**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. **Research Question**: The purpose of this study was to develop a model to predict age- and anthropometry-specific preferred transition cadences in individuals 6-20 years old. **Methods:** Sixty-nine individuals 6-20 years of age performed sequentially faster 5-min treadmill walking bouts, starting at 0.22 m/s (i.e., 0.5 mph) and increasing by 0.22 m/s until completion of the bout during which they freely chose to run. Steps taken during each bout were directly observed (hand tally) and converted to cadence (steps/min). After identifying the best subset of parameters, a logistic regression model was developed to predict preferred transition cadence. **Results:** The logistic regression analysis produced a simple mathematical equation that can accurately predict the preferred transition cadence using age, sex, height, and BMI z-score (k-fold cross-validated prediction accuracy = 97.4%). This transition cadence ranged from 136 to 161 steps/min across the developmental age range studied. **Significance:** 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, gait

**1. Introduction**

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) [1]. When individuals progressively increase their locomotor speeds, the transition from walking to running at around 2 m/s appears to occur spontaneously. Numerous studies have attempted to elucidate a precise ‘triggering mechanism’ that accounts for this preferred transition speed phenomenon (for a review, see Kung et al.[2]. 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 [3, 4], greater metabolic cost [1, 3, 5], greater perceived effort [5-8], or suboptimal energy substrate utilization [9]. Moreover, the Froude number, a dimensionless value that incorporates gait speed and leg length, has been used to provide an index for predicting the speed for this transition [10, 11].

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 accurate 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. Step-based metrics may provide a means by which to classify gait behavior. Wearable sensors that record step-based metrics 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 speed information, yet they do provide minute-by-minute step data (i.e., cadence). Thus, instead of relying on walking speed, perhaps a more accessible approach to describing gait behavior outside of the laboratory 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 practical and understandable index for researchers and clinicians aiming to quantify free-living physical activity behavior, specifically, minutes/day of running. Indeed, a recent study provided further support for use of cadence rather than speed by showing that increasing individuals’ cadence can elicit the transition from walking to running, even when walking speed is held constant and below the *a priori* determined transition speed [12].

Diedrich and Warren [3] reported that the PTC was, on average, 142.8 steps/min in young, healthy adults 18-31 years old. A more recent study by Hansen and colleagues provided concurring evidence that the PTC can be accurately predicted using a cadence of 141.6 steps/min in young adults [13], and a follow-up study provided test-retest reliability (intraclass correlation coefficient = 0.88) of this cadence value [14]. However, while these studies indicated 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. [14], leg length did not affect the observed PTC. This may not be the case in children, adolescents, and young adults who experience physical growth across these stages of maturation. Thus, prediction of the PTC in young people may necessitate the inclusion of leg length measures or other anthropometric values such as height and weight. Therefore, the purpose of this study was to develop a model to predict PTCs in individuals 6-20 years of age. We hypothesized that cadence, age, and anthropometric measures would provide enough information to accurately classify gait behavior.

# 2. Materials and Methods

## *2.1 Study design and regulatory information*

This is a secondary analysis of data from the CADENCE-Kids study (Clinical Trials.gov - NCT01989104). Data were collected between January 2014 and April 2015. A full description of the study design and participant characteristics have been reported elsewhere [15, 16]. All protocols and procedures were approved by an Institutional Review Board.

## *2.2 Participants*

To ensure a uniform age and sex distribution, study enrollment was designed to recruit at least 4 boys and 4 girls from each age year. One hundred twenty-three children, adolescents, and young adults aged 6-20 years volunteered to participate in the original study. For participants 6-17 years of age, informed parental/legal guardian permission and child assent were required. All participants 18-20 years of age provided their own informed consent [16].

## *2.3 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, BMI varies with age and is difficult to interpret in children, adolescents, and young adults. Thus, BMI z-scores (BMIz), which provide age- and sex-adjusted measures of the height-weight relationship, is recommended for children 2 years of age and older by the Centers for Disease Control and Prevention (CDC; [www.cdc.gov/growthcharts/](http://www.cdc.gov/growthcharts/)). BMIz-scores were calculated using reference data provided by the Centers for Disease Control and Prevention [17].

## *2.4 Protocol*

Participants performed a series of 5-minute treadmill walking bouts, with each bout followed by at least 2 min standing rest. Bouts started at 0.22 m/s (i.e., 0.5 mph) and increased by in 0.22 m/s until a termination criterion was reached, including: 1) completion of the terminal bout (i.e., at a speed of 2.23 m/s; 5.0 mph), 2) completion of the first bout during which participants freely chose to run, or 3) voluntary termination of the protocol by the participant. Thus, the total number of bouts varied based on when a given participant reached at least one of these termination criteria.

*2.5 Cadence Measures*

Steps taken during each 5-minute bout were directly observed and manually counted (hand tally). Cadence (steps/min) was then computed as the total number of steps divided by bout duration (hand tallied steps / 5 min). A video recording of each participant’s lower body provided a secondary confirmation that bouts were correctly classified as walking or running. The video recording also provided a redundant record for step verification purposes in the event of miscounting or ambiguous data (n=18 verified bouts).

*2.6 Model Development*

Because the aim of this analysis was to develop a model to predict PTC from walking to running gait, we first filtered (reduced) the dataset to include only individuals who ultimately chose to run on their last treadmill bout (see above termination criteria). We then further reduced the dataset to include two trials from each of these participants: 1) the walking bout that immediately preceded the transition to running; and 2) the running bout. Prior to model development, we first determined if any of the potential variables (cataloged in Table 1) were highly correlated. In the event that there were two highly 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 an easier measurement to obtain.

Logistic regression models were developed using the final filtered dataset and set of independent variables after linear dependencies were removed. The goal of logistic regression is to develop a model that accurately classifies an outcome into one of two groups using a set of independent variables. For this analysis, gait behavior was dichotomized into binary classifications (i.e., running or walking) and was treated as the dependent variable. We mean centered the covariates (i.e., the log odds of transitioning from walk to run when all other covariates are at their mean values) to ensure the intercept of our model had practical meaning. The model was built using the “purposeful selection” technique [18, 19], which ensures minimal collinearity between potential covariates and removes individually insignificant variables (based on the Wald test statistic) prior to building the initial model. Variables were removed sequentially based upon the highest p-value until all remaining variables were statistically significant (i.e. p-value<0.05). Moreover, we tested and confirmed linearity (i.e., linear in the logit) for each of the included independent variables. Additionally, the logistic regression approach works best for at least a 1:10 or 10:1 ratio of success to failures, and herein the ratio was 1:1. To predict individual-specific PTCs using the experimental data, 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). Once the final model was ascertained, we determined the log odds (β), odds ratios (, standard errors of β, Wald test statistics, and p-values.

TABLE 1 AROUND HERE

## *2.7 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 were partitioned into 10 “folds”. A model was trained with nine of the folds and tested on the unused “holdout set”, saving the resulting accuracy (i.e., the percentage of correctly classified individuals in the holdout set at the cut point derived from the training set of participants). After replicating with each fold as the holdout set, the resultant accuracies were compiled and averaged, along with sensitivity, specificity, positive predictive values (PPV), and negative predictive values (NPV).

*2.8 R Shiny App Development*

An interactive R Shiny web app [20] was created to provide a user-friendly interface for applying this model to predict the probability that an individual was walking or running across a range of cadences given their individual-specific anthropometrics.

**3. Results**

*3.1 Participant characteristics*

Of the 123 participants, 69 individuals elected to run during their final treadmill bout. 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 (>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.

*3.2 Mathematical Models*

To reiterate, 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 by one unit, while holding all other variables constant, the log odds of the person being in a running state significantly increased compared to being in a walking state. Conversely, a 1kg increase in weight was associated with a significant decrease in the log odds of being in a running state compared to being in a walking state, while controlling for all other covariates.

TABLE 3 AROUND HERE

Cross-validation results showed that the logistic regression model predicted the walk-to-run transition with 97.4% prediction accuracy (percentage of correctly classified gait bouts relative to the total number of bouts in the holdout sample), 99% sensitivity, 96% specificity, 96% PPV, and 98% NPV, indicating that this model accurately predicted gait classification as either walking or running. A full description of the model coefficients, including SE of the log odds and odds ratio are in Table 3. Across all participants, the transition cadence ranged from 136 to 161 steps/min. Finally, to display summary information, Table 4 provides descriptive statistics of the PTC values (obtained for each individual) that were sorted into age groups 6-8, 9-11, 12-14, 15-17, and 18-20 years.

TABLE 4 AROUND HERE

*3.3 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

# 4. 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 accurately classify gait behavior as either walking or running. The results supported this hypothesis, with a model prediction accuracy of 97.4%. Moreover, the Shiny app (<https://westpointmath.shinyapps.io/KidsStep/>) we developed provides researchers or practitioners 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 improve 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 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 across maturation stages. We observed a large range of heights (mean height for 6-8 and 18-20 year olds ranged from 132 and 171 cm, respectively) across all ages in our sample, which may explain why height indeed functioned as an important variable in the model. The study by Hansen et al [13] concluded that height was not an important factor in predicting the PTC. That study did not report the range of heights, but the mean (SD) for height was 178 (8) cm. Thus, it is apparent that the distribution of heights in that study was narrower than in our sample.

Previous efforts to establish the walk-to-run transition based on walking speed have provided ample evidence that in adults this threshold is between 2.0-2.2 m/s [3, 8, 9, 21-23]. Walk-to-run transition speeds have also been reported in children (mean walk-to-run transition speed ~ 2.01 and 2.12 m/s for 11 and 15 year olds, respectively [24]. 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 derived from the equation in this study or by using the app, a researcher or clinician could easily estimate minutes per day that a participant performed running behavior.

*4.1 Limitations*

The observed PTCs were based on bouts 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 both running to walking and 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 (<https://westpointmath.shinyapps.io/KidsStep/>). Moreover, 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 during a treadmill-based protocol in a laboratory setting. As such, the model we report herein should be tested using accelerometer-based step data in an overground walking, free-living setting. Still, it is promising that accelerometer-based step reporting is highly accurate at these faster walking speeds. 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, but these terms were deemed insignificant (*p*>0.05) when included in the model. Finally, an assumption of logistic regression is that all observations are independent of each other. Our analysis included two observations for each individual. However, the reason for this independence assumption is to avoid the influence of one individual’s observation on any other individual’s performance, and this undue influence did not occur based on our study design.

**5. Conclusion**

Using standard anthropometric information (i.e., age, height, sex, and weight), the PTC (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 PTCs under simulated or free-living conditions, as well as with cadences derived from wearable sensors. 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 who 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.

**Conflicts of Interest**

The authors declare no conflicts of interest.

**Author Contributions**

CTL, JS designed the original study. JS collected and cleaned data. SD, EA, DT, JP, CM analyzed data. SD, EA drafted manuscript. All authors provided data interpretation and draft edits. All authors approve the final version.

**Additional Statement**

CADENCE-Kids was prospectively registered at [ClinicalTrials.gov](http://clinicaltrials.gov/) ([NCT01989104](https://clinicaltrials.gov/ct2/show/NCT01989104)) and served as the data source for this secondary analysis. The original study was supported by an award NIH NICHD 1R21HD073807 and in part by 1 U54 GM104940 from the National Institute of General Medical Sciences of the National Institutes of Health, which funds the Louisiana Clinical and Translational Science Center. These funding bodies had no role in design, in the collection, analysis, or interpretation of data, or in the writing or decision to submit this manuscript for publication. The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health. The work and views expressed in this paper are those of the authors and do not reflect the official policy or position of the Department of the Army, the Department of the Navy, the Department of Defense, or the U.S. Government.

**References**

[1] R.M. Alexander, Energetics and optimization of human walking and running: the 2000 Raymond Pearl memorial lecture, Am J Hum Biol 14(5) (2002) 641-648. <https://www.ncbi.nlm.nih.gov/pubmed/12203818>.

[2] S.M. Kung, P.W. Fink, S.J. Legg, A. Ali, S.P. Shultz, What factors determine the preferred gait transition speed in humans? A review of the triggering mechanisms, Hum Movement Sci 57 (2018) 1-12. <http://www.sciencedirect.com/science/article/pii/S0167945717303433>.

[3] F.J. Diedrich, W.H. Warren, Why change gaits? Dynamics of the walk-run transition, J Exp Psychol Hum Percept Perform 21(1) (1995) 183-202.

[4] L. Li, Stability landscapes of walking and running near gait transition speed, J App Biomech 16(4) (2000) 428-435.

[5] A.E. Minetti, L.P. Ardigo, F. Saibene, The transition between walking and running in humans: metabolic and mechanical aspects at different gradients, Acta Physiol Scand 150 (1994) 315-323.

[6] B.J. Noble, K.F. Metz, K.B. Pandolf, C.W. Bell, E. Cafarelli, W.E. Sime, Perceived exertion during walking and running. II, Med Sci Sports 5(2) (1973) 116-20.

[7] A. Hreljac, Preferred and energetically optimal gait transition speeds in human locomotion, Med Sci Sport Exerc 25(10) (1993) 1158-62.

[8] B.I. Prilutsky, R.J. Gregor, Swing- and support-related muscle actions differentially trigger human walk-run and run-walk transitions, J Exp Biol 204(Pt 13) (2001) 2277-87.

[9] K.J. Ganley, A. Stock, R.M. Herman, M. Santello, W.T. Willis, Fuel oxidation at the walk-to-run-transition in humans, Metab Clin Exp 60(5) (2011) 609-16. <https://ac.els-cdn.com/S0026049510001873/1-s2.0-S0026049510001873-main.pdf?_tid=dc81c0d7-c692-47d0-9f42-3f98ddcc60bb&acdnat=1533665638_864937aad887b634652015d9aec0b993>.

[10] R.M. Alexander, Optimization and gaits in the locomotion of vertebrates, Physiol Rev 69(4) (1989) 1199-227. <https://www.physiology.org/doi/abs/10.1152/physrev.1989.69.4.1199?url_ver=Z39.88-2003&rfr_id=ori:rid:crossref.org&rfr_dat=cr_pub%3dpubmed>.

[11] J.R. Usherwood, Why not walk faster?, Biology Letters 1(3) (2005) 338-341. <https://www.ncbi.nlm.nih.gov/pubmed/17148201>.

[12] M. Voigt, M.K. Hyttel, L.S. Jakobsen, M.K. Jensen, H. Balle, E.A. Hansen, Human walk-to-run transition in the context of the behaviour of complex systems, Hum Movement Sci 67 (2019) 102509. <https://www.ncbi.nlm.nih.gov/pubmed/31415962>.

[13] E.A. Hansen, L.A.R. Kristensen, A.M. Nielsen, M. Voigt, P. Madeleine, The role of stride frequency for walk-to-run transition in humans, Sci Rep 7(1) (2017) 2010. <http://www.ncbi.nlm.nih.gov/pubmed/28515449>.

[14] E.A. Hansen, A.M. Nielsen, L.A.R. Kristensen, P. Madeleine, M. Voigt, Prediction of walk-to-run transition using stride frequency: A test-retest reliability study, Gait Posture 60 (2018) 71-75. <https://www.ncbi.nlm.nih.gov/pubmed/29161625>.

[15] J.M. Schuna Jr, T.V. Barreria, D.S. Hsia, W.D. Johnson, C. Tudor-Locke, Youth energy expenditure during common free-living activities and treadmill walking., J Phys Act Health 6(Suppl 1) (2016) S29-34.

[16] C. Tudor-Locke, J.M. Schuna, Jr., H. Han, E.J. Aguiar, S. Larrivee, D.S. Hsia, et al., Cadence (steps/min) and intensity during ambulation in 6-20 year olds: The CADENCE-Kids study, Int J Behav Nutr Phys Act 15(20) (2018).

[17] R.J. Kuczmarski, C.L. Ogden, L.M. Grummer-Strawn, K.M. Flegal, S.S. Guo, R. Wei, et al., CDC growth charts: United States, Adv Data 314 (2000) 1-27.

[18] J. Hosmer, D. W., S. Lemeshow, R.X. Sturdivant, Applied Logistic Regression, 3rd ed., John Wiley & Sons, Inc., Hoboken, NJ, 2013.

[19] Z. Zhang, Model building strategy for logistic regression: purposeful selection, Ann Transl Med 4(6) (2016) 111. <https://www.ncbi.nlm.nih.gov/pubmed/27127764>.

[20] R Core Team, R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria, 2018.

[21] Y. Shih, Y.C. Chen, Y.S. Lee, M.S. Chan, T.Y. Shiang, Walking beyond preferred transition speed increases muscle activations with a shift from inverted pendulum to spring mass model in lower extremity, Gait Posture 46 (2016) 5-10. <https://www.ncbi.nlm.nih.gov/pubmed/27131169>.

[22] A. Hreljac, Determinants of the gait transition speed during human locomotion: kinematic factors, J Biomech 28(6) (1995) 669-77. <https://ac.els-cdn.com/002192909400120S/1-s2.0-002192909400120S-main.pdf?_tid=8e954dda-c0b3-4a27-9997-0e9d5040660c&acdnat=1533665643_e9b675f998b06b5d6cc6aa870619e2bb>.

[23] I. Ranisavljev, V. Ilic, I. Soldatovic, D. Stefanovic, The relationship between allometry and preferred transition speed in human locomotion, Hum Movement Sci 34 (2014) 196-204. <http://www.ncbi.nlm.nih.gov/pubmed/24703336>.

[24] W. Tseh, J. Bennett, J.L. Caputo, D.W. Morgan, Comparison between preferred and energetically optimal transition speeds in adolescents, Eur J Appl Physiol 88(1-2) (2002) 117-21. <https://link.springer.com/content/pdf/10.1007%2Fs00421-002-0698-x.pdf>.

**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 |

Note: cm = centimeters; kg = kilograms; BMI = Body Mass Index; m = meters.

**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) | 132.3 ± 6.5 | 144.3 ± 4.5 | 159.6 ± 8.1 | 167.4 ± 9.0 | 170.9 ± 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 | 0.062 ± 1.0 |

Note: Data presented as mean ± SD. cm = centimeters; BMI = Body Mass Index; kg = kilograms; m = meters.

**Table 3:** Logistic regression results from the model transition from walking to running

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Predictor** | **β** | **SE β** | **Wald Test** | **p** | **Odds ratio** |
| **constant** | 0.5466 | 42.8697 | -3.279 | .00104 | NA |
| **Age** | .9804 | .4571 | 2.145 | .03195 | 2.67 |
| **Height** | .3170 | .1243 | 2.550 | .01077 | 1.37 |
| **Weight** | -.3620 | .1551 | -2.335 | .01955 | 0.70 |
| **BMIz** | 4.4953 | 1.9442 | 2.312 | .02077 | 89.60 |
| **Cadence** | .6575 | .2033 | 3.234 | .00122 | 1.93 |

**Note**: β = log odds; SE = standard error; Wald test = test statistic

**Table 4:** Preferred transition cadence (PTC) across age groups.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Age Group (years) | PTC (steps/minute) | | | |
| Mean | SD | Range [min, max] | IQR |
| 6-8 | 154 | 5.7 | [146, 161] | 8.4 |
| 9-11 | 146 | 2.5 | [143, 151] | 1.2 |
| 12-14 | 145 | 3.4 | [141, 151] | 4.1 |
| 15-17 | 144 | 4.3 | [140, 158] | 4.8 |
| 18-20 | 140 | 2.4 | [136, 146] | 2.6 |

Note: SD = standard deviation; min = minimum, max = maximum, IQR = interquartile range



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.