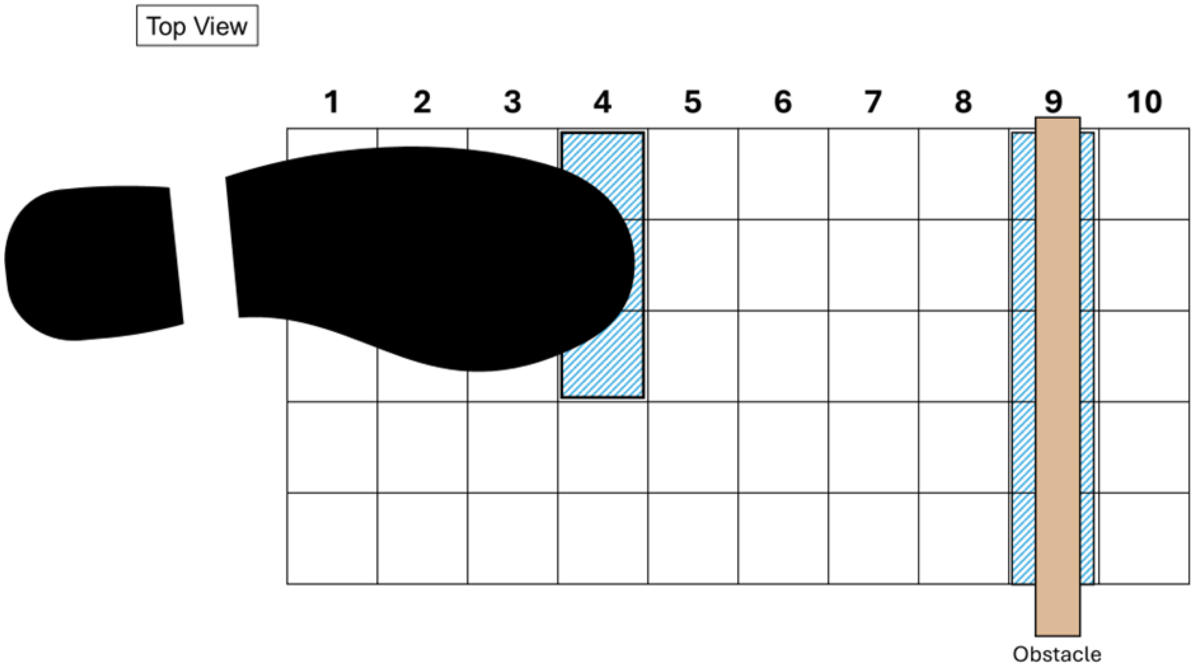

Figure 4: Calculating Approach Distance using the Zeno Electronic Walkway

Data Cleaning in R-Studio

Before running statistical analysis, raw data was loaded into R-Studio, and data was cleaned before several data transformations took place. Several R-Studio packages were installed and loaded for later data analysis.

```
#### Intro to R: Final Project R Code ####
#### Author: Ashlyn Jendro

## Step 1. Install and load necessary packages
### (tidyverse - Reads CSV and allows for data processing)

## NOTE: You will need to un-comment out the packages you need to install
#install.packages("tidyverse") # Use this if tidyverse is not currently installed
#install.packages("readr") # This will ensure that you can open .csv files
#install.packages("dplyr") # This helps build the tables
#install.packages("gt") # This will help create new columns and build tables
#install.packages("ggplot2") # Use this for making Bland-Altman Plots
#install.packages("irr") # Use this to calculate Intraclass Correlations
#install.packages("summarytools") # Use this package to build summary tables
#install.packages("Cairo")
```

```r
#install.packages("tinytex")
library(tidyverse) # This will load the tidyverse package
library(readr) # This will let you read .csv files
library(dplyr) # This will allow for new columns to be created
library(gt) # This will easily build APA tables
library(ggplot2) # This will load ggplot2 for visualizations
library(irr) # This will load irr to calculate Intraclass Correlations
library(summarytools) #This will load summarytools to create summary tables
library(Cairo)
library(tinytex)

knitr::opts_chunk$set(dev = 'CairoPNG')
```

Demographic data and raw data exported in .csv files from the Vicon Motion Capture and pressure sensing walkway analyses were then loaded into the R-Studio

```r
## Step 2. Upload the excel file for data analysis
######### Will need to change this based on where the file is stored #########

data <- read_csv("C:/Users/ashly/Box/Course of Study/Spring 2025/Introduction to R/Final Pro
demographic_data <- read_csv("C:/Users/ashly/Box/Course of Study/Spring 2025/Introduction to
```

Next, the data was viewed to ensure accuracy and length of each datasheet was evaluated. Then data was then cleaned, by dropping any cases with missing values and the demographic data columns headers were re-named for easier evaluation.

```r
## Step 3. View the data was pulled in appropriately by viewing the first
## several rows of data and the column names

data
colnames(data)

demographic_data
colnames(demographic_data)

## Step 4. View the number of cases within this data set

length(data$'Participant_ID') #Should be n = 150

length(demographic_data$'Record ID') #Should be n = 50
```

```r
## Step 5. Clean the data - Omit any cases with missing values

clean_data <- drop_na(data)  # There should be no dropped cases

length(data$'Participant_ID') # Should still be n = 150

## Step 6.  Rename Demographic Columns

colnames(demographic_data)

colnames(demographic_data)[1] <- "ID"
colnames(demographic_data)[2] <- "Age"
colnames(demographic_data)[3] <- "Height_cm"
colnames(demographic_data)[4] <- "Weight_lbs"
colnames(demographic_data)[5] <- "Sex"
colnames(demographic_data)[6] <- "Gender_Man"
colnames(demographic_data)[7] <- "Gender_Woman"
colnames(demographic_data)[8] <- "Gender_Trans"
colnames(demographic_data)[9] <- "Gender_non-binary"
colnames(demographic_data)[10] <- "Gender_None"
colnames(demographic_data)[11] <- "Gender_Prefer_No_Answer"
colnames(demographic_data)[12] <- "Gender_Other"
colnames(demographic_data)[13] <- "Hispanic"
colnames(demographic_data)[14] <- "Race_AI_AN"
colnames(demographic_data)[15] <- "Race_Asian"
colnames(demographic_data)[16] <- "Race_Black_AA"
colnames(demographic_data)[17] <- "Race_NH_OPI"
colnames(demographic_data)[18] <- "Race_White"
colnames(demographic_data)[19] <- "Race_Prefer_No_Answer"
colnames(demographic_data)[20] <- "Dominate_Leg"
colnames(demographic_data)[21] <- "ABC_16"

colnames(demographic_data)
```

Following data cleaning, several columns of data was mutated to convert units or calculate distances for later evaluations.

```r
## Step 7. Create two new columns of data converting cm to mm for PKMAS approach
## and landing distance

clean_data <- clean_data %>%
  mutate(PKMAS_Approach_Dist_MM = PKMAS_Approach_Dist_CM * 10)
```

```
      # Converts cm to mm

clean_data <- clean_data %>%
  mutate(PKMAS_Landing_Dist_MM = PKMAS_Landing_Dist_CM * 10)
      # Converts cm to mm

clean_data
colnames(clean_data) # There should now be 12 variable headers


## Step 8. Create new columns for calculating the difference between the gold
## standard (VICON) variable and the the testing variable (PKMAS)

clean_data <- clean_data %>%
  mutate(Approach_Difference = VICON_approach_dist_trail - PKMAS_Approach_Dist_MM)
# computes the difference between values

clean_data <- clean_data %>%
  mutate(Landing_Difference = VICON_landing_dist_lead - PKMAS_Landing_Dist_MM)
# computes the difference between values

clean_data
colnames(clean_data) # There should now be 14 variable headers


## Step 9. Calculate the mean and standard deviation of the approach_difference
## and the landing_difference variables

Approach_Diff_Mean = mean(clean_data$Approach_Difference)
Approach_Diff_Mean   # Should be 0.609 for this data set

Approach_Diff_SD = sd(clean_data$Approach_Difference)
Approach_Diff_SD     # Should be 52.73 for this data set

Landing_Diff_Mean = mean(clean_data$Landing_Difference)
Landing_Diff_Mean    # Should be 11.826 for this data set

Landing_Diff_SD = sd(clean_data$Landing_Difference)
Landing_Diff_SD     # Should be 63.44 for this data set


## Step 10. Calculate the range of 2 standard deviations outside the means
```

```
## of Approach Difference and Landing Difference

Approach_2SD_Upper = Approach_Diff_Mean + (2 * Approach_Diff_SD)
Approach_2SD_Upper   # Should be 106.07 for this data set

Approach_2SD_Lower = Approach_Diff_Mean - (2 * Approach_Diff_SD)
Approach_2SD_Lower   # Should be -104.85 for this data set

Landing_2SD_Upper = Landing_Diff_Mean + (2 * Landing_Diff_SD)
Landing_2SD_Upper   # Should be 138.70 for this data set

Landing_2SD_Lower = Landing_Diff_Mean - (2 * Landing_Diff_SD)
Landing_2SD_Lower   # Should be -115.051 for this data set
```

Lastly, data outside of 2 standard deviations for both approach distance and landing distance were removed from analysis.

```
## Step 11. Remove Outliers - Omit cases in which the approach distance
## difference is outside of 2 SD form the mean

Approach_filtered_data <-clean_data %>%
  filter(Approach_Difference < Approach_2SD_Upper, Approach_Difference >
           Approach_2SD_Lower)   # 5 cases should be omitted for this data set

length(Approach_filtered_data$'Participant_ID')   #n = 145


## Step 12. Remove Outliers - Omit cases in which the landing distance
## difference is outside of 2 SD form the mean

Landing_filtered_data <-clean_data %>%
  filter(Landing_Difference < Landing_2SD_Upper, Landing_Difference >
           Landing_2SD_Lower)   # 5 cases should be omitted

length(Landing_filtered_data$'Participant_ID')   #n = 145
```

Statistical Analysis

As the purpose of this study is to compare the accuracy and reliability of a pressure sensing walkway against the gold standard, intraclass correlations, Pearson's correlation coefficient, Bland-Altman limits of agreement, and percent error were examined. Each dependent variable was assessed separately, comparing the pressure sensing walkway to the Vicon Motion System.

Reliability or the “magnitude of measurement error in observed measurements” (Camomilla et al. 2017; Michelini, Eshraghi, and Andrysek 2020) was examined via intraclass correlations (ICCs). Separate ICCs, the presented correlation value, and the upper and lower bound limits (interval of agreement) were examined between the methodology pair (i.e., VICON versus pressure sensing walkway). Aligning with previous literature (Rosner 2015; Zaki et al. 2013), ICC values of < 0.4 were considered as having “poor reliability”, 0.4 to < 0.75 were considered to have “fair to good” reliability, with ICC values 0.75 indicating “excellent” reliability. As it is not suggested to use ICCs as a measure alone (Koo and Li 2016; Zaki et al. 2013), a Bland-Altman Martin Bland and Altman (1986) analysis was additionally employed.

Although paired samples t-tests and Pearson product corrections have been used to assess validity, it is not advised to use these statistical tests to examine levels of agreement or validity on their own (Camomilla et al. 2017; Michelini, Eshraghi, and Andrysek 2020). Therefore, a Bland-Altman limits of agreement test was employed. The interval of agreement was set to the 95% confidence interval (CI), and considered acceptable when the measure is $< 10\%$ different than the gold standard (Jakobsen et al. 2014; Saggio, Tombolini, and Ruggiero 2021). Lastly, to assess accuracy, percentage error was calculated for each variable. To align with current thresholds for statistical and clinical significance Jakobsen et al. (2014), as well as for consistency across literature in validation studies of inertial measurement units during walking gait (Fusca et al. 2018; Saggio, Tombolini, and Ruggiero 2021), an absolute error of $< 5\%$ will be considered “excellent”, 5% to $< 10\%$ to be “good”, 10% to $< 20\%$ to be “sufficient”, and 20% or greater to be unacceptable.

Lastly, methodological success was defined *a priori*. Methodologies with ICC values of 0.4 or greater (indicating “fair to good” to “excellent” reliability), a Bland-Altman analysis of $<10\%$ differences within interval agreement, and absolute error of $<10\%$ (considered “good” or “excellent” accuracy) will be considered an accurate or reliable method for collecting that specific obstacle crossing measure.

RESULTS

Participants

Of the 50 participants, 31 were female and identified as a woman, with the other 19 identifying as male/man (Figures 5 & 6). Participants were mostly young adults, 24 ± 6 years; height: 1.72 ± 0.10 m; weight: 76.1 ± 20.9 kg (Table 1). Most of the participants identified as white (n = 47, and six individuals identified as Hispanic ethnicity (44 non-Hispanic; Figures 7 -9). 92% (n = 46) described themselves as being right-leg dominant, however only 46.9% of individuals crossed with their right leg (Figures 10 & 11).

```
## Step 13. Compile and count the sex variable

Sex_Count <- demographic_data %>%
  count(Sex)
Sex_Count


## Step 14. Compile Age, Height & Weight of participants and then find mean and
## standard deviation

age_mean <- mean(demographic_data$Age, na.rm = TRUE) # Need the "na.rm = TRUE"
  # because we have missing data
age_mean  # should be 24.1 for this data set

age_SD <- sd(demographic_data$Age, na.rm = TRUE)
age_SD  # should be 5.5 for this data set


demographic_data <- demographic_data %>%
  mutate(Height_m = Height_cm / 100) # 100 cm = 1 meter

height_mean <- mean(demographic_data$Height_m, na.rm = TRUE)
height_mean # This is in meters

height_sd <- sd(demographic_data$Height_m, na.rm = TRUE)
height_sd # This is in meters


demographic_data <- demographic_data %>%
  mutate(weight_kg = Weight_lbs / 2.2) # 2.2 lbs = 1 kg

weight_mean <- mean(demographic_data$weight_kg, na.rm = TRUE)
weight_mean # This is in kg

weight_sd <- sd(demographic_data$weight_kg, na.rm = TRUE)
weight_sd # This is in kg


## Step 15. Compile and count the gender variable

Man_Count <- sum(demographic_data$Gender_Man =="Checked")
Man_Count
```

```r
Woman_Count <- sum(demographic_data$Gender_Woman =="Checked")
Woman_Count

Trans_Count <- sum(demographic_data$Gender_Trans =="Checked")
Trans_Count

Non_Binary_Count <- sum(demographic_data$`Gender_non-binary` =="Checked")
Non_Binary_Count

Gender_None_Count <- sum(demographic_data$Gender_None =="Checked")
Gender_None_Count

Gender_Perfer_No_Answer_Count <- sum(demographic_data$Gender_Prefer_No_Answer =="Checked")
Gender_Perfer_No_Answer_Count


## Step 16. Create a separate sheet, just for gender for later use

Gender_Counts <- data.frame(
  Gender = c("Man", "Woman", "Trans", "Non-Binary", "None", "Prefer Not to Answer"),
  Count = c(
    sum(demographic_data$Gender_Man == "Checked", na.rm = TRUE),
    sum(demographic_data$Gender_Woman == "Checked", na.rm = TRUE),
    sum(demographic_data$Gender_Trans == "Checked", na.rm = TRUE),
    sum(demographic_data$`Gender_non-binary` == "Checked", na.rm = TRUE),
    sum(demographic_data$Gender_None == "Checked", na.rm = TRUE),
    sum(demographic_data$Gender_Prefer_No_Answer == "Checked", na.rm = TRUE)
  )
)


## Step 17. Compile and count the ethnicity variable

Hispanic_Count <- sum(demographic_data$Hispanic =="Yes")
Hispanic_Count

Non_Hispanic_Count <- sum(demographic_data$Hispanic =="No")
Non_Hispanic_Count


## Step 18. Create a separate sheet, just for ethnicity for later use
```

```r
Ethnicity_Counts <- data.frame(
  Ethnicity = c("Hispanic", "Non-Hispanic"),
  Count = c(
    sum(demographic_data$Hispanic== "Yes", na.rm = TRUE),
    sum(demographic_data$Hispanic == "No", na.rm = TRUE)
  )
)


## Step 19. Compile and count the race variable

Race_AI_AN_Count <- sum(demographic_data$Race_AI_AN =="Checked")
Race_AI_AN_Count

Race_Asian_Count <- sum(demographic_data$Race_Asian =="Checked")
Race_Asian_Count

Race_Black_Count <- sum(demographic_data$Race_Black_AA =="Checked")
Race_Black_Count

Race_NH_OPI_Count <- sum(demographic_data$Race_NH_OPI =="Checked")
Race_NH_OPI_Count

Race_White_Count <- sum(demographic_data$Race_White =="Checked")
Race_White_Count

Race_No_Answer_Count <- sum(demographic_data$Race_Prefer_No_Answer =="Checked")
Race_No_Answer_Count


## Step 20. Create a separate sheet, just for race variable for later use

Race_Counts <- data.frame(
  Race = c("American Indian or Alaska Native", "Asian", "Black or African American", "Native
  Count = c(
    sum(demographic_data$Race_AI_AN == "Checked", na.rm = TRUE),
    sum(demographic_data$Race_Asian == "Checked", na.rm = TRUE),
    sum(demographic_data$Race_Black_AA == "Checked", na.rm = TRUE),
    sum(demographic_data$Race_NH_OPI == "Checked", na.rm = TRUE),
    sum(demographic_data$Race_White == "Checked", na.rm = TRUE),
    sum(demographic_data$Race_Prefer_No_Answer == "Checked", na.rm = TRUE)
  )
```

Descriptive Statistics

Variable	Mean & Standard Deviation
Age (years)	M = 24, SD = 6
Height (meters)	M = 1.72, SD = 0.10
Weight (kg)	M = 76.1, SD = 20.9

```
)


## Step 21. Compile and count the dominate leg variable

Dom_Leg_Count <- demographic_data %>%
  count(Dominate_Leg)
Dom_Leg_Count
```

Table 1. Participant demographic information (n = 50).

```
## Step 22. Build a mean and SD table of participant demographic information

demographic_data %>%
  summarise(
    "Age (years)" = sprintf("M = %.0f, SD = %.0f", age_mean, age_SD),
    "Height (meters)" = sprintf("M = %.2f, SD = %.2f", height_mean, height_sd),
    "Weight (kg)" = sprintf("M = %.1f, SD = %.1f", weight_mean, weight_sd)
  ) %>%
  pivot_longer(
    everything(),
    names_to = "Variable",
    values_to = "Mean & Standard Deviation"
  ) %>%
  gt() %>%
  tab_header(
    title = "Descriptive Statistics"
  )
```

```
## Step 23. Builds a bar graph of the sex data

ggplot(Sex_Count, aes(x = Sex, y = n, fill = Sex)) +
  geom_bar(stat = "identity", color = "black") +
```

```r
  geom_text(aes(label = paste0(round(n, 1), "")),
            vjust = 5,
            size = 8) +
  labs(title = "Sex Distribution", x = "Sex", y = "Count") +
  theme_minimal() +
  theme(legend.position = "none")
```

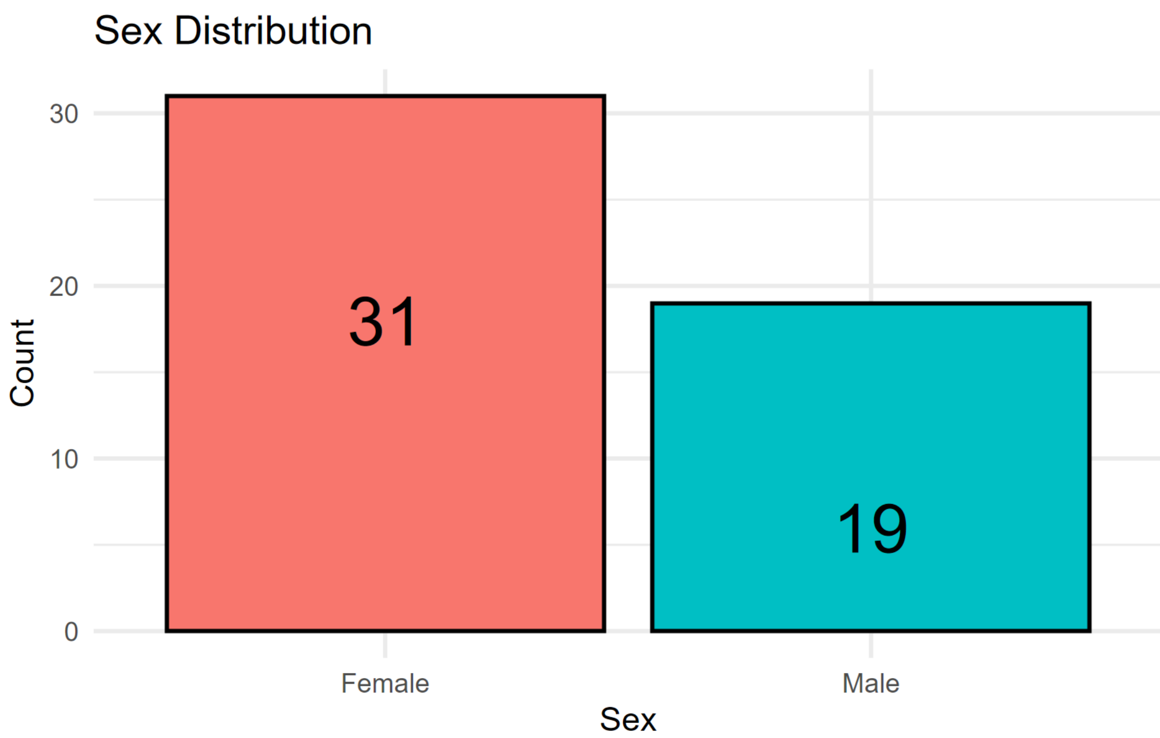

Figure 5. Sex distribution of participants (male = 19, female = 31).

```r
## Step 24. Reorders the gender data to be descending order

Gender_Counts$Gender <- fct_reorder(Gender_Counts$Gender, Gender_Counts$Count)

## Step 25. Build a bar graph of the gender data

ggplot(Gender_Counts, aes(x = Gender, y = Count, fill = Gender)) +
  geom_bar(stat = "identity", color = "black") +
  geom_text(aes(label = Count), vjust = 0.25, hjust = 1.25, size = 5) +
  labs(title = "Gender Identity Distribution",
       x = "Gender",
```

```
      y = "Count") +
  theme_minimal() +
  theme(legend.position = "none") +
  coord_flip()
```

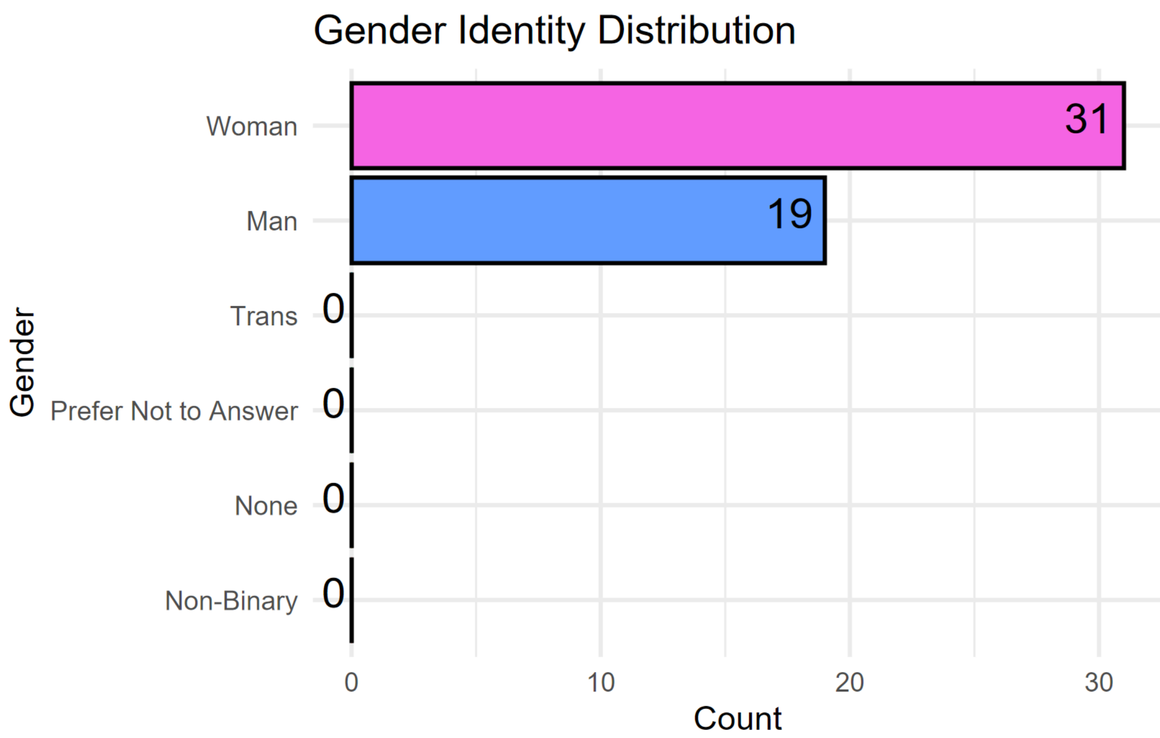

Figure 6. Gender distribution across participants (n = 50).

```
## Step 26. Build a bar graph of the ethnicity data

ggplot(Ethnicity_Counts, aes(x = Ethnicity, y = Count, fill = Ethnicity)) +
  geom_bar(stat = "identity", color = "black") +
  geom_text(aes(label = Count), vjust = 0.25, hjust = 2, size = 5) +
  labs(title = "Ethnicity Distribution",
      x = "Ethnicity",
      y = "Count") +
  theme_minimal() +
  theme(legend.position = "none") +
  coord_flip()
```

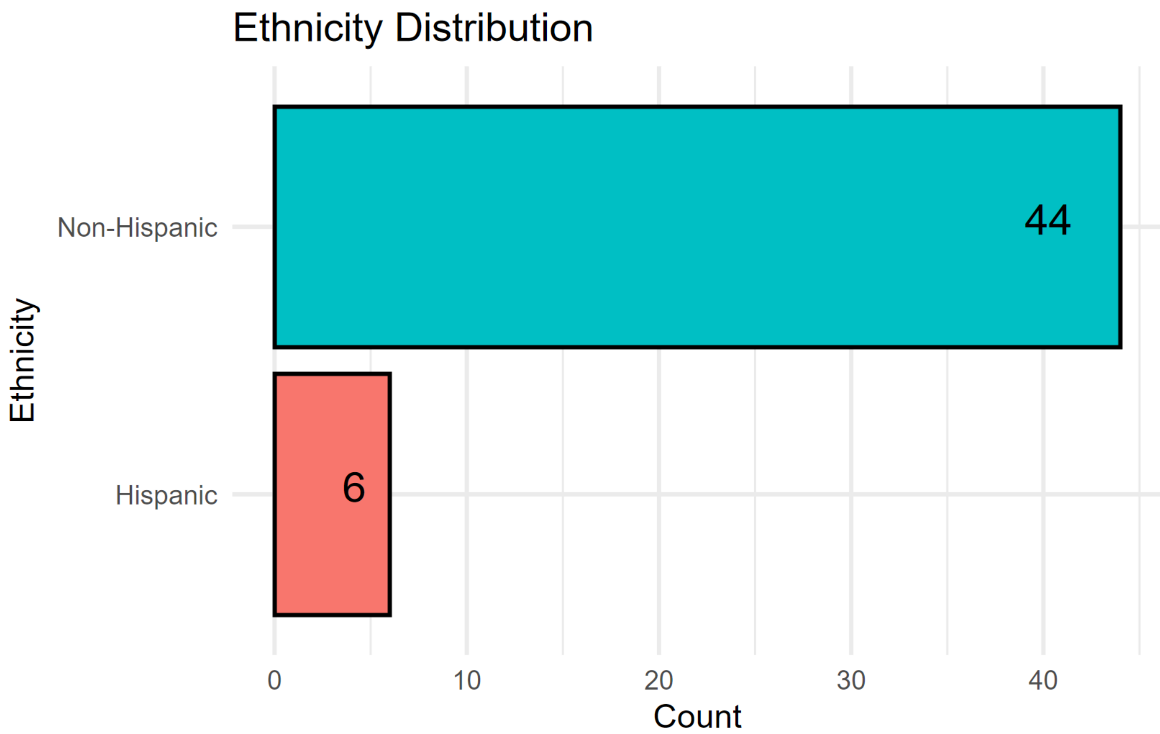

Figure 7. Ethnicity distribution across participants (n = 50).

```
## Step 27. Calculate race data percentage

Race_Counts$Percentage <- (Race_Counts$Count / sum(Race_Counts$Count)) * 100  # Calculate rac


## Step 28. Create a bar chart of race counts

Race_Counts$hjust <- c(0, -1, 0, 0, 1.5, 0)  # Set where you want the data labels
  # horizontally adjusted
  # This will adjust where the labels are in the bar graph

ggplot(Race_Counts, aes(x = Race, y = Count, fill = Race)) +
  geom_bar(stat = "identity", color = "black") +
  geom_text(aes(label = Count, hjust = Race_Counts$hjust), vjust = 0.25, size = 5) +
  labs(title = "Race Distribution",
       x = "Race",
       y = "Count") +
  scale_fill_brewer(palette = "Set3") +
  theme_minimal() +
```

```
  theme(legend.position = "none") +
  coord_flip()
```

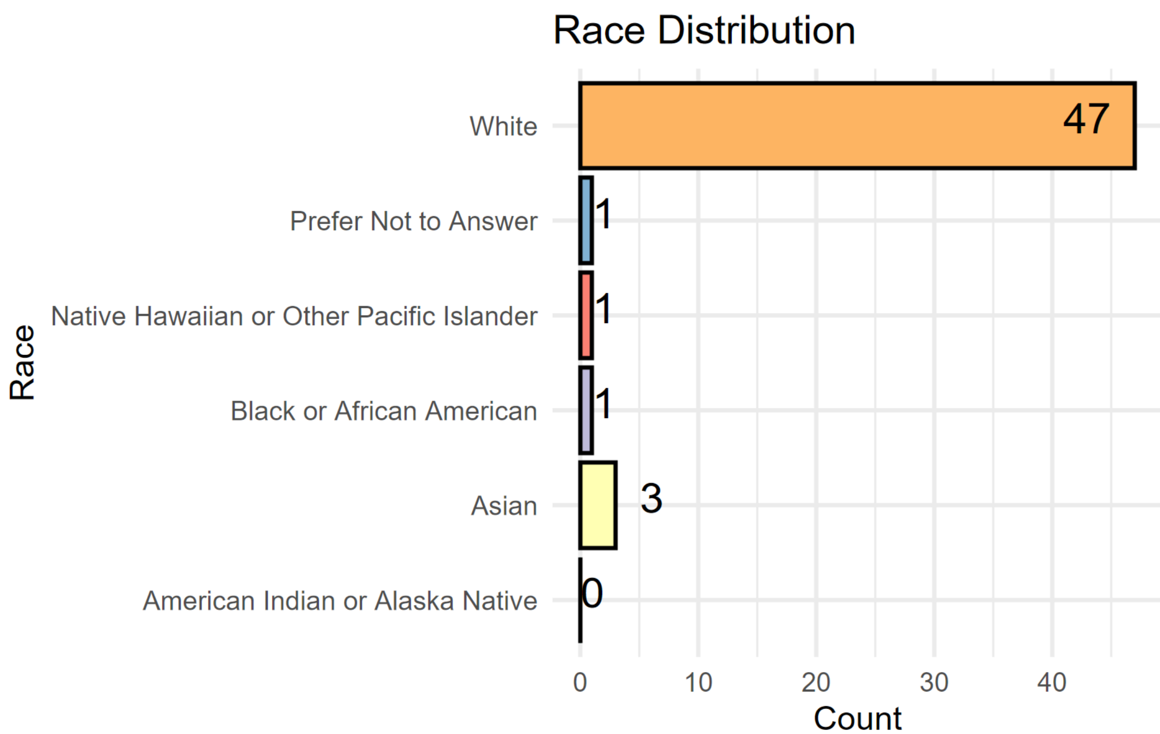

Figure 8. Detailed race distribution across participants (n = 50).

```
## Step 29. Create a pie chart for race counts

ggplot(Race_Counts, aes(x = "", y = Count, fill = Race)) +
  geom_bar(stat = "identity", color = "black", width = 1) +  # Bar chart for pie
  geom_text(aes(label = ifelse(Race == "White",
                               paste0(Count, " (", round(Percentage, 1), "%)"),
                               NA)),
            vjust = 6, hjust = 0, size = 5) +  # Add count and percentage labels
  labs(title = "Race Distribution") +
  scale_fill_brewer(palette = "Set3") +
  coord_polar(theta = "y") +  # Converts the bar chart into a pie chart
  theme_void() +  # Removes background and axes
  theme()
```

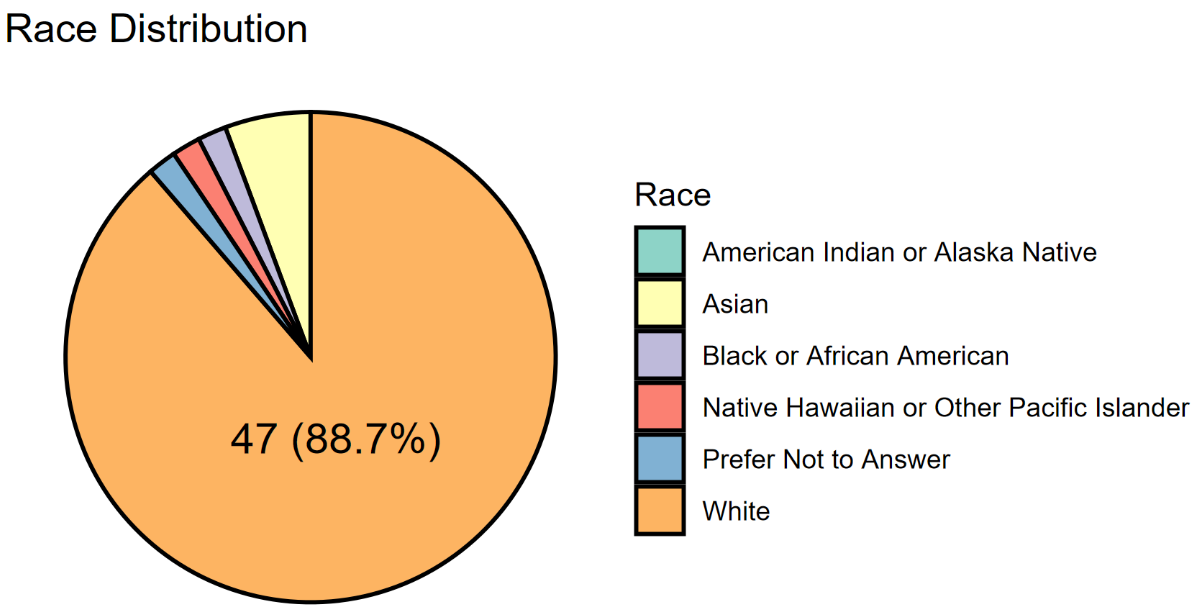

Figure 9. Pie chart of race distribution (n = 50).

```
## Step 30. Calculate a percentage of the dominate leg count

Dom_Leg_Count$Percentage <- (Dom_Leg_Count$n / 50) * 100 # Calculates percent of dominate leg


## Step 31. Build a stacked bar graph of the dominant limb

ggplot(Dom_Leg_Count, aes(x = "Dominant Leg", y = n, fill = Dominate_Leg)) +
  geom_bar(stat = "identity", color = "black") +
  geom_text(aes(label = paste0(Dominate_Leg, ": ", n, " (", round(Percentage, 1), "%)")),
            position = position_stack(vjust = 0.5),
            size = 5) +
  labs(title = "Dominant Limb Distribution",
       subtitle = "Stacked breakdown of leg preference based on the question:
       Which leg would you kick a ball with?",
       x = NULL,
       y = "Count",
       fill = "Dominant Leg") +
  scale_fill_brewer(palette = "Set3") +
```

```
  theme_minimal() +
  theme(axis.text.x = element_blank(),  # Hide x-axis label since it's just one bar
        axis.ticks.x = element_blank(),
        panel.grid.major.x = element_blank())
```

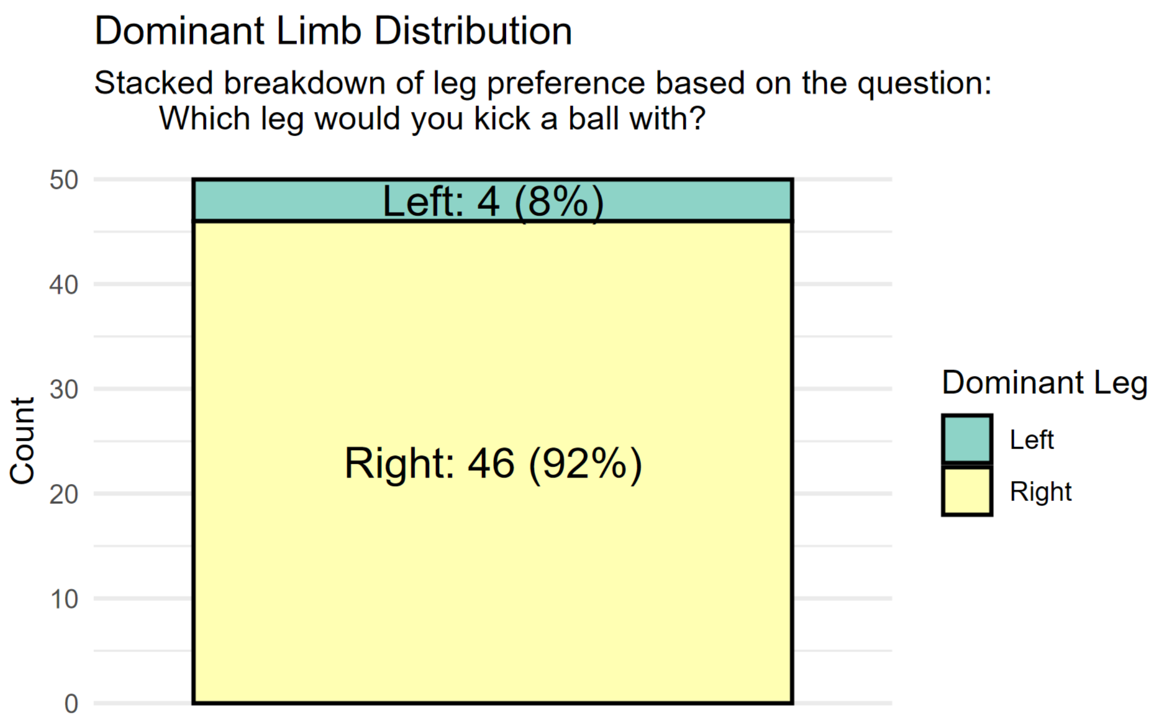

Figure 10. Dominant leg distribution (n = 50).

```
## Step 32. Calculate Lead Limb Distributions

Lead_Foot_Count <- Approach_filtered_data %>%
  count(VICON_Lead_Foot)

Lead_Foot_Count <- Approach_filtered_data %>%
  count(VICON_Lead_Foot) %>%
  mutate(Lead_Foot_Percent = n / sum(n) * 100)

## Step 33. Create a Bar Graph to display lead limb

ggplot(Lead_Foot_Count, aes(x = VICON_Lead_Foot, y = Lead_Foot_Percent, fill = VICON_Lead_Fo
  geom_bar(stat = "identity", color = "black") +
```

```r
  geom_text(aes(label = paste0(round(Lead_Foot_Percent, 1), "%")),
            vjust = 7,
            size = 8) +
  labs(title = "Lead Foot Distributions", x = "Lead Foot", y = "Percentage (%)") +
  theme_minimal()+
  theme(legend.position = "none")
```

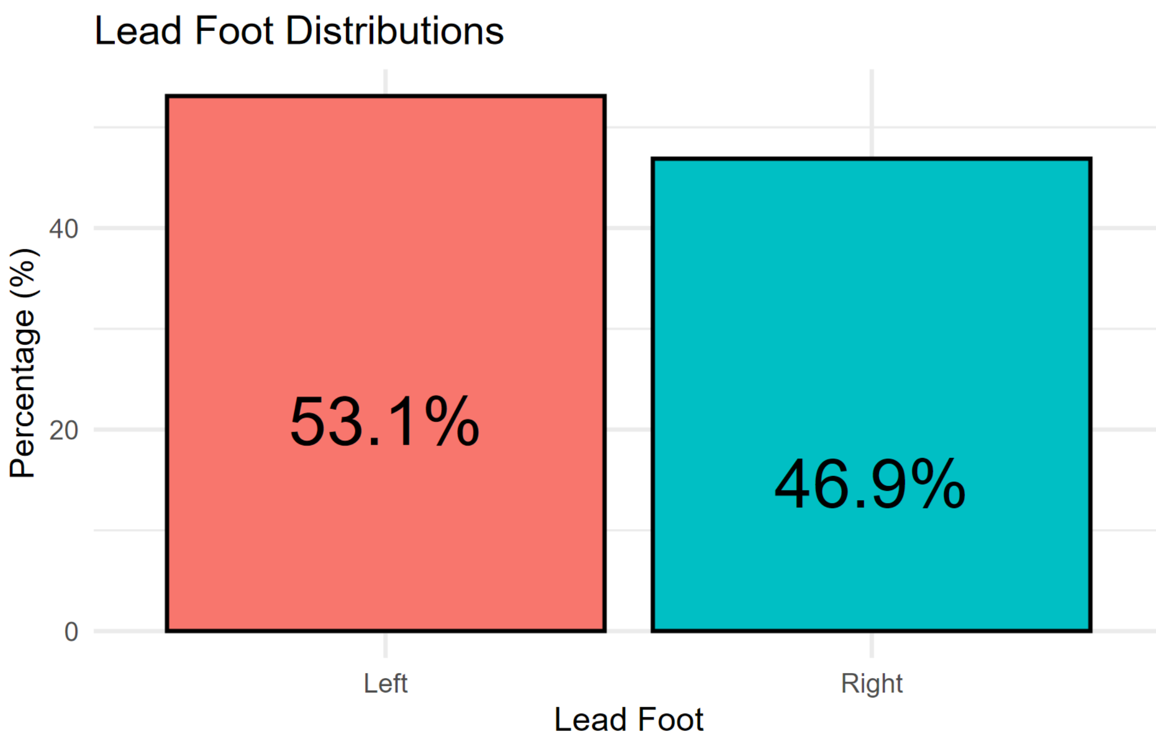

Figure 11. Lead Limb Distribution while crossing.

Pressure Sensing Walkway Accuracy & Reliability

Accuracy and reliability of the pressure sensing walkway was assessed against the gold standard (Vicon Motion Systems) using intraclass correlations, Bland-Altman limits of agreement, Pearson product correlations, and percent error. Mean distance measures for both approach and landing distance are presented in Table 2.

```r
## Step 32. Calculate average measures of the variables of interest

Mean_VICON_Approach <- mean(Approach_filtered_data$VICON_approach_dist_trail)
```

```r
Mean_VICON_Approach

SD_Vicon_Approach <- sd(Approach_filtered_data$VICON_approach_dist_trail)
SD_Vicon_Approach

Mean_PKMAS_Approach <- mean(Approach_filtered_data$PKMAS_Approach_Dist_MM)
Mean_PKMAS_Approach

SD_PKMAS_Approach <- sd(Approach_filtered_data$PKMAS_Approach_Dist_MM)
SD_PKMAS_Approach

Mean_VICON_Landing <- mean(Landing_filtered_data$VICON_landing_dist_lead)
Mean_VICON_Landing

SD_VICON_Landing <- sd(Landing_filtered_data$VICON_landing_dist_lead)
SD_VICON_Landing

Mean_PKMAS_Landing <- mean(Landing_filtered_data$PKMAS_Landing_Dist_MM)
Mean_PKMAS_Landing

SD_PKMAS_Landing <- sd(Landing_filtered_data$PKMAS_Landing_Dist_MM)
SD_PKMAS_Landing


## Step 33. Format the values for table display (whole numbers since working in
## mm)

VICON_values <- c(
  sprintf("M = %.0f, SD = %.0f", Mean_VICON_Approach, SD_Vicon_Approach),
  sprintf("M = %.0f, SD = %.0f", Mean_VICON_Landing, SD_VICON_Landing)
)

PKMAS_values <- c(
  sprintf("M = %.0f, SD = %.0f", Mean_PKMAS_Approach, SD_PKMAS_Approach),
  sprintf("M = %.0f, SD = %.0f", Mean_PKMAS_Landing, SD_PKMAS_Landing)
)


## Step 34. Create comparison of VICON and PKMAS Measures Table

Variable_table <- data.frame(
  Measure = c("Approach Distance", "Landing Distance"),
```

Comparison of VICON and PKMAS Measures

	Mean ± SD (mm)	
Measure	VICON	PKMAS
Approach Distance	M = 227, SD = 89	M = 235, SD = 84
Landing Distance	M = 297, SD = 74	M = 296, SD = 72

```
  VICON = VICON_values,
  PKMAS = PKMAS_values
)
```

```
## Step 35. Format and display the table within manuscript

Mean_Variable_Table <- gt(Variable_table) %>%
  tab_header(
    title = "Comparison of VICON and PKMAS Measures"
  ) %>%
  tab_spanner(label = "Mean ± SD (mm)", columns = c(VICON, PKMAS)) %>%
  cols_align(
    align = "center",
    columns = c(VICON, PKMAS)
  )

Mean_Variable_Table   # Displays Table
```

Table 2. Mean distance measures of approach and landing distance for both the gold standard (VICON) and the pressure sensing walkway (PKMAS) after removal of data outside of 2 standard deviations (n = 145 observations).

Approach Distance

The pressure sensing walkway (Zeno Walkway) showed excellent reliability for assessing approach distance (r= 0.99; 95% CI: 0.98 - 0.99) (Koo and Li 2016; Zaki et al. 2013).

```
#| label: Calculate Approach ICC

## Step 36. Compute Intraclass Correlations between the VICON and PKMAS Approach
## distance variable.

Approach_ICC_Result <- icc(Approach_filtered_data %>% select(VICON_approach_dist_trail, PKMAS
```

```
                             model = "twoway",
                             type = "agreement",
                             unit = "average")
Approach_ICC_Result   # ICC should be 0.99 for this data set
```

```
 Average Score Intraclass Correlation

   Model: twoway
   Type : agreement

   Subjects = 145
     Raters = 2
   ICC(A,2) = 0.99

 F-Test, H0: r0 = 0 ; H1: r0 > 0
F(144,20.3) = 122 , p = 3.47e-18

 95%-Confidence Interval for ICC Population Values:
  0.978 < ICC < 0.994
```

The Bland-Altman analysis (Figure 12) revealed that the pressure sensing walkway overestimated the approach distance by approximately 8 mm with a 95% CI of 5.28 to 11.14 and limits of agreement of -38.6 to 22.5. However, the Bland-Altman plot showed that this difference was significantly different than zero ($t(49)$ = -5.63, p $<$ .001), and biased towards overestimating approach distance in the pressure sensing walkway system (R squared = 0.06, $F(1{,}143)$ = 10.66, $p < .01$).

```
#| label: Calculate Approach Distance Differences

## Step 37. Create average Approach Distance for both PKMAS and VICON for each
## participant. THIS WILL BE USED FOR THE ONE-SAMPLE T-TEST

Mean_Differences_Approach_Distance <- Approach_filtered_data %>%
  group_by(Participant_ID) %>%
  summarise(Approach_Diff_mean_mm = mean(Approach_Difference))

Mean_Differences_Approach_Distance
```

```
#| label: Bland-Altman Step 1 - One-Sample T-Test

## Step 38. Run a one Sample t-test to determine if the differences between
```

```r
## methods is statistically different from zero for Approach Distance.

Approach_Diff_Zero_TTest <- t.test (Mean_Differences_Approach_Distance$Approach_Diff_mean_mm

Approach_Diff_Zero_TTest  # If the t-test value is significant then the data IS
```

```

	One Sample t-test

data:  Mean_Differences_Approach_Distance$Approach_Diff_mean_mm
t = -5.633, df = 49, p-value = 8.561e-07
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -11.136660  -5.279974
sample estimates:
mean of x
-8.208317
```

```r
                           # different from zero, therefore, not what we want.

# Our data indicates that there IS a difference from zero
```

```r
## Step 39. Calculate variables for Approach Distance Bland-Altman Plot

Approach_filtered_data <- Approach_filtered_data %>%
  mutate(
    app_mean = (VICON_approach_dist_trail + PKMAS_Approach_Dist_MM) / 2,
    app_diff = VICON_approach_dist_trail - PKMAS_Approach_Dist_MM
  )

app_bias <- mean(Approach_filtered_data$app_diff)
app_sd_diff <- sd(Approach_filtered_data$app_diff)


## Step 40. Calculate Limits of Agreement for Approach Distance

Approach_Upper_LOA <- app_bias + (1.96*app_sd_diff)
Approach_Upper_LOA

Approach_Lower_LOA <- app_bias - (1.96*app_sd_diff)
Approach_Lower_LOA
```

```
## Step 41. Create the Bland-Altman Plot for Approach Distance

ggplot(Approach_filtered_data, aes(x = app_mean, y = app_diff)) +
  geom_point() +
  geom_hline(yintercept = app_bias, color = "blue", linetype = "dashed", size = 1.5) +
  geom_hline(yintercept = app_bias + 1.96 * app_sd_diff, color = "red", linetype = "dotted",
  geom_hline(yintercept = app_bias - 1.96 * app_sd_diff, color = "red", linetype = "dotted",

  # Add labels to the lines
  geom_text(aes(x = max(Approach_filtered_data$app_mean), y = app_bias, label = "Bias", vjus
  geom_text(aes(x = max(Approach_filtered_data$app_mean), y = app_bias + 1.96 * app_sd_diff,
  geom_text(aes(x = max(Approach_filtered_data$app_mean), y = app_bias - 1.96 * app_sd_diff,

  # Add labels to the chart
  labs(
    title = "Bland-Altman Plot",
    subtitle = "Approach Distance",
    x = "Approach Distance Mean (mm)",
    y = "Difference Between Methods (mm)"
  ) +
  theme_minimal()
```

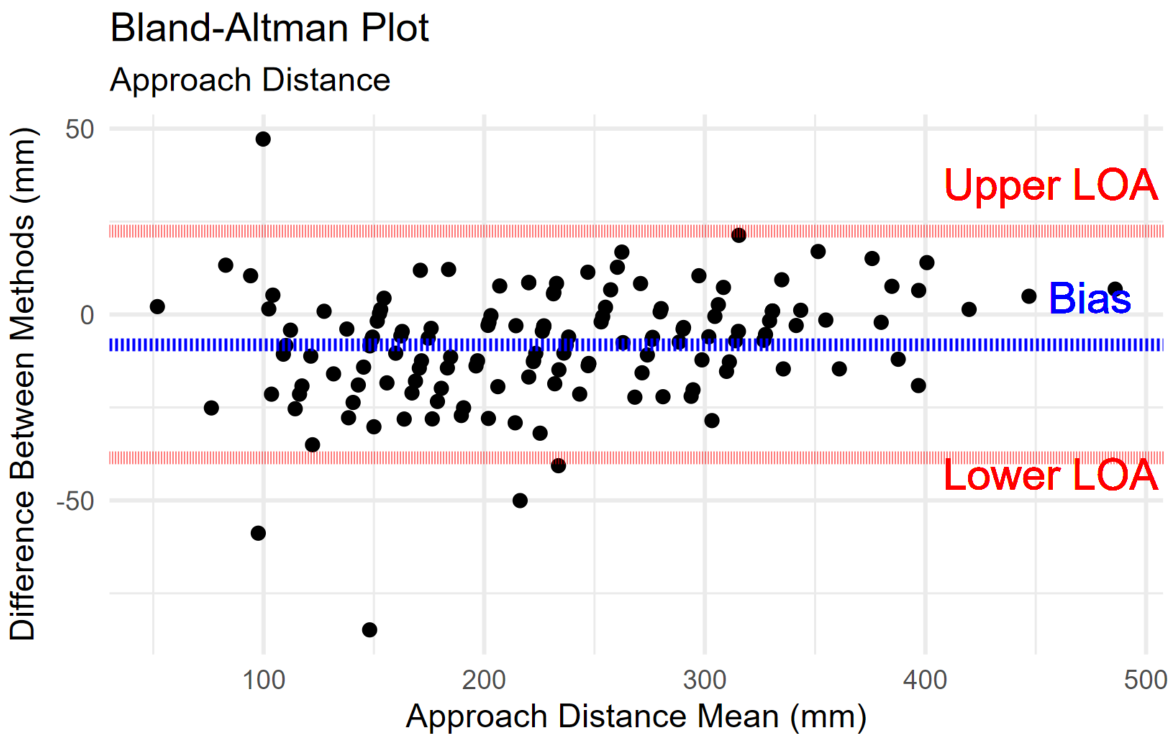

Figure 12. Bland-Altman Plot for Approach Distance.

```r
## Step 42. Run a linear regression to determine proportional bias for Approach
## Distance Variable

Approach_Regression <- lm(Approach_Difference ~ app_mean, data = Approach_filtered_data)

summary(Approach_Regression)  # If the mean t-score is significant, this means
```

```
Call:
lm(formula = Approach_Difference ~ app_mean, data = Approach_filtered_data)

Residuals:
    Min      1Q  Median      3Q     Max
-72.813  -7.890   0.454   7.374  61.530

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -19.08440    3.59649  -5.306 4.17e-07 ***
app_mean      0.04765    0.01460   3.265  0.00137 **
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 15.09 on 143 degrees of freedom
Multiple R-squared:  0.06937,   Adjusted R-squared:  0.06286
F-statistic: 10.66 on 1 and 143 DF,  p-value: 0.001371
```

```
                              # that the methods is bias on one direction. Not
                              # significant = no bias
```

The Pearson product correlation revealed a strong correlation between variables ($r(143) = 0.98$, $p < .001$). Percent error was considered "good" with a 5.47% error, again with the pressure sensing walkway overestimating approach distance (Jakobsen et al. 2014).

```
## Step 43. Run a Pearson Product Correlation to determine if the methods are
## correlated with one another for approach distance

Approach_Pearson <- cor.test(Approach_filtered_data$VICON_approach_dist_trail, Approach_filte

Approach_Pearson             # Correlation Values of 0.985
```

```

    Pearson's product-moment correlation

data:  Approach_filtered_data$VICON_approach_dist_trail and Approach_filtered_data$PKMAS_Appr
t = 67.952, df = 143, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.9790326 0.9890851
sample estimates:
      cor
0.9848658
```

```
## Step 44. Calculate absolute % error for Approach Distance

Approach_filtered_data <- Approach_filtered_data %>%
  mutate(
    Approach_Percent_Error = ((Approach_filtered_data$VICON_approach_dist_trail - Approach_fi
)

Avg_Approach_Percent_Error <- mean(Approach_filtered_data$Approach_Percent_Error)
```

```
Avg_Approach_Percent_Error    # Should be -5.47 for this data set
```

```
[1] -5.467705
```

Landing Distance

The pressure sensing walkway (Zeno Walkway) showed excellent reliability for assessing landing distance (r= 0.99; 95% CI: 0.988 - 0.994) (Koo and Li 2016; Zaki et al. 2013).

```
## Step 45. Compute Intraclass Correlations between the VICON and PKMAS Landing
## distance variable.

Landing_ICC_Result <- icc(Landing_filtered_data %>% select(VICON_landing_dist_lead, PKMAS_Lan
                           model = "twoway",
                           type = "agreement",
                           unit = "average")
Landing_ICC_Result   # ICC should be 0.991 for this data set
```

```
 Average Score Intraclass Correlation

   Model: twoway
   Type : agreement

   Subjects = 145
     Raters = 2
   ICC(A,2) = 0.991

 F-Test, H0: r0 = 0 ; H1: r0 > 0
 F(144,145) = 117 , p = 6.45e-109

 95%-Confidence Interval for ICC Population Values:
  0.988 < ICC < 0.994
```

The Bland-Altman analysis (Figure 13) revealed that the pressure sensing walkway underestimated the landing distance by approximately 1 mm with a 95% CI of -1.91 to 4.01 and limits of agreement of -25.4 to 27.6. However, the Bland-Altman plot showed that this difference was no significant difference from zero ($t(49) = 0.71$, p < .48), and was not biased from the gold standard (R squared = 0.01, $F(1{,}143) = 3.04$, $p = .08$).

```
## Step 46. Create average Landing Distance for both PKMAS and VICON for each
## participant.THIS WILL BE USED FOR THE ONE-SAMPLE T-TEST

Mean_Differences_Landing_Distance <- Landing_filtered_data %>%
  group_by(Participant_ID) %>%
  summarise(Landing_Diff_mean_mm = mean(Landing_Difference))

Mean_Differences_Landing_Distance
```

```
## Step 47. Run a one Sample t-test to determine if the differences between
## methods is statistically different from zero for Landing Distance.

Landing_Diff_Zero_TTest <- t.test (Mean_Differences_Landing_Distance$Landing_Diff_mean_mm, mu

Landing_Diff_Zero_TTest  # If the t-test value is significant then the data IS
```

```
	One Sample t-test

data:  Mean_Differences_Landing_Distance$Landing_Diff_mean_mm
t = 0.71418, df = 49, p-value = 0.4785
alternative hypothesis: true mean is not equal to 0
95 percent confidence interval:
 -1.907798  4.011417
sample estimates:
mean of x
 1.051809
```

```
                         # different from zero, therefore, not what we want.

# Our data indicates that there is NOT a difference from zero -- YAY!
```

```
## Step 48. Calculate variables for Approach Distance Bland-Altman Plot

Landing_filtered_data <- Landing_filtered_data %>%
  mutate(
    land_mean = (VICON_landing_dist_lead + PKMAS_Landing_Dist_MM) / 2,
    land_diff = VICON_landing_dist_lead - PKMAS_Landing_Dist_MM
  )

land_bias <- mean(Landing_filtered_data$land_diff)
```

```r
land_sd_diff <- sd(Landing_filtered_data$land_diff)


## Step 49. Calculate Limits of Agreement for Landing Distance

Landing_Upper_LOA <- land_bias + (1.96*land_sd_diff)
Landing_Upper_LOA

Landing_Lower_LOA <- land_bias - (1.96*land_sd_diff)
Landing_Lower_LOA
```

```r
## Step 50. Create the Bland-Altman Plot for Landing Distance

ggplot(Landing_filtered_data, aes(x = land_mean, y = land_diff)) +
  geom_point() +
  geom_hline(yintercept = land_bias, color = "blue", linetype = "dashed", size = 1.5) +
  geom_hline(yintercept = land_bias + 1.96 * land_sd_diff, color = "red", linetype = "dotted"
  geom_hline(yintercept = land_bias - 1.96 * land_sd_diff, color = "red", linetype = "dotted"

  # Add labels to the lines
  geom_text(aes(x = max(Landing_filtered_data$land_mean), y = land_bias, label = "Bias", vjus
  geom_text(aes(x = max(Landing_filtered_data$land_mean), y = land_bias + 1.96 * land_sd_dif
  geom_text(aes(x = max(Landing_filtered_data$land_mean), y = land_bias - 1.96 * land_sd_dif

  # Add labels to the chart
  labs(
    title = "Bland-Altman Plot",
    subtitle = "Landing Distance",
    x = "Landing Distance Mean (mm)",
    y = "Difference Between Methods (mm)"
  ) +
  theme_minimal()
```

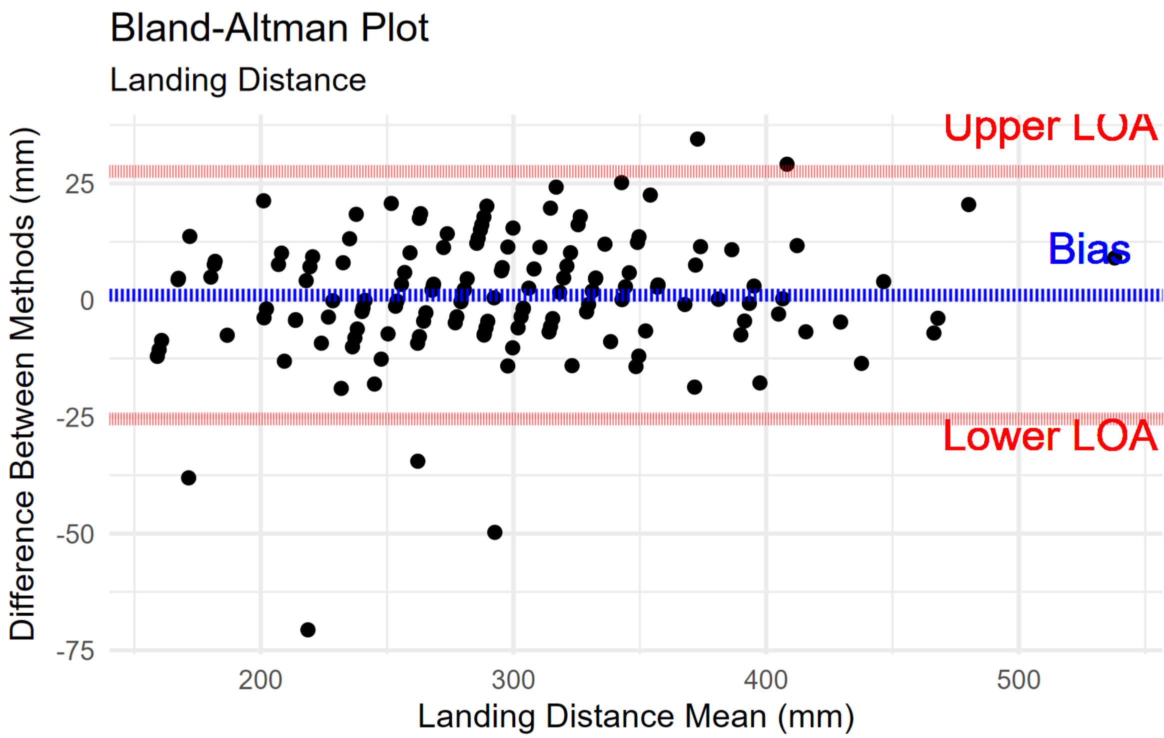

Figure 13. Bland-Altman Plot for Landing Distance.

```
## Step 51. Run a linear regression to determine proportional bias for Landing
## Distance Variable

Landing_Regression <- lm(Landing_Difference ~ land_mean, data = Landing_filtered_data)

summary(Landing_Regression)  # If the mean t-score is significant, this means
```

```
Call:
lm(formula = Landing_Difference ~ land_mean, data = Landing_filtered_data)

Residuals:
    Min      1Q  Median      3Q     Max
-69.638  -7.083  -0.069   8.628  31.383

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -6.82312    4.67601  -1.459   0.1467
land_mean    0.02669    0.01531   1.743   0.0835 .
```

```
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13.42 on 143 degrees of freedom
Multiple R-squared:  0.02081,   Adjusted R-squared:  0.01396
F-statistic: 3.039 on 1 and 143 DF,  p-value: 0.08346
```

```
                             # that the methods is bias on one direction. Not
                             # significant = no bias
```

The Pearson product correlation revealed a strong correlation between variables ($r(143) = 0.98$, $p < .001$). Percent error was considered "excellent" with a 0.04% error (Jakobsen et al. 2014).

```
## Step 52. Run a Pearson Product Correlation to determine if the methods are
## correlated with one another for landing distance

Landing_Pearson <- cor.test(Landing_filtered_data$VICON_landing_dist_lead, Landing_filtered_d

Landing_Pearson             # Correlation Values of 0.983
```

```

    Pearson's product-moment correlation

data:  Landing_filtered_data$VICON_landing_dist_lead and Landing_filtered_data$PKMAS_Landing_
t = 64.75, df = 143, p-value < 2.2e-16
alternative hypothesis: true correlation is not equal to 0
95 percent confidence interval:
 0.9769673 0.9880040
sample estimates:
      cor
0.9833702
```

```
## Step 53. Calculate % error for Landing Distance

Landing_filtered_data <- Landing_filtered_data %>%
  mutate(
    Landing_Percent_Error = ((Landing_filtered_data$VICON_landing_dist_lead - Landing_filtere
  )

Avg_Landing_Percent_Error <- mean(Landing_filtered_data$Landing_Percent_Error)
```

```r
Avg_Landing_Percent_Error     # Should be 0.04 for this data set
```

```
[1] 0.04016654
```

DISCUSSION

The purpose of this study was to compare the accuracy and reliability of a well established methodology for examining walking gait (i.e., a pressure sensing walkway), in a novel application of assessing obstacle crossing measures. Since this pressure sensing walkway is valid and reliable for capturing spatiotemporal gait measures (Vallabhajosula et al. 2019), I hypothesized that the pressure sensing walkway would perform "good" or "excellent" for accuracy through evaluation of percent error, for reliability through evaluation of intra-class correlation coefficients, and have acceptable agreement when examining validity through a Bland-Altman analysis.

Analysis overall showed that although both approach and landing distance were considered to have "excellent" reliability through intraclass correlations (Koo and Li 2016; Zaki et al. 2013), the approach distance was overestimated by the pressure sensing walkway with a bias of 8mm, through evaluation of Bland-Altman plots. Pearson product correlations revealed strong correlations between methods for both variables, however percent error was only considered "good" for approach distance, but "excellent" for landing distance.

Although the pressure sensing walkway performed well for the landing distance measurements, approach distance measurements should be further investigated. This particular finding was interesting due to observing flipped results when compared to subsample analysis for a previous conference. In the previous findings, the pressure sensing walkway performed better for assessing approach distance than landing distance. We originally attributed this difference to shoe design and marker locations at heel strike. Current running and walking shoes tend to have additional padding in the heel, altering where the pressure sensing walkway would come in contact with the mat compared to where the heel marker is placed. However, with these new results, the heel shape of the shoe, may not be an issue, and further investigation is needed to determine why there is a difference in approach distance between measures.

Several limitations should be addressed when evaluating this study. First, the participant sample was taken from a convenient sample of young adults. Young adults tend to cross obstacles similarly (Rietdyk and Rhea 2011), therefore, although validated for young adults, it may be advantageous to examine if these methods are still valid in older adults or clinical populations. Second, three trials from each participant were used in evaluations. Although all trials were treated as individual data points, this may have led to data clustering, therefore affecting study results.

This study concludes that the Zeno Walkway can be used to accurately and reliably collect landing distance during obstacle crossing of a dowel, however future research needs to further examine why differences in accuracy and reliability occur between approach and landing distance. This study will additionally be expanded on to include an additional methodology to assess obstacle crossing approach and landing distances, along with other vertical clearance variables, that the pressure sensing walkway could not calculate. At the conclusion of this study (dissertation), my hope is that we will now have an accurate and reliable way to collect obstacle crossing measures outside of a laboratory environment.

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