# Determining relative population-specific acceleration intensity thresholds in soccer using game locomotion data: Methodological challenges and possible solutions

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## Abstract

In soccer, relative population-specific acceleration intensity thresholds are required to create meaningful activity profiles. These thresholds can be derived from the *maximal acceleration-initial running speed ($a_{max}$-$v_{init}$) regression line*, whose determination has so far required time-consuming testing. The aims of this study were to present a new method for determining population-specific $a_{max}$-$v_{init}$ regression lines in soccer using game locomotion data and to assess its validity. Game locomotion data from 41 male youth elite soccer players were collected using a GPS-based tracking system. The $a_{max}$-$v_{init}$ regression lines were determined using locomotion data from one to five games per athlete. The proposed method overcomes several limitations of existing

methods by accounting for the number of games combined and the individual distribution of high-intensity accelerations over the velocity measurement range when identifying maximal accelerations. Further, the athletes took an acceleration test to determine their test-based $a_{max}$-$v_{init}$ regression line. Mean biases were estimated for the regression coefficients (i.e., $a_{max}$-intercept and slope) and assessed via standardization and Bayesian analysis. Regression lines based on two or three combined games showed trivial biases for both coefficients. However, due to the large uncertainty in the estimates, the chance of equivalence was only assessed as *possibly equivalent*. Thus, the presented game-based method represents a viable and easy-to-implement alternative to the test-based method for determining population-specific $a_{max}$-$v_{init}$ regression lines in soccer. This simplifies the process of determining relative population-specific acceleration intensity thresholds, which are required for creating meaningful activity profiles.

## Introduction

In soccer, tracking technologies are widely used to assess players' activity during training sessions and matches (Akenhead & Nassis, 2016; Weldon et al., 2021). However, describing the complex activity of soccer in a meaningful way using locomotion data is a major challenge.

In terms of locomotion, soccer is characterized by frequent changes in running speed (Harper et al., 2019). This makes the use of acceleration-based metrics essential for creating meaningful activity profiles. Therefore, a metric often used in the scientific literature as well as in training practice is the number of accelerations above certain intensity thresholds, with absolute generic intensity thresholds predominantly used. This means that the same threshold values are applied to all acceleration actions and all athletes. For instance, 2 $m \cdot s^{-2}$ or 3 $m \cdot s^{-2}$ are frequently used thresholds for assessing an acceleration action as highly intense (see reviews by Delves et al., 2021; Harkness-Armstrong et al., 2022; Silva et al., 2022). However, the use of such thresholds is problematic. First, maximal reachable acceleration decreases with increasing running speed

(Sonderegger et al., 2016). This means that when an absolute intensity threshold is used, the intensity of acceleration actions initiated from a standing position or a low running speed is overestimated compared to that of accelerations initiated from a higher speed (Sonderegger et al., 2016). Second, athletes differ in their maximal acceleration capacity. Thus, a generic intensity threshold overestimates the intensity of acceleration actions in athletes with a relatively high maximal acceleration capacity (e.g., elite athletes) and underestimates the metric in athletes with a lower maximal acceleration capacity (e.g., amateur athletes) (Sweeting et al., 2017).

Therefore, absolute generic intensity thresholds do not allow for a valid intensity assessment of acceleration actions in soccer and should consequently not be used for activity descriptions. An alternative approach is the use of *relative population-specific intensity thresholds* (Sonderegger et al., 2016). These thresholds assess the intensity of an acceleration action in relation to the maximal acceleration that can, on average, be reached in a population from a certain initial running speed (e.g., in soccer players of various performance levels, age categories, or genders) (Sonderegger et al., 2016). This makes it possible to validly assess the intensity of acceleration actions in soccer and to create meaningful activity profiles (de Hoyo et al., 2018; Fischer-Sonderegger et al., 2019).

The concept of relative population-specific intensity thresholds was initially introduced by Sonderegger et al. (2016). Recently, Osgnach et al. (2023) presented a slightly modified version. In the original approach, the thresholds are defined in relation to the *maximal acceleration-initial running speed ($a_{max}$-$v_{init}$) regression line*. In the modified approach, they are derived from the *acceleration-speed (AS) regression line*. The current reference methods for determining these regression lines are *isolated* performance tests (i.e., sprint tests) (Morin et al., 2019; Samozino et al., 2016; Sonderegger et al., 2016). However, in the recent past, various methods have been proposed to determine these regression lines for soccer players using training or game locomotion data instead of performance test data (Cormier, Tsai, Meylan, & Klimstra, 2023; Miguens et al., 2024; Morin et al., 2021; Silva et al., 2023). The basic intention behind these *integrated* methods is to replace their *test-based* reference method. By using locomotion data automatically collected during training sessions and matches, they offer the great advantage of not imposing additional expenditure of time or physical load on the athletes. However, to replace an existing reference method with a new method, rigorous validation is required (Impellizzeri & Marcora, 2009).

In this validation process, two studies have examined the validity of an integrated measured population-specific AS regression line, so far (Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023). For validation, the integrated measured regression line was compared to a test-based regression line (i.e., a regression line determined by means of a sprint test). Traditional hypothesis tests have been used to decide whether the integrated measured regression line could replace the test-based line. Based on statistically non-significant differences between the two measures, the authors concluded that an integrated measured regression line is valid and can be used instead of the test-based line. However, the appropriate inferential statistical procedure to assess whether two measures can be used interchangeably is an equivalence test (Lakens, 2017; Walker & Nowacki, 2011). This procedure requires a definition of the smallest meaningful deviation between two measures (the equivalence bounds). Simply put, the deviation between the measures must be smaller than this smallest meaningful value for them to be considered equivalent. In team sports, where there is usually no clear relationship between indicators of athletic performance and game performance, a value of 0.2 times the between-subject standard deviation (*SD*) can be used as the smallest meaningful deviation (Hopkins, 2004). In previously conducted validity studies, if an equivalence test with equivalence bounds of 0.2 times the between-subject *SD* had been used, at least one of the tested variables (i.e., *A*-intercept, slope, or *S*-intercept of the regression line) would always have been outside these bounds. Therefore, the conclusions made by the authors are questionable. Based on these previous results (Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023), a more appropriate conclusion should have been that it is not possible to determine a valid population-specific AS regression line using existing integrated methods.

The determination of a valid $a_{max}$-$v_{init}$ or AS regression line using soccer training or game locomotion data relies on the presence of multiple maximal accelerations in the data used (i.e., accelerations of the same magnitude as in an isolated sprint test performed in a non-fatigued state). Combining locomotion data from multiple training sessions and/or games is a logically valid approach to increasing the probability of observing multiple maximal accelerations. This reasoning is the basis for the prevailing assumption that the validity of an integrated measured $a_{max}$-$v_{init}$ or AS regression line will improve steadily with increasing amounts of data (i.e., that the line will get closer and closer to the test-based line). However, previous studies on the validity of an integrated measured $a_{max}$-$v_{init}$ or AS regression line could not confirm this assumption (Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023). Further, Cormier, Tsai, Meylan, and Klimstra (2023) observed an integrated measured AS regression line overestimating either the *A*- or *S*-intercept compared to the test-based line. This finding suggests that maximal accelerations can occur in training sessions or games, but existing integrated methods may not be able to determine a valid regression line from them.

The methodological challenge in the integrated determination of an $a_{max}$-$v_{init}$ or AS regression line is identifying the maximal accelerations from the totality of accelerations in the underlying locomotion data. This challenge is primarily due to the non-negligible random measurement error of locomotion tracking systems used in soccer (e.g., global positioning system (GPS) based systems) when measuring maximal acceleration (Crang et al., 2023; Fischer-Sonderegger et al., 2021). Simply put, the random measurement error makes it necessary for an integrated method to identify either all maximal accelerations (i.e., those with a positive as well as a negative random measurement error) or several with the true maximal acceleration value (i.e., maximal accelerations without a random measurement error) from the totality of accelerations in order to generate a valid output (i.e., a regression line equivalent to a test-based regression line). In our view, existing methods lack a clear rationale for why they should fulfill one of these requirements. Therefore, we believe that a new method is required.

To facilitate the determination of relative population-specific acceleration intensity thresholds, the aims of this study were (1) to present a new method for determining the $a_{max}$-$v_{init}$ regression line of soccer players using game locomotion data and (2) to investigate how the validity of a population-specific $a_{max}$-$v_{init}$ regression line, determined by this new method, changes as a function of the amount of data used for determination.

## Materials and methods

### Participants

A total of 41 male youth elite soccer players from six youth elite soccer teams of age level under 18 and under 21 from Switzerland participated in the study (age 18.2 ± 2.3 years). Goalkeepers were excluded from the study. The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Bern (Project ID: 2019-01586, 19 November 2019). Players received verbal and written information about the study design before giving written informed consent.

### Design

For validity testing, a fully paired comparative diagnostic test accuracy study design was used (Yang et al., 2021). During the 2021/22 soccer season, locomotion data from all official championship matches were collected. Midway through the second half of the season, the participants took an acceleration test to determine their $a_{max}$-$v_{init}$ regression line (Sonderegger et al., 2016). One week before the actual test, a familiarization test was performed. The test-based regression line served as the criterion measure. The *game-based* regression line was determined based on the locomotion data of the game closest to the test. In determining a game-based regression line based on data from multiple games, the games closest to the test were always combined. For each athlete, only games in which he had participated for at least 80 minutes were used.

**Measurements**

All games as well as the acceleration test were recorded with a 10 Hz GPS-based tacking system (Advanced Sport Instruments, FieldWiz V2, Lausanne, Switzerland). To prevent measurement errors due to possible inter-unit variation, each athlete always wore the same sensor for all measurements. The GPS units derived instantaneous velocity via the Doppler shift method. Unfortunately, the number of connected satellites and the horizontal dilution of precision during the measurements are not provided by the manufacturer for the FieldWiz V2 devices. For 10 Hz GPS devices, good intra-unit reliability and validity in measuring instantaneous velocity in various movement tasks have been reported (for review, see Crang et al., 2021). However, intra-unit reliability and validity in measuring maximal acceleration in high-intensity movement tasks are worse (Crang et al., 2023).

The acceleration test was performed according to the protocol of Sonderegger et al. (2016) and consisted of four maximal accelerations from four different initial running speeds. All tests were performed on an artificial turf soccer field at the training site of the respective club. In each case, the test was performed at the beginning of a normal training session after a warm-up led by the club’s athletic coach. On the test day, players were in a recovered state (i.e., match day +3 or +4 and no intensive training session the day before).

## Data analysis

### Data processing and event detection

The Doppler shift velocity signal and time stamp of all measurements were exported from FieldWiz online software. All analyses were then performed based on these data using a custom Matlab script (Version 9.8.0 (R2020a), MathWorks Inc., Natick, USA). According to the manufacturer the exported velocity signal has already been smoothed with a one-second moving average filter. Therefore, no further filtering techniques were applied. The acceleration signal was calculated as the first derivative of the velocity signal. The two signals were then used to detect acceleration actions, applying the same procedure as Fischer-Sonderegger et al. (2019). Each action was described by its initial running speed ($v_{init}$) and the maximal acceleration reached ($a_{max}$).

### Event selection and model fitting

To determine the $a_{max}$-$v_{init}$ regression line of an athlete based on the totality of detected acceleration actions in one or multiple games, maximal acceleration actions from different initial running speeds have to be identified and subsequently described by a linear model (Sonderegger et al., 2016). For this purpose, the following procedure was used (see Figure 1 for a graphical illustration): First, all acceleration actions detected in a game were plotted in a two-dimensional cartesian coordinate system with $a_{max}$ on the *y*-axis and $v_{int}$ on the *x*-axis. If the $a_{max}$-$v_{init}$ regression line was to be determined based on the locomotion data of multiple games, the actions of all underlying games were inserted into the same coordinate system. Second, depending on the number of games pooled together, the *x*-axis of the coordinate system was divided into intervals of a certain length (4.3, 2.1, 1.4, 1.1, and 0.9 km·h$^{-1}$ in the case of one, two, three, four, and five games, respectively), and within each interval, the action with the highest $a_{max}$ was selected. The selected actions were then described by a linear model using a robust regression technique (Yohai, 1987) (Figure 1A). Third, the estimated regression line was used to select all high-intensity actions (i.e., actions with an $a_{max}$ >75% of the $a_{max}$ predicted by the regression line). Fourth, depending on the number of games pooled together, a certain number of quantiles were calculated for the *x*-values of the high-intensity actions (6, 13, 20, 27, and 34 in the case of one, two, three, four, and five games, respectively). Fifth, within each interval between successive quantiles, the action with the highest $a_{max}$ was selected, and the actions selected in this way were then described by a linear model using a robust regression technique (Yohai, 1987). The regression line of this analysis shows the $a_{max}$-$v_{init}$ regression line of an athlete (Figure 1B).

The athletes' test-based $a_{max}$-$v_{init}$ regression lines were determined according to the reference method of Sonderegger et al. (2016) by a linear least squares regression analysis of the four acceleration actions recorded in the test. From both regression lines (game- and test-based), the coefficients of the regression equation ($a_{max}$-intercept and slope) were then used for the statistical analysis.

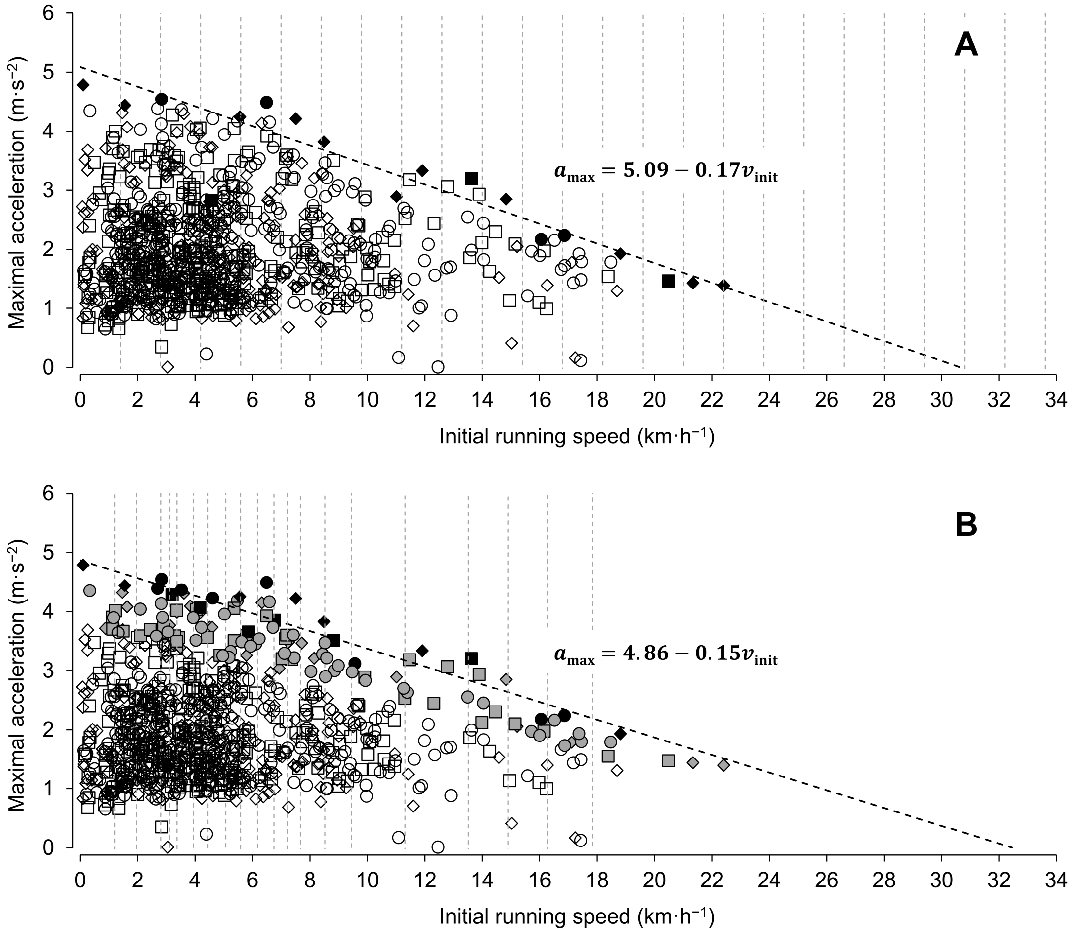


*Figure 1*. Procedure for determining a maximal acceleration-initial running speed ($a_{max}$-$v_{init}$) regression line using game locomotion data, shown as an example for the case of three combined games. Different symbols represent the actions of a representative athlete from different games. A: (1) the *x*-axis is divided into intervals with a length of 1.4 km·h$^{-1}$ (gray dashed vertical lines), (2) within each interval the action with the highest $a_{max}$ is selected (black filled symbols), and (3) the selected actions are described by a linear model (black dashed line). B: (1) High-intensity acceleration actions are selected (gray filled symbols), (2) 20 quantiles are calculated for the *x*-values of the high-intensity acceleration actions (gray dashed vertical

lines), (3) within each interval between successive quantiles, the action with the highest $a_{max}$ is selected (black filled symbols), and (4) the actions selected in this way are described by a linear model, resulting in the $a_{max}$-$v_{init}$ regression line of the athlete (black dashed line).

**Statistical analysis**

The measures of centrality and dispersion are the mean ± *SD*. Statistical modeling was performed using SAS Studio (Version 3.81; SAS Institute Inc., Carry, USA). To account for non-uniform effects of groups formed based on playing positions, the mixed linear modeling procedure (PROC MIXED) was used (Hopkins, 2006). The coefficients of the $a_{max}$-$v_{init}$ regression equations were the outcome variables, and a separate analysis was performed for each. The fixed effect was playing position × measurement condition (to estimate the mean of the outcome variable for the different measurement conditions [i.e., test and game] within groups formed by playing positions [center-backs, central midfielders, forwards, and outside players [i.e., full-backs and wide midfielders combined]]). The random effect was the intercept (to account for differences in the outcome variable between players). Player identity was the subject variable (to model the nesting of measurements within players), and playing position was the group variable (to model the nesting of players within positions). The estimated, position-specific means of the outcome variable were then combined to obtain a single mean for the test condition, the game condition, and the bias (i.e., game − test) (using a LSMESTIMATE statement). In this combination, the outside players' mean was weighted double that of the other position-specific means. This results in effects that are similar to those of a fully pooled analysis (i.e., only measurement condition as a fixed effect in the model) if the sample contained the same number of center-backs, central midfielders, and forwards and a double number of outside players. Thus, the position groups were weighted according to their proportions in the population. The mean bias in raw, percentage, and standardized units was the measure of validity. Standardization was performed using the between-subject *SD* of the test condition (i.e., the criterion measure).

Plots of residual versus predicted values from the analyses showed no evidence of nonuniformity of error, and no outliers (defined as observations with a studentized residual >3.5) were detected. Uncertainty in the estimates of effects (mean biases) is presented as 90% compatibility intervals (CI), derived by assuming a *t* sampling distribution. Analogous to the effect estimates, CIs were obtained from combining position group-specific intervals (Hopkins, 2006). Decisions about magnitudes of effects accounting for the uncertainty were based on a reference-Bayesian analysis with a minimally informative prior (Hopkins & Batterham, 2016; Hopkins & Batterham, 2018), which provided estimates of chances that the true magnitude was a substantial negative value, a trivial value (i.e., game measure equivalent to the test measure), and a substantial positive value. For these calculations, a previously published spreadsheet was used (Hopkins, 2007).

All effects are reported with a qualitative descriptor for the chance of the effect to be trivial using the following scale: ≤0.005, *most unlikely*; >0.005–0.05, *very unlikely*; >0.05–0.25 *unlikely*; >0.25–0.75, *possibly*; >0.75–0.95, *likely*; >0.95–0.995, *very likely*; >0.995, *most likely* (Hopkins, 2020; Hopkins et al., 2009). Magnitudes of standardized effects were assessed as ≤0.2 *trivial*, >0.2–0.6 *small*, >0.6–1.2 *moderate*, >1.2–2.0 *large*, >2.0–4.0 *very large*, and >4.0 *extremely large* (Hopkins et al., 2009).

## Results

Table 1 shows the final sample sizes, descriptive statistics, and mean bias estimates in raw and percentage units. Figure 2 shows the standardized mean bias estimates, their magnitude, and the decision on equivalence. Compared to a single game, the combination of locomotion data from two games led to a reduction in the mean bias estimates of both regression coefficients ($a_{max}$-intercept and slope). However, with the addition of further games, the mean bias for the $a_{max}$-intercept did not change meaningfully. By contrast, for the slope, the addition of a fourth and fifth game led to a new gradual increase in the mean bias. Thus, with trivial mean biases for both coefficients, the regression lines based on two and three combined games were equivalent to the test-based regression line. However, due to the large uncertainty in the estimates, the chance that the true effect of the coefficients of these two regression lines is trivial, or that the coefficients are indeed equivalent to the coefficients of a test-based line was only assessed as *possibly trivial* or *equivalent*.

Table 1

*Means (and Standard Deviations) of the Test- and Game-based Regression Coefficients and Mean Bias Estimates in Raw and Percentage Units [with 90% Compatibility Intervals]*

| | | Game-based coefficients | | Test-based coefficients | | Mean bias raw units | | Mean bias percent units | |
|---|---|---|---|---|---|---|---|---|---|
| Games[a] | $n$ | $a_{max}$-intercept | Slope | $a_{max}$-intercept | Slope | $a_{max}$-intercept | Slope | $a_{max}$-intercept | Slope |
| 1 | 41 | 4.65 (0.62) | −0.128 (0.081) | 4.85 (0.32) | −0.158 (0.025) | −0.20 [−0.36, −0.03] | 0.030 [0.007, 0.052] | −4.06 [−7.42, −0.70] | 18.96 [4.74, 33.19] |
| 2 | 32 | 4.85 (0.33) | −0.152 (0.033) | 4.85 (0.34) | −0.156 (0.028) | 0.00 [−0.12, 0.11] | 0.004 [−0.007, 0.016] | −0.04 [−2.44, 2.35] | 2.86 [−4.40, 10.12] |
| 3 | 29 | 4.86 (0.28) | −0.151 (0.025) | 4.83 (0.36) | −0.155 (0.028) | 0.03 [−0.08, 0.14] | 0.004 [0.007, 0.014] | 0.61 [−1.66, 2.89] | 2.28 [−4.59, 8.80] |
| 4 | 28 | 4.83 (0.22) | −0.145 (0.015) | 4.82 (0.35) | −0.153 (0.027) | 0.02 [−0.09, 0.12] | 0.008 [−0.001, 0.017] | 0.33 [−1.92, 2.57] | 5.12 [−0.96, 11.20] |
| 5 | 23 | 4.84 (0.21) | −0.143 (0.017) | 4.85 (0.36) | −0.155 (0.029) | −0.01 [−0.14, 0.13] | 0.012 [0.000, 0.024] | −0.18 [−2.94, 2.58] | 7.74 [0.06, 15.41] |

[a]Number of games combined for determining the games-based regression line.

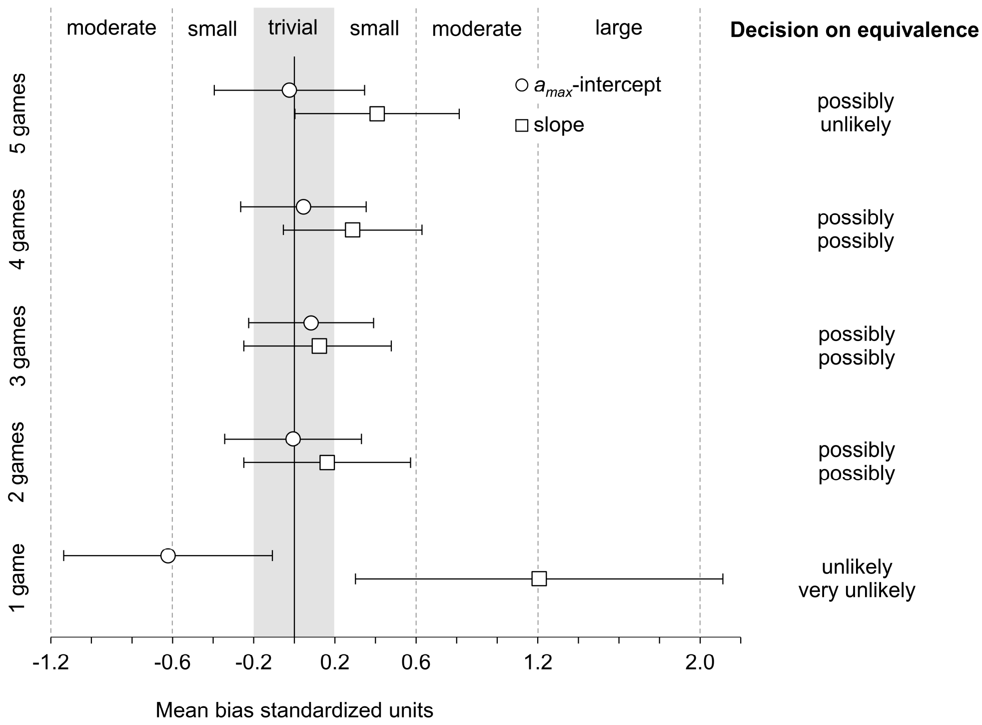


*Figure 2*. Standardized mean bias estimate of the coefficients of the game-based maximal acceleration-initial running speed ($a_{max}$-$v_{init}$) regression line as a function of the number of games combined and the respective decision on equivalence to the coefficients of the test-based regression line. The gray shaded area shows the trivial effect or equivalence range. Error bars show 90% compatibility intervals.

# Discussion

In this article, we present a new method for determining $a_{max}$-$v_{init}$ regression lines of soccer players using game locomotion data. Unlike existing methods, our method accounts for the amount of locomotion data used and the individual distribution of high-intensity accelerations over the velocity measurement range when identifying maximal accelerations. This is intended to allow for the identification of all maximal accelerations (both those with a positive and those with a negative random measurement error) and, thus, to determine valid $a_{max}$-$v_{init}$ regression lines. $A_{max}$-$v_{init}$ regression lines allow for the derivation of relative acceleration intensity thresholds and are therefore essential for creating meaningful activity profiles in soccer. The advantage of a game-based method over a test-based method for determining $a_{max}$-$v_{init}$ regression lines is that it is easier to implement, as no time-consuming testing is required.

Using the new method and varying amounts of game locomotion data from male youth elite soccer players, we determined population-specific regression lines and compared them to a test-based regression line. Game-based regression lines based on locomotion data from two or three games differed only trivially from the test-based line. However, due to the large uncertainty in the estimates, the chance that regression lines based on two or three combined games are indeed equivalent to a test-based line was only assessed as *possibly equivalent*. The use of data from fewer than two or more than three games resulted in larger differences. Thus, in situations in which the determination of a test-based, population-specific $a_{max}$-$v_{init}$ regression line is not possible, our game-based method represents a viable alternative. Contrary to what is assumed for existing game-based methods, for our method, there seems to be an optimal amount of locomotion data to be used and not a minimally required one.

**Comparison with previous studies: Method**

The method presented in this study differs in several aspects from previously published methods for determining $a_{max}$-$v_{init}$ (Silva et al., 2023) or AS (Cormier, Tsai, Meylan, & Klimstra, 2023; Miguens et al., 2024; Morin et al., 2021) regression lines using soccer players' training or game locomotion data. However, the differences described below and their related mechanisms apply only to the methods of Silva et al. (2023), Morin et al. (2021), and Miguens et al. (2024). These methods are conceptually comparable to our method. The method proposed by Cormier, Tsai, Meylan, and Klimstra (2023) takes a fundamentally different approach.

Compared to the methods proposed by Silva et al. (2023), Morin et al. (2021), and Miguens et al. (2024), a first difference is that in our method, the number of combined games is taken into account when selecting accelerations for the regression analyses. The increase in the number of accelerations to be selected with an increasing number of combined games is intended to reflect the likely increase in the number of maximal accelerations associated with it. This is because it can be assumed that if the number of accelerations to be selected (i.e., the assumed number of maximal accelerations) does not correspond to the (unknown) true number of maximal accelerations in the underlying data, the regression line is likely to be biased. If the number of accelerations to be selected is larger than the existing number maximal accelerations, submaximal accelerations will inevitably be selected. This results in an underestimation of an athlete's true regression line (i.e., a too-low $a_{max}$- *or A*-intercept). Conversely, if the number of accelerations to be selected starts to exceed the existing number of maximal accelerations, the applied acceleration selection procedure increasingly selects only maximal accelerations with a positive random measurement error. This results in an overestimation of an athlete's true regression line (i.e., a too-high $a_{max}$- *or A*-intercept). The occurrence of a random measurement error is unavoidable when something is measured (Rabinovich, 2005). Moreover, when measuring maximal acceleration using a GPS-based tracking system, the random error is of meaningful magnitude (Crang et al., 2023; Fischer-Sonderegger et al., 2021). Notably, an $a_{max}$-$v_{init}$ or AS regression line based primarily on maximal accelerations with a positive random measurement error is also expected to have a steeper slope than the true $a_{max}$-$v_{init}$ or AS regression line. This is due to the higher random measurement error in the low velocity region compared to the high velocity region (Fischer-Sonderegger et al., 2021). Based on these mechanisms, we can therefore assume that the methods of Silva et al. (2023), Morin et al. (2021), and Miguens et al. (2024) can determine a regression line with a valid $a_{max}$- *or A*-intercept only for a specific number of combined games.

A second difference is that in our method, the individual frequency distribution of high-intensity accelerations over the velocity measurement range is taken into account when selecting maximal accelerations. Simply put, in areas of the velocity measurement range where an athlete performed more high-intensity accelerations, more accelerations are selected. The rationale for this methodological approach is that we assume that the frequency distribution of maximal accelerations is similar to the frequency distribution of high-intensity accelerations (or is optimally equal to it). An incorrect assumption regarding the frequency distribution of maximal accelerations over the velocity measurement range leads to two problems. First, in areas where a too-low frequency of maximal accelerations is assumed, primarily maximal accelerations with a positive random measurement error are selected. Second, in areas where a too-high frequency of maximal accelerations is assumed, either maximal accelerations with a lower positive or no random measurement error are selected or it comes to the selection of submaximal accelerations. Consequently, this leads to a bias in the slope of the regression line. In Silva et al.'s (2023), Morin et al.'s (2021), and Miguens et al.'s (2024) methods, an even, non-individual distribution of maximal accelerations over the velocity measurement range is assumed. However, in soccer games, it is unlikely that maximal accelerations will be evenly distributed. A right-skewed distribution is more likely (i.e., more maximal accelerations in the low-velocity range than in the high-velocity range) (de Hoyo et al., 2018; Fischer-Sonderegger et al., 2019; Martínez-Cabrera et al., 2021). Therefore, these methods are unlikely to determine an $a_{max}$-$v_{init}$ or AS regression line with a valid slope for soccer players using game locomotion data.

A third difference is that in our method, a robust regression technique (Yohai, 1987) is used to determine the $a_{max}$-$v_{init}$ regression line. In brief, this regression technique down-weights the influence of unusual observations and, thus, yields parameter estimates that fit the bulk of the data well. This makes this technique well-suited for automated data analysis (Andersen, 2008). Silva et al.'s (2023), Morin et al.'s (2021), and Miguens et al.'s (2024) methods use different regression techniques and/or outlier detection procedures. Whether a certain procedure in the linear modeling process generates a more valid output than others requires further research.

**Comparison with previous studies: Bias**

The present study is the first to assess the validity of an integrated measured population-specific $a_{max}$-$v_{init}$ regression line. In our study, the regression lines based on locomotion data from two or three games were the most similar to the test-based line. Both coefficients showed only trivial bias ($a_{max}$-intercept 0.00 m·s$^{-2}$ or −0.04% and 0.03 m·s$^{-2}$ or 0.61%; slope 0.004 or 2.86% and 0.004 m·s$^{-2}$ or 2.28%). However, our results can be compared to the results regarding the validity of integrated measured AS regression lines. Depending on the method used for determination, Cormier, Tsai, Meylan and Klimstra (2023) reported a moderate (0.48 m·s$^{-2}$ or 6.79%) and trivial (−0.05 m·s$^{-2}$ and −0.98%) bias for the *A*-intercept of such a regression line. The bias of the slope was not reported. For determination, they used locomotion data from 15–19 training sessions or games per athlete. Cormier, Tsai, Meylan, Soares, et al. (2023) and Alonso-Callejo et al. (2023) examined how the bias of an integrated measured AS regression line changes as a function of the amount of locomotion data used for determination. In Cormier, Tsai, Meylan, Soares, et al.'s (2023) study, the bias of the *A*-intercept was minimized using 16 training sessions or games per athlete (−0.28 m·s$^{-2}$, small) and that of the slope using 6 (exact value not evident in article but tending towards zero). In Alonso-Callejo et al.'s (2023) study, the bias of the *A*-intercept was minimized using six training sessions or games per athlete (−0.03 m·s$^{-2}$ or −0.41%). The bias of the slope was not reported. In summary, the present study is the first to determine an $a_{max}$-$v_{init}$ or AS regression line showing only trivial bias for both coefficients. This required a relatively small amount of locomotion data from only two or three games.

**Mechanisms**

The trivial biases observed for the regression lines based on two or three games show that in these cases, the method's assumptions regarding the number and distribution of actions with maximal acceleration were sufficiently well met in the underlying data. As our method adjusts the assumption regarding the number of actions with maximal acceleration to the number of combined games, we expected regression lines of equal validity, regardless of the number of combined games. However, this was not the case. Further analysis of our data showed that the slope of the regression line used in the method for identifying high-intensity acceleration actions gradually decreased with an increasing number of combined games (i.e., became flatter). Due to the gradual nature of this decrease, we consider it to be effectively caused by the number of games combined rather than by sampling variation. Accordingly, we also consider the observed mean bias changes to be actually caused by the number of games combined and not by sampling variation.

**Strengths and limitations**

The main strength of the present study is the proposal and in-depth discussion of a new method for determining game-based $a_{max}$-$v_{init}$ regression lines. This method is the first to account for the amount of locomotion data used and the individual distribution of high-intensity accelerations over the velocity measurement range when identifying maximal accelerations. Further, compared to previous studies (Alonso-Callejo et al., 2023; Cormier, Tsai, Meylan, & Klimstra, 2023; Cormier, Tsai, Meylan, Soares, et al., 2023), this study presents a superior methodology for validity assessment. This relates to the selection of the study participants (athletes from multiple teams instead of a single team), the type of locomotion data used (exclusively data from official championship games instead of a mixture of training and game data), and the statistical analysis (equivalence test instead of traditional hypothesis test). A limitation of the study is the unknown reliability of the test-based regression line. Due to the familiarization test, we consider a systematic bias to be unlikely. However, an assumption regarding random measurement variation is not possible.

### Practical application

The test-based $a_{max}$-$v_{init}$ regression line provided in this study can be used to derive relative acceleration intensity thresholds for the population of male youth elite soccer players (Sonderegger et al., 2016). These thresholds can then be used to validly assess the intensity of acceleration actions and thus create meaningful activity profiles. The presented game-based method is a viable and easy-to-implement alternative to the test-based method for determining $a_{max}$-$v_{init}$ regression lines in additional populations of soccer players (e.g., women, other age categories, or performance levels). However, it is important to be aware of the factors that influence the validity of a game-based $a_{max}$-$v_{init}$ regression line (number and frequency distribution of actions with maximal acceleration in the underlying locomotion data).

## Conclusion

The method presented in this study for determining the $a_{max}$-$v_{init}$ regression line of soccer players using game locomotion data overcomes several limitations of existing methods. Our results show that the method is a viable alternative to the test-based method for determining population-specific $a_{max}$-$v_{init}$ regression lines in soccer. This greatly simplifies the process of determining relative population-specific acceleration intensity thresholds in soccer. Such thresholds are essential for a valid intensity assessment of acceleration actions and, consequently, for creating meaningful activity profiles.

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## Disclosure statement

The authors report there are no competing interests to declare.

## Data availability statement

The data that support the findings of this study are available from the corresponding author, Pascal Andrey, upon reasonable request.

## Code availability statement

The code used for the statistical analysis presented in this study is available from the corresponding author, Pascal Andrey, upon reasonable request.

## Ethics approval and informed consent

The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of Bern (Project ID: 2019-01586, 19 November 2019). Participants received verbal and written information about the study design before giving written informed consent.

## Participating investigators

Lionel Castella and Nicco Vögeli both wrote parts of the Matlab script that was used to determine the game-based $a_{max}$-$v_{init}$ regression lines.

## Author contributions

| | |
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| Data curation: | Pascal Andrey. |
| Formal Analysis: | Pascal Andrey. |

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|---|---|
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| Methodology: | Pascal Andrey. |
| Project administration: | Pascal Andrey. |
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| Visualization: | Pascal Andrey. |
| Writing – original draft: | Pascal Andrey. |
| Writing – review & editing: | Pascal Andrey, Karin Fischer-Sonderegger, Wolfgang Taube, Markus Tschopp. |

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