Using Cadence to Predict the Walk-to-Run Transition in Children and Adolescents: A Logistic Regression Approach

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Abstract

**Background:** Preliminary evidence suggests that the transition from walking to running, i.e., preferred transition cadence, occurs in adults at ≅140 steps/min. It is unknown when this transition occurs in children and adolescents, and to what extent individual characteristics, such as age or height, impact this threshold. Understanding which cadences correspond to walking versus running can inform physical activity research using wearable sensors. **Purpose:** To develop a model to predict age- and anthropometry-specific preferred transition cadences in individuals 6-20 years old (i.e., across the developmental lifespan). **Methods:** Sixty-nine children and adolescents 6 to 20 years of age performed sequentially faster 5-min treadmill walking trials, starting at 0.22 m/s (i.e., 0.5 mph) and increasing by 0.22 m/s until completion of the trial during which they freely chose to run. Steps taken during each trial were directly observed (hand tally) and converted to cadence (steps/min). After identifying the best subset of parameters, a logistic regression model was developed. **Results:** The logistic regression analysis produced a simple mathematical equation that can be used to estimate the preferred transition cadence using age, sex, height, and BMI z-score. This transition cadence ranged from 136 to 161 steps/min across the developmental age range studied. **Conclusions:** The preferred transition cadence represents a simple and practical index to characterize gait behavior from wearable sensors in children, adolescents, and young adults. Moreover, herein we provide an equation and an open access online R Shiny app that researchers, practitioners, or clinicians can use to predict an individual-specific preferred transition cadence.

**Keywords:** preferred transition speed, step frequency, locomotion, physical activity

Preferred transition cadences and the walk-to-run phenomenon in 6-20 year-olds

During upright locomotion, individuals generally choose to walk at relatively slow speeds (i.e., < 2.0 m/s) and run at faster speeds (i.e., > 2.0 m/s) (Alexander, 2002). When individuals progressively increase their locomotor speeds, the transition from walking to running appears to be spontaneous. Numerous studies have attempted to explain this preferred transition speed phenomenon. For example, the transition to running may occur because, compared to running at a given speed, fast walking at that same speed is associated with reduced stability (Diedrich & Warren, 1995; Li, 2000), greater metabolic cost (Alexander, 2002; Diedrich & Warren, 1995; Minetti, Ardigo, & Saibene, 1994), greater perceived effort (Hreljac, 1993; Minetti et al., 1994; Noble et al., 1973; Prilutsky & Gregor, 2001), or suboptimal energy substrate utilization (Ganley, Stock, Herman, Santello, & Willis, 2011). Mathematically, the Froude number (Fr) is expressed as Fr = v2/(g\*l), where v = velocity, g = acceleration due to gravity, and l = leg length, assuming a paradigm wherein gait is modeled as an inverted pendulum that incorporates leg length. The Froude number provides an index for predicting the speed for this transition (Alexander, 1989; Usherwood, 2005). Specifically, the model suggests that walking cannot occur when the centrifugal acceleration forces exceed the centripetal forces due to gravity, which thereby requires a flight phase (i.e., during which neither foot is in contact with the ground in bipedal locomotion) within the gait pattern.

While biomechanics researchers use the Froude number to predict transitions in gait behavior (i.e., walking or running) in laboratory settings, its applicability outside of the laboratory is limited because of its necessity to include precise measures of both leg length and speed. Conversely, step-based metrics such as steps/day and cadence (steps/min) have gained popularity in physical activity research because most individuals intuitively understand what a ‘step’ is. Moreover, step-based metrics may provide a means by which to classify gait behavior (i.e., walking and running). To attain step-based measures, wearable sensors are becoming increasingly popular for use in laboratory and free-living research and by consumers. Importantly most of these wearable sensors do not directly provide the precise speed information required to calculate the Froude number and preferred transition speed. However, many sensors do provide minute-by-minute step data (i.e., cadence [steps/min]). Thus, instead of relying on walking speed, perhaps a better approach to describing gait behavior entails understanding the cadences that correspond with walking and running. That is, the preferred transition cadence (PTC, or the cadence that corresponds with the shift from walking to running) may be a more practical and understandable index for researchers, clinicians, and the general public aiming to quantify physical activity behavior, specifically, minutes per day of running.

Diedrich & Warren (1995) reported that the PTC was, on average, 142.8 steps/min in young, healthy adults 18-31 years old. A more recent study provided concurring evidence that the PTC can be accurately predicted using a cadence of 141.6 steps/min in young adults (Hansen, Kristensen, Nielsen, Voigt, & Madeleine, 2017). However, while these two initial studies indicate a PTC of ~140 steps/min may be appropriate in adults, the PTC of children and adolescents remains unclear. Furthermore, in the study by Hansen et al. (2017), leg length did not affect the observed PTC. However, this may not be the case in children, adolescents, and young adults who experience physical growth at these stages of maturation. Thus, accurate prediction of the PTC in young people may necessitate the inclusion of precise measures of leg length, as well as other anthropometric values such as height and weight. Therefore, the purpose of this study was to develop a model to predict age- and anthropometry-specific PTCs in individuals 6-20 years old. We hypothesized that cadence and anthropometric measures would classify gait behavior reasonably, i.e., with a prediction accuracy > 0.70.

# Methods

## Study design and regulatory information

This is a secondary analysis of data from the CADENCE-Kids study (Clinical Trials.gov - NCT01989104). A full description of the study design and participant characteristics have been reported elsewhere (Schuna Jr, Barreria, Hsia, Johnson, & Tudor-Locke, 2016; Tudor-Locke et al., 2018). All protocols and procedures were approved by an Institutional Review Board.

## Participants

One hundred twenty-three children, adolescents, and young adults aged 6 to 20 years volunteered to participate in the original study. For participants 6-17 years of age, informed parental/legal guardian permission and child assent was required. All participants aged 18-20 years provided informed consent. Because of the considerable differences in body anthropometrics within this age group, and to ensure a uniform age distribution, study enrollment was designed to recruit at least 4 boys and 4 girls from each age year.

## Anthropometric Measures

Barefoot standing height was measured via a stadiometer (Harpenden; Holtain Ltd., Crosswell, Crymych, Pembrokeshire, UK). Seated height was also measured with the stadiometer, whereby participants sat on a table with legs freely hanging. Leg length was quantified as standing height minus seated height. Weight and body fat percentage were measured using a Tanita bioelectrical impedance scale (Tanita SC-240; Tanita corporation, Tokyo, Japan). Waist circumference was determined using a non-distensible nylon tape measure and identified as the narrowest circumference between the iliac crest and lower costal border. Height and waist circumference measurement precision was to the nearest 0.1 cm, while weight was to the nearest 0.1 kg. All measurements were performed twice. If the height or waist circumference measurements differed by > 0.5 cm, or weight by > 0.5 kg, a third measurement was taken, and the average of the two closest measurements were used. BMI was calculated as weight (kg) divided by height squared (m2), and reported in kg/m2. However, because BMI is difficult to standardize in children, adolescents, and young adults, BMI z-scores (BMIz) were calculated using reference data from the Centers for Disease Control and Prevention (Kuczmarski et al., 2000). BMIz provide age- and sex-adjusted measures of the height-weight relationship.

**Cadence Measures**

Steps taken during each 5-minute trial were directly observed and manually counted (hand tally). Cadence (steps/min) was then computed as the total number of steps divided by trial duration (hand tallied steps / 5 min). A video recording of each participant’s lower body provided a redundant record for step verification purposes in the event of miscounting or ambiguous data.

## Protocols

Participants performed sequentially faster treadmill walking trials, starting at 0.22 m/s (i.e., 0.5 mph) and increasing in 0.22 m/s increments until: 1) completion of the fastest speed (2.23 m/s; 5.0 mph) for the protocol 2) completion of the first trial during which participants freely chose to run, or 3) voluntary cessation of the protocol by the participant.

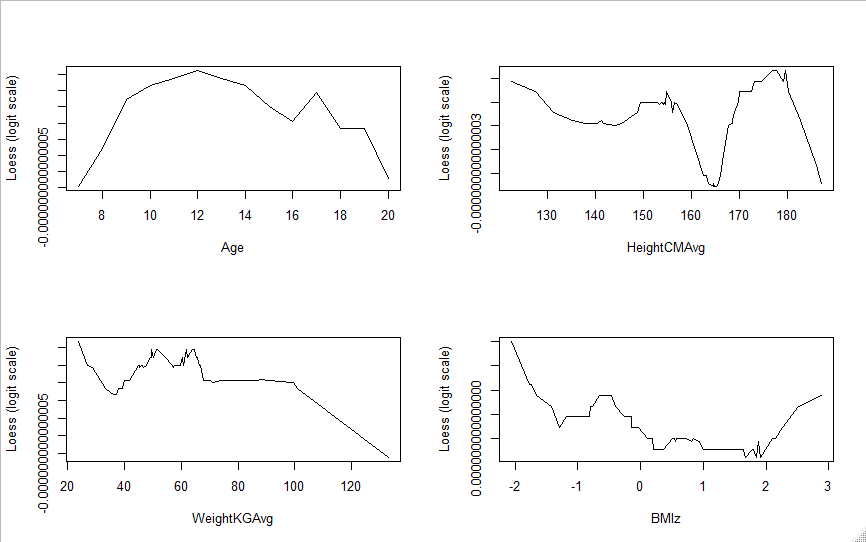
**Model Development**

Prior to model development, we first determined if any of the potential variables (Table 1) were highly correlated (i.e., > 90%). In the event that there were two correlated variables, and in an effort to provide the most feasible model for clinicians to use, we selected the easiest variable to obtain. For example, if height and leg length were highly correlated, we selected height because it is a simpler measurement to obtain.

Logistic regression models were developed using the final set of independent variables after linear dependencies were removed. The goal of this logistic regression analysis was to develop a model that accurately classifies an outcome into one of two groups using these variables. For this analysis, gait behavior was dichotomized (0,1) into running or walking and was used as the dependent variable. The model was built using the “purposeful selection” technique (Hosmer, Lemeshow, & Sturdivant, 2013), which ensures minimal collinearity between potential covariates and removes individually insignificant variables prior to building the initial model. Variables are then removed sequentially based upon the highest p-value until all remaining variables are statistically significant (i.e. p-value < 0.05). To determine PTC, we assessed the cadence at which the model was most uncertain with regards to gait classification (i.e., where the probability of running or walking was 0.5).

Dusty’s comments about assumptions. Please feel free to edit/delete/summarize into a ‘yes assumptions are met’ statement if you like. Maybe some of this is good to keep in our back pocket if one of the reviewers care. Logistic regression has 5 assumptions.

1. Independent variable to be binary: Our independent variable is run/walk, so yes, this is binary.
2. Observations are independent of each other. So – this is mostly true and where we took the most liberty. Each individual in the data set is independent (therefore one person’s dependent variables are not influenced by other people’s dependent variables – except that we’ve purposefully selected larger children in the study, but we acknowledge that as the study population) – except where independence falls a part is that we have each person in there twice. This violates independence because, since each individual is in the data set twice (once walking, once running), those two data points aren’t unrelated. I think this is fine because they are the exact some people which we’ve just tweaked the speed which they walk. The intent of independence is to avoid one individual’s results influencing another individuals – for example. Person A decides to run at an earlier pace (thought they don’t have too) because they see person B start to run. Because of this distinction, I think we are good.
3. Little or no multicollinearity. Jim and I removed factors that were correlated greater than .9 (a reasonable threshold) and kept factors that were most interpretable.
4. Assume linearity of the independent variables and log odds. This is also known as being linear in the logit. The four plots below show the linearity. I do not include the once for cadence because its completely ‘determined’ aka – if I know your cadence I can with certainty (with the data we have) split you into walk/run. The linearity of these plots are heavily influenced by individual observations. That’s why age/bmiz look parabolic – the few end observations are heavily impacting the line. Also, Height has a few observations around 165 that are all the same outcome (walk) that cause the dip in the line.



1. Last assumption: Large sample size and at least a 1/10 ratio (or 10/1 ratio) of success to failures. We have quite a few data points and we are 50/50 on successes and failures.

TABLE 1 AROUND HERE

## Data and Statistical Analysis

To assess the prediction accuracy of the final model, we performed a k-fold cross-validation, with k=10. The purpose of cross-validation is to determine how well the model will perform on out-of-sample data. For this validation method, the data is partitioned into 10 “folds”. A model is built with nine of the folds and tested on the unused “holdout set”, saving the resulting accuracy (ie. the number of correctly classified individuals in the holdout set). After replicating with each fold as the holdout set, the resultant accuracies are compiled and averaged, along with sensitivity, specificity, positive predictive values (PPV), and negative predictive values NPV).

**R Shiny App Development**

An interactive R Shiny web app (R Core Team, 2018) was created to provide a user-friendly interface for applying this model to predict the probability that an individual is walking or running across a range of cadences given their individual-specific parameters.

**Results**

**Participant characteristics**

Of the 123 potential participants, 69 individuals transitioned to running for the duration of their final trial. Thus, only these data were used for model development. The total analytical sample of 69 individuals consisted of 37 male and 32 female participants. Demographic and anthropometric data are reported in Table 2.

TABLE 2 AROUND HERE

The list of independent variables considered for model development are presented in Table 2. Two sets of highly correlated (greater than 90%) independent variables were identified: waist circumference strongly correlated with weight (92%); height correlated with leg length (92%). Waist circumference and leg length were removed from consideration because weight and height are easier and more practical measures to obtain.

**Mathematical Models**

Each participant provided two data points in the training data, one with their last walking cadence and another with their first running cadence, resulting in 138 total observations in the analytical data set. Using the 138 training observations and the “purposeful selection” model-building technique, the final logistic regression model was the following:

As either age, height, BMIz, or cadence respectively increased, while holding all other variables constant, the probability of the person being in a running state increased. The opposite was true for weight. Cross validation results showed that the logistic regression model predicted the walk-to-run transition with 97.4% prediction accuracy (correctly classified observations over total number of observations), 99% sensitivity, 96% specificity, 96% PPV, and 98% NPV, indicating that this model accurately predicted gait classification as either walking or running. Descriptive statistics of the PTC values for each age group are presented in Table 3.

TABLE 3 AROUND HERE

**App Development**

Figure 1 depicts a screenshot of the user interface for the R Shiny app that was developed (available at <https://westpointmath.shinyapps.io/KidsStep/>). After the user inputs age, sex, height, and weight, the app returns the expected PTC and produces a graphical representation of the probability of being in either gait behavior.

FIGURE 1 AROUND HERE

# Discussion

The purpose of this secondary analysis of the CADENCE-Kids data was to develop a model to predict age- and anthropometry-specific PTCs in individuals 6-20 years of age. We hypothesized that the logistic regression approach using cadence and anthropometric parameters would classify gait behavior with reasonable accuracy. The results supported this hypothesis, as the model we report herein displayed a prediction accuracy value of 97.4%. Moreover, the Shiny app we developed provides researchers, practitioners, and the lay public with an easy-to-use tool for predicting the PTC for locomotor behavior assessment or training purposes.

The independent variables selected for the final model improves the potential for application of this model in clinical settings and by the general population. Three of the four variables used in the model (age, weight, and height) are easily attained. The fourth variable, BMIz, is calculated within the R Shiny app using age, weight, height and sex. In the development of this model, sex was removed as it was not found to be a significant factor in the presence of other variables such as height and BMI z-score, both of which accounted for much of the sex-related differences in cadence in this data set of young people.

We speculated that leg length and/or height may serve as key information in predicting the PTC in children, adolescents, and young adults, given the physical differences in maturation stages. We observed a large range of heights [X] across all ages in our sample, which may explain why height indeed turned out to be an important variable in the model. The study by Hansen et al (2017) concluded that height was not an important factor in predicting the PTC. However, the authors did not report descriptive information for height or leg length; thus, we can only speculate that the distribution of heights in that study was less than in our sample.

Previous efforts to establish the walk-to-run transition based on walking speed (i.e., preferred transition speeds) have provided ample evidence that this threshold is between 2.0-2.2 m/s (Diedrich & Warren, 1995; Ganley et al., 2011; Hreljac, 1995; Prilutsky & Gregor, 2001; Ranisavljev, Ilic, Soldatovic, & Stefanovic, 2014; Shih, Chen, Lee, Chan, & Shiang, 2016) adults. Preferred transition speeds have also been reported in children (mean transition speed 2.01 and 2.12 m/s for 11 and 15 year olds, respectively; Tseh, Bennett, Caputo, & Morgan, 2002). Although previous research has indicated that the transition from walking to running occurs at a PTC ≅140 steps/min in adults, to our knowledge, the findings presented herein are the first to report PTC in children, adolescents, and young adults. This information has potential to enhance the measurement of physical activity behavior. For example, accelerometer software commonly allows users to export minute-by-minute step data (i.e., cadence), but not gait speed. Using the PTC values reported in this study or by using the app, a researcher or clinician could easily estimate minutes per day that a participant performed running behavior.

**Limitations**

One limitation for this study was that the observed PTC was based on trials that always began with walking and progressed to running. Considering there may be a hysteresis effect (i.e., running to walking may yield a different PTC), future research should incorporate protocols that include running to walking transitions as well as walking to running transitions. Also, the logistic regression model reports the value at which there is a 50% chance that the individual is walking, and a 50% chance that the individual is running. For researchers wishing to perform analyses of running behavior from a more conservative approach (i.e., maximizing true positives while risking increasing false negatives), they may choose to shift the cadence value upwards to select a higher probability of running. These choices can be easily assessed qualitatively using the R Shiny app. Finally, while the goal of this R Shiny app is for application of accelerometers in free living settings, the model has been developed using directly observed steps in a laboratory setting. As such, the model we report herein should also be tested using accelerometer-based step data and in a free-living setting. It should also be noted that this study’s model treats all of the included variables as linear variables. We recognize that non-linear relationships or interactions could occur between components. However, we ultimately chose to build the model using linear relationships because 1) linearity helps optimize model interpretation, and 2) including non-linearities and interactions did not improve the model accuracy.

**Conclusion**

Using standard anthropometric information (i.e., age, height, sex, and mass), the preferred cadence corresponding with the transition from walking to running (ranging from 136 to 161 steps/min across all ages) can be accurately predicted in children, adolescents, and young adults in a laboratory setting on a treadmill. Future research should explore overground PTC under simulated or free-living conditions. Our findings, pending confirmation in the aforementioned overground and free-living paradigms, may be beneficial for researchers, practitioners, wearable device manufacturers, and the general public that aim to characterize locomotor behavior in the free-living setting. Moreover, herein we provide a free, user-friendly app that can be used to determine an individual’s PTC without the need to program the equation.

# Acknowledgements

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**Conflicts of Interest**

The authors declare no conflicts of interest

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Table 1

List of independent variables used to develop models

|  |  |
| --- | --- |
| Independent Variable | Explanation |
| Sex | Male or Female biological sex at birth |
| Age (years) | Age of participant |
| Height (cm) | Height of participant |
| Weight (kg) | Body mass |
| Waist (cm) | Waist circumference |
| BMI (kg/m2) | Body Mass Index |
| BMI z-score | Age- and sex-specific standardized BMI score |
| Body fat percentage | Body fat measured using bioelectrical impedance |
| Cadence (steps/min) | Accumulated step count in five minutes divided by 5 |

Table 2

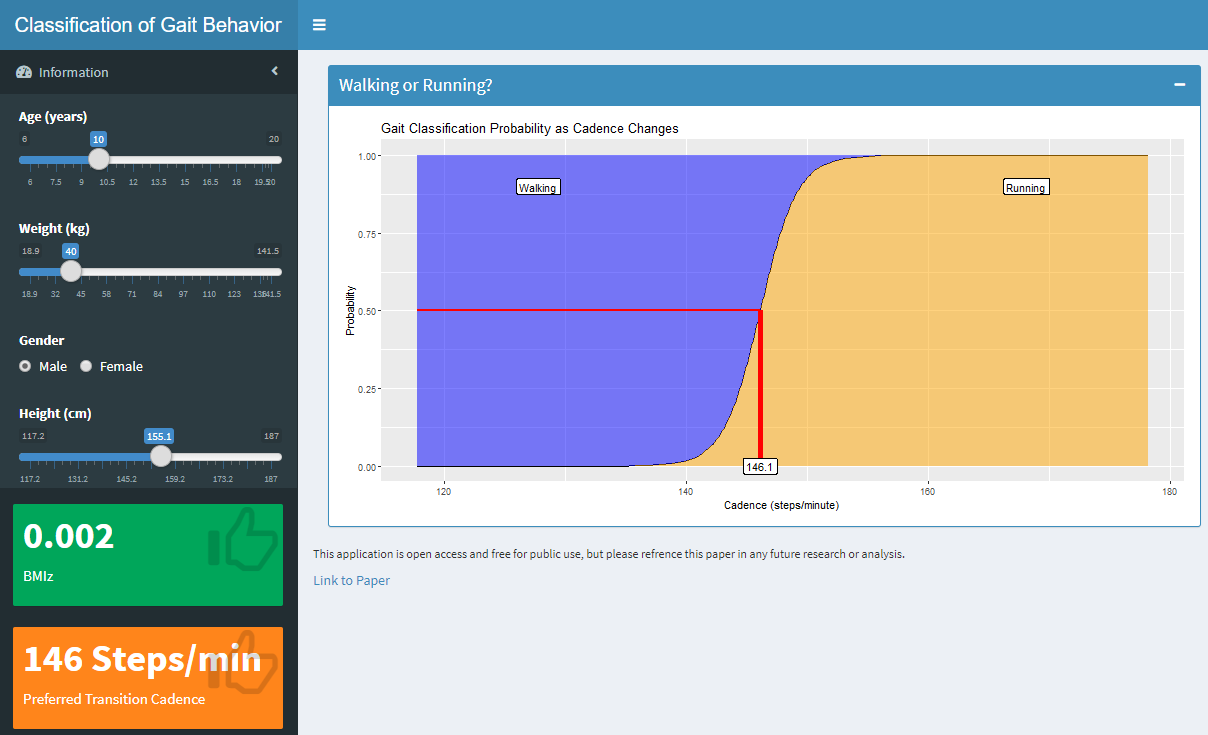
Participant characteristics across age groups

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Age (years) | 6-8 | 9-11 | 12-14 | 15-17 | 18-20 |
| n | 6 | 7 | 15 | 19 | 22 |
| Height (cm) | 132 ± 6.5 | 144 ± 4.5 | 160 ± 8.1 | 167 ± 9.0 | 171 ± 8.6 |
| Weight (kg) | 29.2 ± 5.5 | 42.5 ± 6.5 | 56.7 ± 16.8 | 66.9 ± 21.6 | 68.0 ± 13.3 |
| Waist Circumference (cm) | 56.9 ± 7.2 | 68.0 ± 9.6 | 73.4 ± 15.6 | 76.3 ± 16.0 | 77.4 ± 10.4 |
| BMI (kg/m2) | 16.7 ± 3.0 | 20.4 ± 3.0 | 22.1 ± 5.7 | 23.8 ± 6.9 | 23.2 ± 3.7 |
| BMI z-score | 0.064 ± 1.3 | 0.923 ± 0.9 | 0.538 ± 1.2 | 0.371 ± 1.3 | 0.0624 ± 1.0 |

Note: Data presented as mean ± SD. F = female; M = male. PTC = preferred transition cadence

Table 3: Preferred transition cadence (PTC) across age groups

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Age Group | PTC | | | |
| Mean | SD | Range | IQR |
| 6-8 | 154.2 | 5.7 | 146.4 to 160.8 | 8.4 |
| 9-11 | 146.4 | 2.5 | 143.4 to 151.4 | 1.2 |
| 12-14 | 145.0 | 3.4 | 141.4 to 151.4 | 4.1 |
| 15-17 | 143.7 | 4.3 | 140.0 to 157.8 | 4.8 |
| 18-20 | 140.1 | 2.4 | 136.4 to 145.8 | 2.6 |



**Figure 1**

Screenshot of the R Shiny app. After user input (age, weight, height, sex), BMIz (green) is displayed with predicted preferred transition cadence (orange). The graph on the right displays the probabilities associated with being in either gait classification.