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

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ABSTRACT

The natural transition from walking to running occurs in adults at ≅ 140 steps/min. It is unknown when this transition occurs in children and adolescents. The purpose of this study was to develop a model to predict age- and anthropometry-specific preferred transition cadences in individuals 6–20 years of age. Sixty-nine individuals performed sequentially faster 5-min treadmill walking bouts, starting at 0.22 m/s and increasing by 0.22 m/s until completion of the bout during which they freely chose to run. Steps accumulated during each bout were directly observed and converted to cadence (steps/min). A logistic regression model was developed to predict preferred transition cadences using the best subset of parameters. The resulting model, which included age, sex, height, and BMI z-score, produced preferred transition cadences that accurately classified gait behaviour (k-fold cross-validated prediction accuracy =97.02%). This transition cadence ranged from 136–161 steps/min across the developmental age range studied. The preferred transition cadence represents a simple and practical index to predict and classify gait behaviour 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 individual-specific preferred transition cadences.

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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) (Alexander, 2002). 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.(2018). 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 et al., 1994), greater perceived effort (Hreljac, 1993; Minetti et al., 1994; Noble et al., 1973; Prilutsky & Gregor, 2001), or suboptimal energy substrate utilization (Ganley et al., 2011). 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 (Alexander, 1989; Usherwood, 2005).

While biomechanics researchers use the Froude number to predict transitions in gait behaviour (i.e., walking to running) in laboratory settings, its applicability outside of the laboratory is limited as it requires accurate measures of both speed and leg length. Conversely, cadence (steps/min) may provide a simpler means by which to classify gait behaviour. Step-based metrics, including steps/day and cadence, have gained popularity in physical activity research (both laboratory and free-living settings) and in the general population. Reasons explaining this broad application and appeal include the increasing availability of wearable sensors, combined with the notion that most individuals intuitively understand what a "step" is. Importantly, many 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 behaviour outside of the laboratory entails understanding the cadences that correspond with walking versus running. Being able to classify gait state is important because walking and running are two distinct forms of locomotion with different intensity profiles. For example, the compendium of physical activities estimates that walking at typical speeds (2.5–3.2 mph) requires 3.0–3.5 Metabolic equivalents (METs), while jogging even at slow speeds requires ~ 6.0 METs (Ainsworth et al., 2011). Therefore, 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, clinicians and wearable device companies aiming

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to classify free-living physical activity behaviour and estimate volume and intensity (minutes/day) of walking versus running using step data. Beyond intensity considerations, PA researchers may want to simply use this information as a gross, descriptive measure of PA behaviour (e.g., minutes/week spent running). Currently, cadence bands have been established in adults that associate with incidental, sporadic, and purposeful stepping and slow, medium, and brisk walking (Tudor-Locke, Han et al., 2018). Obtaining cadences corresponding with running would provide more specific upper bounds of brisk walking.To reiterate the utility of cadence over speed, a recent study showed that increasing individuals' cadence can elicit the transition from walking to running, even when walking speed is held constant and is below the *a priori* determined transition speed (Voigt et al., 2019).

Previous research has established a PTC in young adults. For example, Diedrich and 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 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 Hansen et al., 2017), and a follow-up study provided test-retest reliability (intraclass correlation coefficient = 0.88) of this cadence value (Hansen et al., 2018). 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. (2018), leg length did not affect the observed PTC. This may not be the case in children, adolescents, and young adults who display larger variations in stature 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 predict the PTC and therefore accurately classify gait behaviour.

2. Materials and methods

2.1 Study design and regulatory information

This is a secondary analysis of data collected between January 2014 and April 2015. These data were originally collected from a laboratory-based, cross-sectional study that aimed to establish cadences that corresponded with absolutely-defined metabolic intensities (i.e., metabolic equivalents [METs]) across a range of developmental ages between 6–20 years. A full description of the study design and participant characteristics are reported elsewhere. All protocols and procedures were approved by an Institutional Review Board.

2.2 Participants

Potential participants were recruited via print and email advertisements throughout the community. These advertisements directed individuals to a web-screener to determine initial eligibility based on health history, demographic information, and ambulatory ability. One hundred twenty-three children, adolescents, and young adults aged 6–20 years volunteered to participate in the original study. This age range was selected because the original study purpose was to determine cadence values corresponding with metabolic intensity while taking into account changes to cadence based on age and height from very young age (6 years old) up to the stature attained in adulthood. Because the study aimed to study ambulatory behaviour, individuals were excluded if they required walking aids (e.g., cane) or wheelchair. Individuals were also excluded if they: had been hospitalized for mental illness in the past 5 years, were taking any medication that would affect their heart rate response to exercise, had a pacemaker, were pregnant, or had implanted medical devices such as a metal joint. To ensure a uniform age and sex distribution, study enrolment was designed to recruit at least 4 boys and 4 girls from each age year. 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 (Tudor-Locke, Schuna et al., 2018).

2.3 Anthropometric measures

All assessments and data collections were performed by trained researchers. 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. Subischial leg length was then calculated 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 (m^2), and reported in kg/m^2. However, BMI varies with age and is difficult to interpret in children and adolescents. Thus, BMI z-scores (BMI_z), which provide age- and sex-adjusted measures of the height-weight relationship, is recommended for children 2 years of age and older by the Centres for Disease Control and Prevention (CDC; www.cdc.gov/growthcharts/). BMIz-scores were calculated using reference data provided by the Centres for Disease Control and Prevention (Kuczmarski et al., 2000).

2.4 Protocol

All trials were performed on a standard treadmill (Trackmaster TMX425C, Full Vision Inc., Newton, KS, USA). Each participant wore their own sneakers/tennis shoes. Participants performed a series of 5-minute treadmill walking bouts, with each bout followed by at least 2 min standing rest. Participants were instructed to begin each stage walking, and to transition to running if that felt more comfortable. Bouts started at 0.22 m/s (i.e., 0.5 mph) and increased by 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

The available information included whether the participant was walking or running during a given bout, their cadence during that bout, and simple demographic/anthropometric factors, but not a true PTC. Our approach used logistic regression to determine which features contribute to the probability that a participant is walking or running and to what extent they do so (based on their coefficients). We then used this logistic regression model to find the cadence at which the model produces an equal probability that a subject is running or walking. This is established as the PTC.

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 (catalogued 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.

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/m^2)	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

Abbreviations: cm = centimetres; kg = kilograms; BMI = Body Mass Index; m = metres.

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 behaviour was dichotomized into binary classifications (i.e., running or walking) and was treated as the dependent variable. We mean centred 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 (Hosmer, 2013; Zhang, 2016), 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 (that is also > 0.05) 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, while the logistic regression approach is typically performed on datasets with a 1:10 or 10:1 ratio of success to failures, the ratio herein was 1:1, which represents a balanced data set. 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 (aaa,standard errors of β, Wald test statistics, and p-values.

2.7 Data and statistical analysis

To assess the gait classification (walk, run) 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 then 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). For each participant, both observations were always in the same fold. After replicating with each fold as the holdout set, the resultant accuracies (percentage of correctly categorized holdout observations) 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 (Core Team, 2017) was created to provide a user-friendly interface for applying this model to predict the probability that an individual would be 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. All other participants reached a different termination criterion prior to transition to running. Thus, only data from individuals who transitioned to running during the protocol 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.

The list of independent variables considered for model development are presented in Table 1. 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:

$$\begin{aligned} log\left(\frac{p(run)}{p(walk)}\right) = {} & 0.5466 + 0.980(Age - mean(Age)) \\ & + 0.317(Height - mean(Height)) \\ & - 0.362(Weight - mean(Weight)) \\ & + 4.495(BMI_Z - mean(BMI_Z)) \\ & + 0.658(Cadence - mean(Cadence)) \end{aligned} \tag{1}$$

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 1 kg 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.

Cross-validation results showed that the logistic regression model classified gait (walking or running) with 97.02% prediction accuracy (i.e., percentage of correctly classified gait bouts relative to the total number of bouts in the holdout sample), 98% sensitivity, 96% specificity, 96% PPV, and 99% NPV. A full description of the model coefficients, including standard error (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, for descriptive purposes, Table 4 provides summary statistics for the PTC values (obtained for each individual) sorted into age groups 6–8, 9–11, 12–14, 15–17, and 18–20 years.

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 behaviour.

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 a logistic regression approach using cadence and anthropometric parameters would accurately classify gait behaviour as either walking or running. The results supported this hypothesis, with a model prediction accuracy of 97.02%. 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 behaviour 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. One interesting finding is the large beta value observed for BMIz (Table 3, β = 4.5). However, it should be noted that a 1-unit increase in BMIz is equal to an entire standard deviation change relative to the normal distribution of age- and sex-matched individuals. Thus, a 1-unit increase in BMIz is considerably

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/m^2)	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

Notes: Data presented as mean ± SD. cm = centimetres; BMI = Body Mass Index; kg = kilograms; m = metres.

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

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

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

	PTC (steps/minute)			
Age Group (years)	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

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

more significant than a 1-unit increase in other variables, such as weight in kgs.

We speculated a priori that leg length and/or height may serve as key explanatory variables in predicting the PTC in children, adolescents, and young adults, given the variability in stature across maturation stages. Indeed, we observed a large range of heights across all ages in our sample, with a mean height for 6–8 and 18–20 year olds ranging from 132 to 171 cm, respectively. This may explain why height functioned as a significant explanatory variable in the final model. Our finding contrasts that of Hansen (Hansen et al., 2017), who concluded that height was not an important factor in predicting the PTC. Notably, the mean [SD] for height in their sample was 178 (Prilutsky & Gregor, 2001) cm (range not reported). As such, their conclusion may have been confounded by a lack of variability in height.

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 (Diedrich & Warren, 1995; Ganley et al., 2011; Hreljac, 1995; Prilutsky & Gregor, 2001; Ranisavljev et al., 2014; Shih et al., 2016). 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 (Tseh et al., 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. We expected the PTC to be higher in the youngest participants and decrease with age, based on changes to leg length and height during these developmental years. Indeed, the oldest participants (i.e., 18–20 years old) displayed PTCs (mean = 140 steps/minute) similar to that of young adults (Diedrich & Warren, 1995; Hansen et al., 2017). Interestingly, the biggest change in PTC appeared between 6–8 and 9–11 year olds, that is, prior to pubertal ages typically associated with accelerated growth rates. This finding suggests that other changes to locomotion may be occurring during pre-puberty, such as enhanced coordinative patterns.

Knowledge of the PTC has potential to enhance the measurement and classification of physical activity behaviour. 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 classify gait state as walking versus running, and subsequently estimate minutes/day that an individual was either walking or running.

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, herein we evaluated one walking and one running trial for each participant. Future studies should also evaluate numerous walking and running trials at speeds that correspond with cadences around the PTC. Regarding the model, the logistic regression model reports the cadence 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 behaviour 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. However, while overground walking validation studies should be performed, it should be noted that accelerometer-based step reporting is highly accurate at these faster walking speeds. Additionally, the logistic regression model developed herein treated all 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. Furthermore, our dataset included relatively less younger individuals, which may explain the greater observed variance (e.g., standard deviation and interquartile range, Table 4). Future studies should evaluate the PTC in a greater sample size of younger individuals. 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 assumption of independence 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

In this study, we developed a model using standard demographic and anthropometric information (i.e., age, height, sex, and weight) that was able to predict PTCs and accurately classify gait behaviour in children, adolescents, and young adults. The PTCs ranged from 136 to 161 steps/min

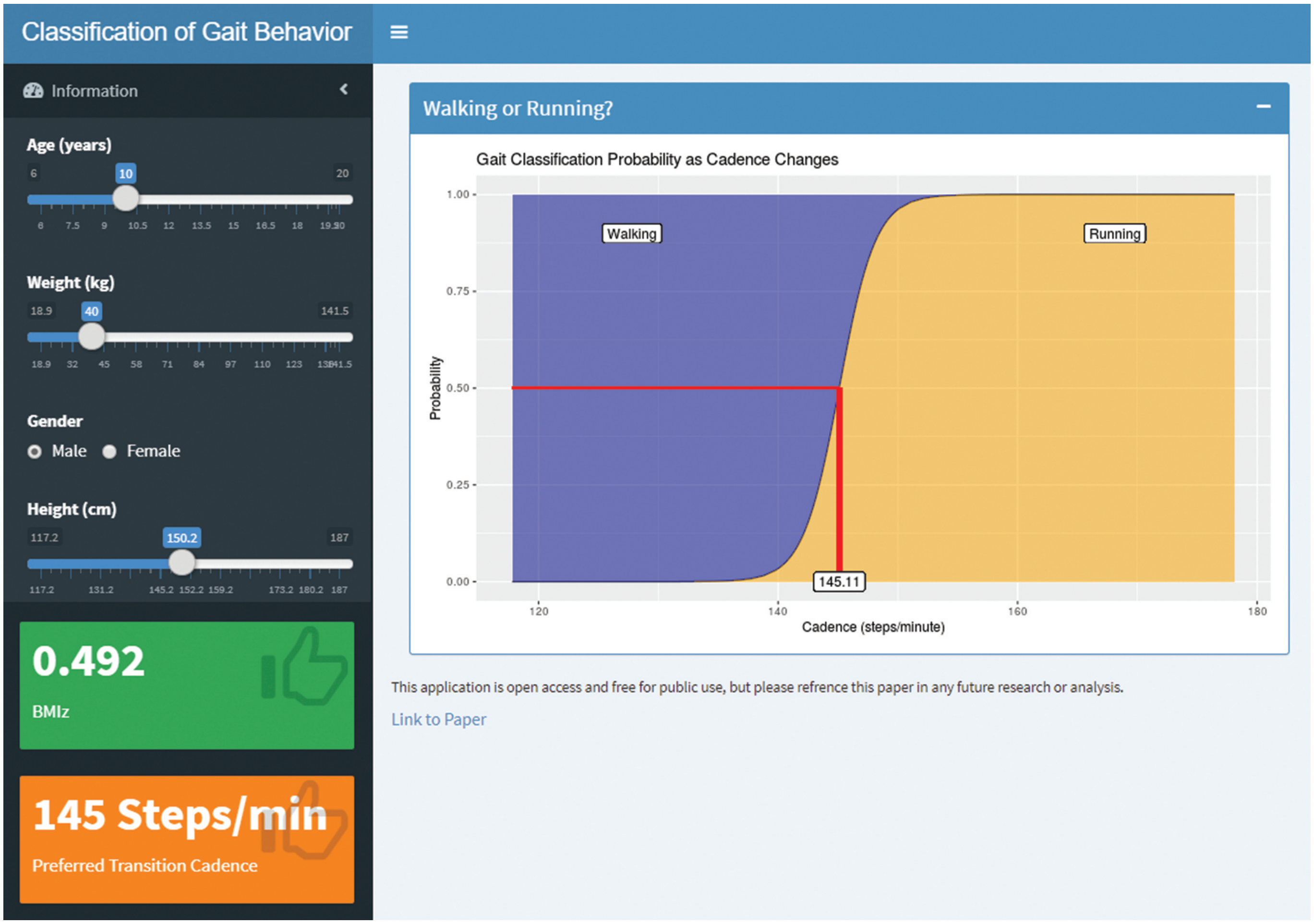

Figure 1. Screenshot of the R Shiny app. After user input (age, weight, height, sex), BMIz (green) is displayed with predicted preferred transition cadence (orange). The graph on the right displays the probabilities associated with being in either gait classification (walking or running).

across all ages. 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 behaviour in the free-living setting. Moreover, this information may help clinicians performing gait assessments in populations with motor impairments or help guide the development of interventions to improve gait. Finally, herein we provide a free, user-friendly app that can be used to predict an individual's PTC without the need to program the equation.

Disclosure statement

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