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original article

Tracking and its applicability to Physical Education and Sport

A noção de tracking *e sua aplicação à Educação Física e ao Esporte*

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Abstract – Tracking refers to the idea of maintaining a relative position within a given group of individuals as they change in time. This paper presents several approaches to study and analyze tracking (i.e., stability and predictability) and its application in physical education and sport. We will use data from a mixed-longitudinal study conducted in the city of Porto, Portugal, comprising 486 girls that were divided into two age cohorts: 12-14 years and 14-16 years. Body mass index (BMI) was the chosen variable in all statistical analyses of tracking. Statistical techniques to describe tracking included: autocorrelations, Foulkes & Davis gamma and Goldstein constancy index. Regardless of statistical procedure used, tracking BMI was moderate to high in each cohort, which could be due to the short follow-up period. However, each tracking statistics showed different aspects of inter-individual differences in intra-individual changes of girls' BMI. The use of any of the suggested procedures to study aspects of stability and predictability (i.e., tracking) in longitudinal studies requires a careful scrutiny of main goals and hypotheses to be tested.

Key words: Body mass index; Growth and development; Longitudinal studies; Monitoring; Tracking.

Resumo – *O termo Tracking refere-se à noção de manutenção de posição relativa de valores de um dado grupo de sujeitos em função do tempo. O presente artigo apresenta diversas técnicas de estudo e análise do tracking (i.e., estabilidade e previsibilidade). Os dados utilizados provêm de um estudo longitudinal-misto da Região do Grande Porto, Portugal, compreendendo 486 meninas, divididas em duas coortes que abrangem as faixas etárias dos 12 aos 14 e dos 14 aos 16 anos. A variável eleita para as análises foi o índice de massa corporal (IMC). Os procedimentos estatísticos utilizados para descrever o tracking foram: autocorrelações, gama de Foulkes & Davis e índice de constância de Goldstein. Independentemente da estatística utilizada e face à curta duração do estudo, o tracking do IMC foi moderado a elevado em cada coorte. Contudo, cada procedimento de análise mostrou aspetos distintos das diferenças interindividuais nas mudanças intraindividuais do IMC das meninas. O uso parcimonioso de qualquer um dos procedimentos sugeridos para estudar aspetos da estabilidade e previsibilidade (i.e., do tracking) em estudos longitudinais exige o estabelecimento muito criterioso dos objetivos e hipóteses a serem testados.*

Palavras-chave: *Crescimento e desenvolvimento; Estudos longitudinais; Índice de massa corporal; Monitoramento.*

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INTRODUCTION

Obesity is one of the major modifiable risk factors for chronic diseases and its adverse effects on health are well-known[1], in addition to its elevated economic impact on health systems. For example, the annual cost of obesity between 2008 and 2010 was estimated as $ 2.1 billion, representing ~14% of the total cost of Brazilian Health Systems[2].

The adverse consequence of excess weight on individual's health has prompted the establishment of prevention strategies early in pediatric settings[1,3]. Furthermore, childhood and adolescence are viewed as critical windows in terms of obesity development, and there is a high likelihood that behaviors consolidated in this period of life remain in adulthood[1,3].There is evidence suggesting that obese children are 50 to 70% more likely to become obese adults due to family history, sedentarism and unhealthy lifestyles[4].

In epidemiology, the analysis that deals with the tendency of maintaining a state and/or behavior in a series of longitudinal data is generally called tracking[3,5]. Although there is no universally accepted definition of the term, tracking refers to the notion of maintaining a relative position of values of a given group of individuals as a function of time; it is also linked to the idea of prediction[3,5]. Stability, change and predictability are tracking facets, requiring longitudinal information. The statistical analysis of tracking and its application have already been researched in Portugal and Brazil, mainly in Physical Education and Sports Sciences[6,7].

This study aims to present a set of statistical techniques of tracking in order to allow researchers a better understanding of their use and interpretation. Firstly, we will deal with auto-correlations[8]; secondly, we will use Foulkes & Davis gamma (γ)[9]; thirdly, we will refer to the γ statistics again, but according to suggestions made by Rogosa[10]; finally, we will present the Goldstein growth constancy index[11].

METHODOLOGICAL PROCEDURES

The data used in this study are from a mixed-longitudinal study conducted in the city of Porto, Portugal, designed to investigate the interaction among individual characteristics, environmental factors, and lifestyle that affect growth, development, and health of adolescents aged 10-18 years. The project was approved by the Ethics Committee of the University of Porto (process number 15/CEUP/2012). This research, almost in its final stages, intends to analyze a total of 1000 randomly selected subjects, stratified and divided into four age cohorts and evaluated for three consecutive years. The first cohort was followed from 10 to 12 years; the second from 12 to 14 years; the third from 14 to 16 years; and the fourth from 16 to 18 years. The present study considered information from 486 girls from the second (n_{c2}=215) and third (n_{c3}=169) cohorts. Body mass index (BMI): [weight (kg)/height (m^2)] was the chosen variable for all analyses. This marker is used in epidemiological studies to define nutritional status and/or weight categories[12,13].

The decision to use only girls' information is based on the fact that their body composition undergoes marked changes during the pubertal period usually resulting in larger fat deposits[14]. The increased body fat, combined with differences in maturational timing and tempo may result in a lower engagement in physical activity and practice of sports[7,14], as well as in increased weight[14].

The concept of Tracking

As there is no universal definition for tracking, different approaches have been proposed to define tracking from a statistical point of view[5]. In 1991, Foulkes & Davis[9] were the first to systematize the two main methodological views about tracking.The first approach focuses on the study of correlations between successive measures (auto-correlations), and linear or non-linear regression that allows future predictions[15]. A substantial number of studies within Physical Education and Sports Science have adopted several ideas from this view [8,16]. The second approach is based on the recognition that the distribution of values changes naturally at each point of time and it is expected that individuals maintain the same relative position in each of these distributions. Several analytical procedures are based on this suggestion, but the problem lies in the precision of how "relative position" is defined[5].

Tracking: statistics, results and meaning

Descriptive statistics for BMI values from each cohort are shown in Table 1. Mean BMI values increased with time. It is important to highlight that kurtosis and skewness values suggest violations to normality.

Table 1. Descriptive statistics for BMI values from cohorts 2 and 3.

	Cohort 2 (n=215)				Cohort 3 (n=169)			
	Mean±sd	Min-Max	Kurt	Skew	Mean±sd	Min-Max	Kurt	Skew
M1	20.68±3.80	13.40-38.30	1.39	5.67	22.30±3.50	16.60-32.10	0.66	2.83
M2	21.15±3.34	14.10-36.40	1.17	5.30	22.80±3.52	16.40-34.40	0.75	3.42
M3	21.57±3.16	14.80-37.10	1.12	5.66	22.97±3.48	17.00-34.30	0.86	3.63

M1: First year of assessment; M2: Second year of assessment; M3: Third year of assessment; sd: standard deviation; Min: minimum; Max: maximum; Kurt: kurtosis coefficient; Skew: skewness coefficient.

Auto-correlations

An important part of tracking studies in Physical Activity Epidemiology and Physical Fitness resorts to the calculation of correlations (r) among the same variables sequentially measured in time, calculating what is known as auto-correlations[16]. Regardless of interpretation of r values based on formal tests of the null hypothesis(H_0:r=0), Malina[16] subjectively suggested cut-off points for auto-correlation interpretation (r<0.3=low; 0.30≤r≤0.60=moderate; r>0.60=moderate to high).However, as well known, the use of any statistical procedure in inferential terms is based on a series of assumptions for results to be valid. When computing simple correlations it is assumed that: (i) there is a linear relationship among variables; (ii) variables are randomly distributed; (iii) have homoscedasticity; and (iv) have bivariate or multivariate normal distributions[17]. In Table 1, skewness and kurtosis suggest potential violation to normality of the BMI distributions at each age group in each cohort.

The analysis of univariate, bivariate and multivariate normality of BMI distributions at different time points in each cohort was performed in STATA 12. The results (not included in the text) showed violation of these assumptions. When BMI values were transformed (1/BMI), univariate normality was achieved, but violations to bivariate and multivariate normality still could be found. To solve this problem, some authors suggest using Spearman correlation coefficient (less efficient than Pearson, but not sensitive to kurtoses problems in the distributions or presence of outliers[17]). However, our choice was different as we decided to make a robust analysis suggested by Hadi[18] and implemented in SYSTAT 13 in which a resampling method (bootstrap) with 500 samples equal to the size of samples for each cohort was added in order to obtain standard errors to helps us in the construction of confidence intervals for all r values, providing a more precise view of tracking coefficients (see Table 2).

Table 2. Auto-correlations and their respective confidence intervals (CI 95%) between BMI measurements over 3 years in each cohort.

	Cohort 2		
Year	BMI1	BMI2	BMI3
BMI1	1.00		
BMI2	0.94 (0.92-0.96)	1.00	
BMI3	0.85(0.79-0.89)	0.93 (0.90-0.95)	1.00
	Cohort 3		
Year	BMI1	BMI2	BMI3
BMI1	1.00		
BMI2	0.95 (0.92-0.96)	1.00	
BMI3	0.89 (0.83-0.92)	0.93 (0.90-0.95)	1.00

BMI1: Body mass index-first year of assessment; BMI2:Body mass index-second year of assessment;BMI3: Body mass index-third year of assessment.

Based on the correlational strength rubric of Malina[16], there was a strong stability of BMI in girls aged 12-14 years and 14-16 years. In addition, the width of confidence intervals is extremely low, which confirms the accuracy of estimates. It was also possible to verify that the auto-correlation is lower between BMI1 and BMI3 in both cohorts, which reflects the higher temporal spacing between measurements. Despite the simplicity in the interpretation of r-values, some authors[16,19] highlighted the need to consider (i) the age of the first observation (the lower the child's age, the lower the correlation coefficients), and (ii) individual characteristics given the obvious biological variation among subjects (maturational timing and tempo).

In short, although auto-correlations are widely used in tracking studies, and the BMI values obtained in both cohorts were very high, Rogosa et al.[20] and Twisk et al.[21] pointed out some of the problems with this approach: (i) the assumptions of bivariate and multivariate normality are rarely tested and/or reported, and no alternatives are presented to solve this problem; (ii) the Malina[16] cut-off points are arbitrary; and (iii) there is no single auto-correlation value to describe stability. In our example, three auto-correlations were reported, because we have three time measurements; if we had 6 time points, we would have an auto-correlation matrix with 15 values (the general formula to compute the number of possible auto-correlations is k(k-1)/2, where k=number of points in time).

Foulkes & Davis γ[9]

Foulkes & Davis γ examined the probability that two growth curves do not intersect (cross) over time; in addition, it is based on the notion that the greater the number of pairs of individuals that maintain their relative position within a distribution over the study time frame, the greater the tracking[9]. The γ only takes positive values, ranging from 0 to 1. The higher the γ, the lower the number of crossings among growth curves. Foulkes & Davies presented reference values for γ: $\gamma \leq 0.50$ no tracking; $0.50<\gamma<1.00$ tracking is present; γ= 1:00, perfect tracking[9].

Foulkes & Davisg have two formulations: a simple (FD1) and a more complex version (FD2)[22]. The simple version does not require any a priori definition of the change trajectory shape (linear or nonlinear), since it is a non-parametric statistic that assumes the following: 1) the simpler the trajectory, the higher the γ value ; and 2) the tracking of the extremes is much higher when compared to those who are situated close to the mean trajectory[21-23]. In our example, we chose the complex version (FD2), which requires, in addition, a formal and sequential test of the better function (limited to a 4th degree polynomial) that best describes individual trajectories[24,25]. This analysis was performed on the Longitudinal Data Analysis program (LDA) developed by Schneiderman and Kowalski[26].

Table 3. Results of the best function that describes data and the Foulkes & Davis γ statistics for cohort 2.

Test for adequacy of fit of a linear equation		
F-statistic		0.1103
Probability		0.7401
Tracking statistics		
Foulkes & Davis γ	Sd-error	95% CI
0.8278	0.0063	0.8152-0.8405

γ: Gamma; 95% CI: 95% Confidence Interval.

LDA software output has a wealth of numerical and graphical information. Table 3 highlights only the main results: (1) the test for the best fitting model (F statistics and the corresponding p-value); and (2) γ value, its standard error and the 95% CI. Thus, Foulkes & Davis γ of girls from cohort 2 is 0827 ± 0.006 (95% CI = 0815-0840) and 0.828 ± 0.008 (95% CI = 0812-0845) of those from cohort 3. It could be concluded that girls aged 12-14 years, as well as those aged 14-16 years, show a high BMI tracking over 3 years.

Although Foulkes & Davis γ have a more complex mathematical-statistical structure when compared to auto-correlations and requires specialized software for its computation, its formulation has several advantages[24,25] including: 1) collected data do not need to be equally spaced in time; 2) there is no special need for Gaussian distributions; 3) a test is available to identify the best fitting model describing change; 4) it has a unique tracking statistics and is associated with 95% CI; and 5) it allows the identification of individuals whose growth curves are more or less stable and therefore more or less predictable.

γ Statistics according to David Rogosa[10,20,27]

The method proposed by Rogosa[20], detailed in the software developed with Ghandour (TIMEPATH)[10], is based on a seminal paper published with Sanner[28], as well as in his "classic" work reprinted in 1995[27]. The software output offers the following: 1) best fitting models for individual growth curves as well as group statistics; 2) values of a single individual g, and 3) population estimates with standard-errors, which allows for computations of 95% CI.

Since there is an individual γ and therefore 169 g's in cohort 3, the software presents relevant descriptive statistics (mean, standard deviation, minimum and maximum), and the five-number summary: minimum, P25 (quartile 1), median (P50), P75 (quartile 3), as well as Rates R^2 and γ statistics. It is important to highlight that individual γ refers to the probability of an individual trajectory to cross other trajectories. The information provided by the software is very rich in order to have a detailed description of modal BMI trajectory as well as an individualized view of its stability (given by γ) and change (given by Rates). Finally, tracking population estimates are presented.

Table 4. Descriptive statistics and γ tracking index according to Rogosa's suggestions (cohort 3).

	Rate	R^2	Gamma (γ)
Mean	0.336	67.829	0.835
Standard deviation	0.917	32.807	0.098
Minimum	-3.450	0.000	0.411
P5	-1.450	2.420	0.613
Q1	-0.150	42.907	0.798
Median	0.450	77.997	0.839
Q3	0.900	96.430	0.899
P95	1.550	99.734	0.976
Maximum	3.100	100.000	0.994
	Gamma (γ)	0.852	
	Standard Error	0.008	

P5: Percentile 5; Q1: Quartile 1; Q3: Quartile 3; P95: Percentile 95

In Table 4, the standard deviation of Rate (i.e., the slope) is much higher than the mean (0.917 to 0.336), indicating great variability in BMI individual changes over the three years. The lowest γ value was 0.411, indicating no individual tracking. From P5, γ values rises to 0.613, and the median is 0.839, which is already high. The global γ is 0.852 ± 0.008 showing high BMI tracking in this cohort. In cohort 2, results (not shown) were similar.

Rogosa's suggestions[10,20,27] as well as the versatility and richness of the TIMEPATH output are very important in order to have a detailed view of tracking, allowing researchers a more detailed examination, in modal and individual ways, of BMI trajectories over the three years.

Goldstein's growth constancy index[11,29]

The Goldstein's growth constancy index, represented as ξ by Furey et al.[11], is a tracking measure aimed at determining the stability and variability of individual growth (i.e., height) trajectories. According to Goldstein[29], the analysis of change patterns occurring in children and adolescents' growth would provide insight into the detection of stable (maintenance of a relative position) or unstable growth curves (relatively high proportion of intersecting curves). Its importance in Auxology and paediatrics is evident to timely identify children or adolescents with instability in their physical growth. Goldstein[29] proposed that in a random sample of individuals, an individual whose growth curve crosses a relatively high proportion of other subjects´ curves is characterized as having a low tracking.

Goldstein[29] presented two ways of estimating the growth constancy index, i.e., tracking measures. In the first approach, ξ and its confidence interval are based on a Jackknife estimator. In the second approach, the use of the intraclass correlation obtained from the analysis of variance (ANOVA) was suggested. These two options can be formulated, as stressed by Furey et al.[11], in the context of two ANOVA models[29]. Thus, in model I or II, the problem lies in the way the true value of each individual is formulated, its true stability and interpretation. In model I, this value is considered as an unknown (i.e., a constant), whereas in model II, it is considered as a random variable. The interpretation in the case of ANOVA I is the following: tracking inferences are valid only for cases included in the study; in ANOVA II, the inferences are made to the population consisting of individuals from where the sample was randomly extracted. Table 5 shows examples of these analyses. In Model I, a typical ANOVA table is shown, and ξ is presented (its values vary from 0 to 1, and 1 is the perfect tracking). According to Furey et al.[11], this index may be overestimated and may assume positive values even when there is no evident tracking. In this case, it is necessary to consider its modified or corrected value (ξ^*) with a maximum value of 1, but it becomes 0 if auto-correlations are equal to 0 in successive values. The last part of model I shows point estimates as well as confidence intervals obtained by the Jackknife resampling technique. In Model II, an ANOVA table is also presented. However, tracking is expressed as an intraclass correlation coefficient. In addition, the 95% confidence interval is also shown[11].

In our example, we used model I (without any purpose of generalization); ξ values were high in both cohorts indicating strong stability for BMI (ξ_{c2}=0.918 andξ_{c3}=0.940). As expected, the values of the modified index decreased, but remained high (ξ^*_{c2}=0.878 and ξ^*_{c3}=0.910). The Jackknife estimates and corresponding 95% CI were 0.916 (0.873, 0.946) and 0.874 (0.809, 0.919) for cohort 2; 0.939 (0.915, 0.957) and 0.909 (0.873, 0.936) for cohort 3.

Table 5. Model I and II of the Golsdstein's growth constancy index[11,29] of the BMI of girls from cohort 2.

ANOVA Table Model I			
Source	Degrees of freedom	Sum of squares	Mean Square
Between	214	589.623	2.755
Within	430	52.377	0.122
Total	644	642.000	
Growth constancy index: 0.918			
Modified growth constancy index: 0.878			
Jackknifed estimator: 0.916 [0.873,0.946]			
Modified *Jackknife* estimator: 0.874 [0.809,0.919]			
ANOVA Table Model II			
Source	Degrees of freedom	Sum of squares	Mean Square
Between	214	589.623	2.755
Within	430	52.377	0.122
Total	644	642.000	
Intraclass correlation coefficient: 0.878 [0.834,0.912]			

Results of model II (generalization allowed for girls of the same population), the intraclass correlation coefficient and 95% CI was 0.878 (0.834, 0.912) for girls in cohort 2 and 0.910 (0.876, 0.935) in cohort 3. These results show, once again, BMI stability for girls aged 12-14 years and 14-16 years.

In short, the wealth of Goldstein's suggestion[11,29] can be extended to tracking studies covering other variables without additional problems. In addition to obtaining a single tracking measure, its computation does not require equidistant observations, and Gaussian distribution is not required. One of the advantages of Goldstein propositions is the identification of individuals with high or low separation to the mean, allowing efficient monitoring and intervention of flagged cases.

CONCLUSION

This paper presents a set of different tracking approaches aimed at helping a novice researcher in the field. The importance of the tracking concept, its various statistical analysis techniques, and meaning may constitute important methodological lessons in the Physical Education and Sports Science fields, especially when dealing with longitudinal data arising from observational and/or intervention designs. Notwithstanding, the variety of statistical approaches, it may be important for researchers to become acquainted with their versatility, implementation in different software, utility and application.

In our example, a moderate-to-high tracking was expected given its short duration (2 years), regardless of procedure used. Differences among subjects in their BMI individual changes are relatively small auto-correlations, so Foulkes & Davies γ and Goldstein's constancy index showed similar high values. However, when LDA or TIMEPATH outputs were explored, a more individualized view of each subject becomes more evident, allowing identifying adolescents who may require individual care and more efficient interventions from Physical Education teachers or paediatricians.

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