Motivation and Performance In Athletes: Can Group Results be Generalized to Individuals?

Lucas Reijnhoudt

S4746546

Department of Psychology, University of Groningen

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Group Number: 06

Supervisor: Niklas D. Neumann

Second evaluator: PhD Ben Gutzkow

In collaboration with: Minsoe Veenstra, Thomas Klunder, Tim van der Kooi, Sietse Witteveen, Aaron Connemann

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Abstract

Over the past decades, research on motivation and performance has increased. However most studies have focused on group-level analyses, despite practitioners' interest in individual athletes. In addition, previous literature typically measured constructs at one, or at most a few time points, neglecting possible temporal dynamics. These issues–the homogeneity assumption (group-to-individual generalizability) and the stationarity assumption (stability over time)–are central to ergodicity. The present study attempts to test these two assumptions to check for ergodicity in the context of sport psychology.

We used a sample of 73 male youth football players in three different teams from a Dutch professional football club. We measured both motivation and performance by using a single item self report questionnaire before every training session over the span of two seasons. To test the homogeneity assumption, we compared individual means, SDs and the CIs to the group statistics. For the stationarity assumption, we examine the fluctuation of the correlation between motivation and performance over time. The results showed significant differences between group and individual level, more specifically the SDs in individuals were up to 2.26 times larger than the group SDs, suggesting non homogeneity. Correlations between motivation and performance fluctuated strongly across time, indicating the data is not stationary. The results suggest the data is nonergodic, implying that group-derived recommendations may be suboptimal for individual athletes. Practitioners should prioritize individualized assessments to enhance motivation and performance.

Keywords: ergodicity, motivation, performance, homogeneity, stationarity, sport psychology

Motivation and Performance in Athletes: Can Group Results be Generalized to Individuals?

You stand on the sideline, watching the whistle blow to start another youth football practice. Around you, teammates buzz with energy, while you feel a dull ache in your legs and a heaviness in your mind after a week of stress and poor sleep. The coaches, eager to push the group's limits, design today's drills based on what they observe across the squad: the group looks strong, so the training is intensified. You push through the exercises, ignoring your fatigue, determined not to appear uncommitted. Yet inside, your body and mind are signaling that something is wrong—a warning no group-level data can detect. The session ends with you limping off the field, injured.

This scenario exposes a hidden flaw in modern sports science: using group-level patterns to guide training decisions can overlook the lived experiences of individual athletes. Aggregated data may tell a compelling story about the group, but that story can break down in dangerous ways when applied to a single person. As Rose (2016) argued, "Any system designed around the average person is doomed to fail" (p. 8). In scientific terms, this is a consequence of nonergodicity—the mismatch between group-level statistics and individual-level dynamics (Molenaar, 2004; Molenaar & Campbell, 2009).

Motivation is a fundamental driver of athletic performance (Cerasoli et al., 2014). As Murphy (1957) posited, performance can be understood as the behavioral expression of motivation. One influential framework that elaborates this relationship is Self-Determination Theory (SDT) (Deci & Ryan, 1985). SDT distinguishes between two types of motivation: intrinsic motivation, which involves engaging in an activity for its inherent satisfaction, and extrinsic motivation, which is driven by external factors. Research on SDT suggests that intrinsic motivation is more sustainable and is associated with better overall performance (Ryan & Deci, 2000).

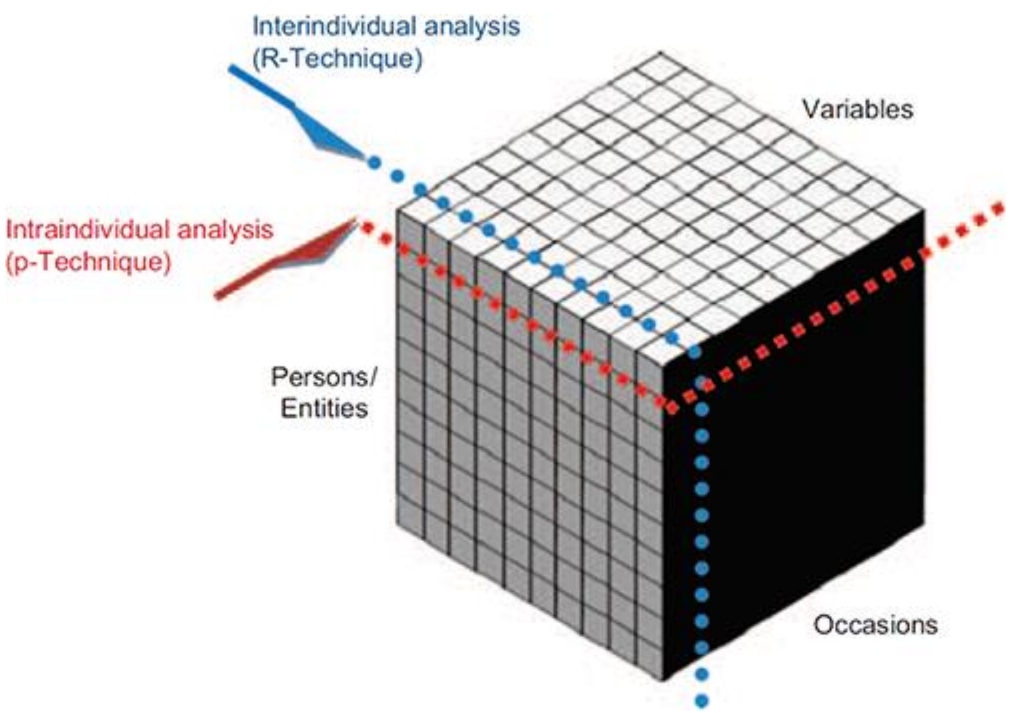
Decades of research in sport and performance psychology have emphasized the central role of motivation in shaping athletes' effort, persistence, and commitment (Ryan & Deci, 2000; Pinder, 2011; Zuber et al., 2014; Vink et al., 2014). A comprehensive meta-analysis by Cerasoli et al. (2014), synthesizing over 40 years of empirical findings, concluded that intrinsic motivation is a moderate to strong predictor of performance outcomes. Although previous research has robustly established the link between motivation and performance (e.g., Cerasoli et al., 2014; Ryan & Deci, 2000), these findings are largely based on group-level or cross-sectional data. As a result, it remains unclear whether such relationships persist at the individual level over time. This gap underscores the importance of testing whether motivation and performance behave ergodically—i.e., whether group-level patterns can be meaningfully generalized to the individual athlete in dynamic, real-world settings.

In the context of sport psychology, the nonergodicity problem has significant implications. Although the primary aim of research and applied practice is often to enhance *individual* motivation and performance, most studies analyze data at the group level. These analyses assume that group-level findings (e.g., means and correlations) can be generalized to individuals. However, this assumption only holds if the underlying data meet the conditions of *ergodicity*—a situation where what is true is also true for each individual (Fisher et al., 2018; Molenaar & Campbell, 2009). Ergodicity requires that two assumptions are satisfied: homogeneity (i.e., the statistical model applies uniformly to all individuals) and stationarity (i.e., the model remains stable over time for each individual) (Molenaar & Campbell, 2009).

To clearly illustrate the homogeneity assumption we use a Cattell Data Box (see **Figure 1;** Cattell, 1952), a three-dimensional model that organizes data by *individuals*, *variables*, and *time*. A vertical slice through the box represents the group level, where we calculate statistics (e.g., mean, standard deviation, median) for the entire group at a single time point, and then aggregate across time. A horizontal slice, by contrast, represents the individual level, where we calculate the same statistics for a single athlete across all time points, and then aggregate across individuals. By comparing the group-level and individual-level statistics, we can assess whether the same statistical model applies across the sample—i.e., whether the homogeneity assumption is met.

Figure 1

Cattell data box illustrating group-level and individual-level slices



Note: From *The new person-specific paradigm in psychology* (p. 113), by P. C. Molenaar & C. G. Campbell, 2009, *Current Directions in Psychological Science, 18*(2), p. 113

The stationarity assumption posits that an individual's behavior remains stable over time. In practical terms, this implies that the relationship between variables–in this example motivation and performance–should not change from month to month. If an athlete's motivation strongly predicts performance for one month, but fails to predict performance next month, the assumption of stationarity is violated. Violations of either assumption can lead to misleading conclusions when applying group-level findings to individuals. Indeed, previous research has shown that the means and variances of variables such as motivation and performance often differ between group-level and individual-level data (Fisher, Medaglia, & Jeronimus, 2018; Den Hartigh, Hill, & Van Geert, 2018; Hill et al., 2020). If individual athletes fluctuate differently over time or respond differently to similar stimuli than the group average suggests, relying on group-level data may impair rather than enhance performance.

To address this, the present study tests whether motivation and performance meet the conditions of ergodicity in a sample of youth football players. Specifically, we examine (a) the homogeneity assumption by comparing individual-level means, standard deviations, and correlations with group-level statistics to determine if the same model applies across players, and (b) the stationarity assumption by analyzing whether the relationship between motivation and performance remains stable over time using rolling window correlations. If these assumptions are violated, it would indicate that group-level averages fail to capture individual-level dynamics. As a result, coaches and practitioners should be cautious when applying group-derived data to guide personalized training decisions. By using individual-level time-series analyses, this study highlights the importance of tailoring performance interventions to the athlete rather than relying on group averages.

Methods

Subjects

The original data set consisted of 94 male youth football players from a professional football club from the Netherlands. 73 players were included after applying the inclusion criteria for the first step of our analysis (see more details under dataset). This subset consisted of- players from the under-16 (U-16), players from the under-18 (U-18) and players from the under-21 (U-21) teams. Due to privacy reasons the teams are randomly referred to as team 1, 2 and 3, and the players were given code names. For the second step of our analysis we included two players with the most consecutive days. To further ensure that the participants remain anonymous, other identifiable variables such as height, age, and weight, are not reported.

The players were informed about the questionnaire and data collection once they started playing at the club. They were asked whether they agreed to the use of their data for research purposes. The players' weeks consisted of two strength training sessions of 60 to 75 min and four to six in field training sessions of 75 to 90 minutes.

Design

The current study was conducted according to the requirements of the Declaration of Helsinki and was approved by the ethics committee of the Faculty of Behavioral and Social Sciences of the University of Groningen The Netherlands; research code: (PSY-2425-S-0016).

The study was conducted using a time-series design, collecting repeated measures of motivation and performance across two seasons. Motivation was reported up to 30 minutes before every regular training session or match, and perceived performance was reported up to 30 minutes afterward. Both measures were collected via a tablet-based questionnaire that was integrated into the athletes' daily routines.

Methodology

Motivation was measured with the question: *"How motivated are you to perform maximally today?"*, and performance was assessed with *"How well did you perform today?"* Both were answered on a visual analogue scale ranging from 0 (not at all) to 100 (maximally), consistent with prior research in performance monitoring (e.g., Barte et al., 2019; Brink et al., 2010; Den Hartigh et al., 2022; Neumann et al., 2021). These items were adapted from established scales used in earlier studies on psychological determinants of sports performance and adjusted to fit the practical demands and language used in elite youth football environments (see also Brink et al., 2010; Barte et al., 2018; Totterdell, 2000; Neumann et al., 2024).

We are aware of the limitation of subjective self-reports such as social desirability, response fatigue and compliance issues (De Mortel t al., 2008; Scollon et al., 2003). However, the questionnaires were part of the players daily routines since they were 15, and the coaches emphasize the importance of the questionnaires by stressing that they help with individual development, enhance the players performance, and reduce injuries. This approach helps to reduce limitations of subjective self-report questionnaires (Saw et al., 2015).

We used single item questions to reduce time costs and participant burden (Song et al., 2022). We acknowledge that using single item questionnaires may have limitations in capturing the full complexity of certain constructs, but research has shown that adding more items results only in modest improvements (Barte et al., 2018; Cohen et al., 2006).

Data Sets

The aim of the current study is to test the homogeneity and stationarity assumption of ergodicity. These two assumptions require different statistical analysis to check. To achieve the most accurate results we applied separate inclusion criteria for both assumptions. The original data set consisted of 94 players from three youth teams and 17,426 observations across two seasons.

For the homogeneity analysis, we included only days that contained data on both motivation and performance. Days with fewer than six athletes were excluded to ensure sufficient power, and players with fewer than 15 observations were excluded to avoid distorting correlation estimates (Guo et al., 2013). This resulted in 81 players divided over three teams and a total of 12,302 observations. Specifically, team 1 had 21 players across 121 days with an average of 12.7 data points per player, team 2 had 28 players across 402 days with an average of 191.7 data points per player and team 3 had 32 players across 402 days with an average of 169.1 data points per player.

In addition to the large dataset, a symmetrical subset was created to facilitate the testing of ergodicity assumptions under controlled conditions. This subset included data from the three teams, consisting of data from 7, 9 and 8 players. Furthermore, within each team, players contributed data across the same number of consecutive days (7, 9 and 8 respectively). This design ensured that the structure of observations was balanced across teams and individuals, allowing for clearer interpretation of inter- and intra-individual comparisons. The symmetrical subset was used to minimize potential confounding effects arising from unequal data density and observation windows across participants.

For the stationarity analysis, we created a dataset that included only days where both motivation and performance values were available, resulting in 12,695 observations. From this filtered dataset, we selected the two players with the highest number of consecutive observation days to enable clear visualization of potential changes over time. Player 1 contributed data for 78 consecutive days, and Player 2 for 139 consecutive days. In addition, we included the team of Player 1, which consisted of 36 players, to allow comparison between individual-level and team-level fluctuations.

Statistical Analysis

All analyses were conducted using SPSS28 and Rstudio (version 12.1).

The analyses of the homogeneity and stationarity assumptions were conducted following the recommendations of Molenaar and Campbell (2009) and Fisher et al. (2018). Both the large dataset and the symmetrical subset were examined using identical procedures to allow consistent comparison.

We began by testing the homogeneity assumption, starting with the group-level analysis. For this, we selected all athletes on day 1 and focused on the variables motivation and performance. We computed univariate statistics (mean, median, and standard deviation) and bivariate statistics (Pearson's *r* and standard deviation) for that day. This process was repeated for each day in the dataset. The daily statistics were then averaged across all days. For bivariate correlations, we applied the Fisher *z* transformation prior to averaging and transformed the resulting mean *z* value back to Pearson's *r*. This procedure helps prevent bias associated with averaging raw correlation coefficients (Silver & Dunlap, 1987).

The individual-level analysis followed the same procedure for each athlete. For each player, we selected all available days and calculated the univariate (mean, median, SD) and bivariate (Pearson's *r* and SD) statistics for motivation and performance. As with the group-level analysis, correlations were Fisher *z* transformed, averaged, and converted back to Pearson's *r*.

Finally, group-level statistics were compared with individual-level statistics. For univariate statistics, 95% confidence intervals were calculated for the means and standard deviations. For bivariate correlations, 95% confidence intervals were computed for Pearson's *r*. Correlation magnitudes were interpreted following the guidelines of Hopkins et al. (2008): trivial (< .10), small (.10–.29), moderate (.30–.49), large (.50–.69), very large (.70–.90), nearly perfect (> .90), and perfect (1.00).

For the stationarity assumption analysis, we examined the relationship between motivation and performance using rolling window correlations. For each player, we first calculated the daily correlation between these two variables. We then computed the average correlation within rolling windows of 30 consecutive days (e.g., days 1–30, 2–31, 3–32, etc.). To allow comparison at different levels of analysis, the same 30-day rolling window correlation analysis was conducted for the entire team of Player 1. Rolling correlations for both individual players and the team were plotted over time to visualize potential differences in the stability of associations between motivation and performance across levels.

Results

Homogeneity Check

We started by investigating the univariate statistics of the variable's motivation and performance at the group level and individual level for all 3 teams. As shown in *Table 1*, the means of motivation and performance at the group and individual levels were similar for all three teams. The 95% confidence intervals of the individual means overlapped with those of the group means, indicating no significant differences.

Table 1

Mean (95%CI) of Motivation and Performance for Groups and Individuals

	Group	**Individual**
Team	**Mean (95% CI)**	**Mean (95% CI)**
Team 1		
Motivation	82.1 [81.4, 82.9]	82.1 [79.3, 85.0]
Performance	76.3 [75.7, 77.0]	76.8 [74.3, 79.3]
Team 2		
Motivation	91.1 [90.8, 91.34]	89.9 [87.0, 92.7]
Performance	72.3 [71.9, 72.6]	72.4 [70.4, 74.5]

Team 3		
Motivation	80.4 [79.8, 81.0]	80.8 [77.4, 84.2]
Performance	71.8 [71.3, 72.3]	72.3 [70.4, 74.2]

Note: The means are the mean values of all single means of either the day (group) or the player (individual).

Table 2 presents the medians and standard deviations (SDs) of motivation and performance at both the group and individual levels, along with their 95% confidence intervals (CIs). In contrast to the means, notable differences were observed between the SDs at the group and individual levels. For most SD comparisons, the 95% CIs did not overlap, indicating greater variability at the individual level than at the group level. For example, in Team 2, the SD of individual-level performance (10.98, 95% CI [9.47, 12.50]) was more than twice as large as the group-level SD (4.85, 95% CI [4.55, 5.19]). However, for some SDs—such as the SD of motivation in Team 3—the 95% CIs showed partial overlap (group-level SD = 6.18, 95% CI [5.80, 6.62]; individual-level SD = 9.35, 95% CI [7.82, 10.88]), suggesting less pronounced differences in variability for this team and variable.

Table 2

Median and SD (95%) of Motivation and Performance for Groups and Individuals

	Groups		**Individuals**		**G:I**
Team	**Median**	**SD (95%)**	**Median**	**SD (95%)**	
Team 1					
Motivation	82.7	9.2 [8.6, 9.8]	82.3	6.7 [4.6, 8.8]	1.45
Performance	77.7	10.9 [10.1, 11.7]	78.0	5.8 [4.0, 7.6]	1.76
Team 2					
Motivation	94.0	9.9 [9.6, 10.1]	89.9	7.7 [5.7, 9.8]	1.96
Performance	72.8	11.5 [11.2, 11.7]	72.4	5.6 [4.1, 7.1]	2.26
Team 3					
Motivation	81.3	12.0 [11.6, 12.4]	82.1	9.91 [7.4, 12.4]	1.51

Performance	73.4	12.6 [12.1, 13.0]	74.0	5.5 [4.1, 6.9]	2.05

Abbreviation: I:G, individual: group. *Note*: Medians, and SDs are the mean values of all single medians, and SDs of either the day (group) or the player (individual). The I:G ratio illustrates the ratio of individual SD to group SD.

We computed the bivariate correlations between the motivation and performance for both the analyses. Table 3 displays the mean correlation (*r*), the SD and the 95% CI of the mean correlation, for each team at the individual-level analysis. Table 4 displays the mean correlation (*r*), the SD and the 95% CI of the mean correlation, for each team at the group level. The correlations ranged from trivial (<.10) to small (.10-.29). The magnitude of correlations was comparable between the two types of analysis for all teams, this is reflected by the fact that the 95% CI of the mean correlation for all teams overlap.

Table 3

Bivariate Correlations of Motivation and Performance for Groups and Individuals

	Groups		**Individuals**	
Team	***r***	**95%CI**	***r***	**95%CI**
Team 1	0.25	[0.18, 0.31]	0.07	[-0.01, 0.02]
Team 2	0.04	[0.01, 0.07]	0.03	[-0.06, 0.12]
Team 3	0.19	[0.15, 0.22]	0.13	[0.07, 0.18]

Abbreviation: r, Pearson's r. *Note*: Pearson r is the mean value of all single correlations of either the day (group) or the player (individual).

Symmetrical Subset

To verify that our main findings were not influenced by unequal data contributions across players or teams, we analyzed a symmetrical subset in which each team contained the same number of players, and each player contributed data for the same number of consecutive days.

Table 5 presents the means and standard deviations (SDs) for motivation and performance at both group and individual levels within this subset. The means were comparable across levels, with overlapping 95% confidence intervals (CIs), suggesting no significant differences. In contrast, individual-level SDs were consistently larger than group-level SDs. For example, in Team 3, the individual-level SD for motivation was 13.1 (95% CI [6.7, 19.5]) compared to a group-level SD of 3.4 (95% CI [1.7, 5.0]), resulting in a group-to-individual SD ratio (G:I) of 3.88.

Bivariate correlations between motivation and performance are shown in *Table 6*. The patterns varied across teams and levels of analysis. For instance, in Team 1, the group-level correlation was $r = -.07$ (95% CI [−.26, .13]), while the individual-level correlation was $r = .33$ (95% CI [.01, .59]). In contrast, Team 2 showed a positive group-level correlation ($r = .04$, 95% CI [.00, .16]) but a negative individual-level correlation ($r = -.32$, 95% CI [−.59, .02]). These inconsistent patterns between levels further highlight the lack of generalizability from group-level findings to individual athletes.

Table 4

Mean (95%CI) of Motivation and Performance for Groups and Individuals of the Symmetrical Subset

	Group		**Individual**		
Team	**Mean**	**SD(95%CI)**	**Mean**	**SD(95%CI)**	**G:I**
Team 1					
Motivation	84.3	2.6 [1.2, 4.0]	84.3	6.5 [3.1, 10.0]	2.51
Performance	71.7	3.3 [1.6, 5.1]	71.7	7.0 [3.3, 10.7]	2.11
Team 2					
Motivation	92.4	3.7 [1.6, 5.7]	92.4	9.7 [4.2, 15.3]	2.66
Performance	74.1	6.3 [2.7, 9.9]	74.1	7.7 [3.3, 12.0]	1.21
Team 3					
Motivation	75.0	3.4 [1.7, 5.0]	75.0	13.1 [6.7, 19.5]	3.88
Performance	72.7	3.2 [1.6, 4.8]	72.7	9.3 [4.8, 13.9]	2.92

Abbreviation: I:G, individual: group. *Note*: Means, and SDs are the mean values of all single means, and SDs of either the day (group) or the player (individual). The I:G ratio illustrates the ratio of individual SD to group SD.

Table 5

Bivariate Correlations of Motivation and Performance for Groups and Individuals of the Symmetrical Subset

	Groups		**Individuals**	
Team	***r***	**95%CI**	***r***	**95%CI**
Team 1	-0.07	[-0.26, 0.13]	0.33	[0.01, 0.59]
Team 2	0.04	[0.00, 0.16]	-0.32	[-0.59, 0.02]
Team 3	0.19	[-0.19, 0.13]	-0.05	[-0.25, 0.16]

Abbreviation: r, Pearson's r. *Note*: Pearson's r is the mean value of all single correlations of either the day (group) or the player (individual).

Stationarity Check

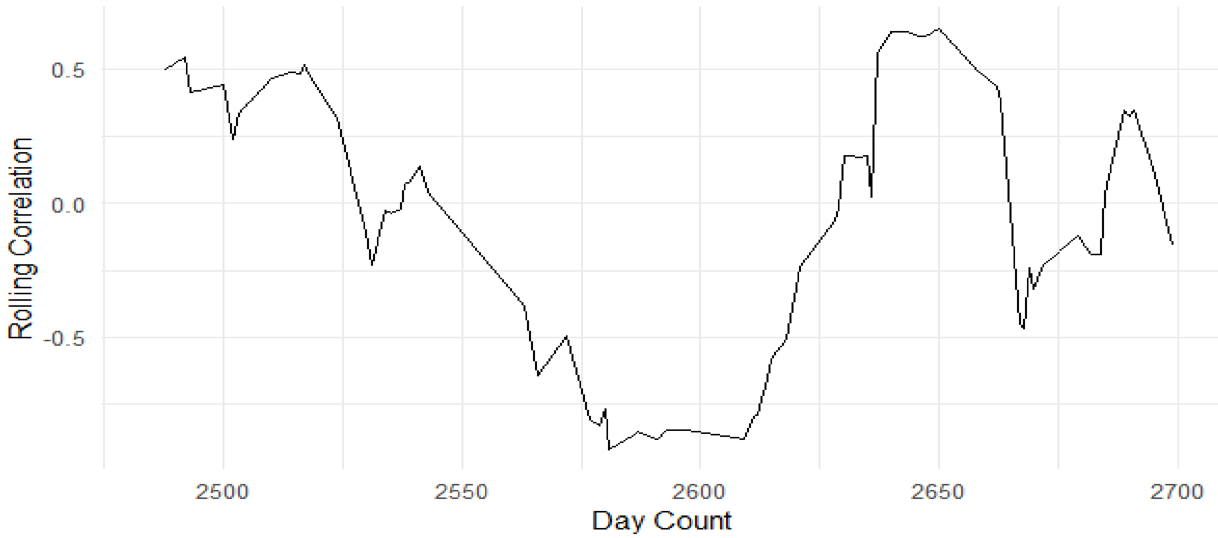
To test the stationarity assumption, we examined the within-person correlations between motivation and performance over time using rolling window analyses. *Figures 1 and 2* display the rolling Pearson correlations for two athletes.

For Player 1, the correlation fluctuated substantially across the observation period, ranging from approximately −.10 to .65. Similarly, Player 2’s correlation varied between about .05 and .55. These pronounced fluctuations demonstrate that the relationship between motivation and performance was not stable over time, indicating a violation of the stationarity assumption.

Finally, we created a plot comparing the 30-day rolling correlations of Player 1 with those of their team. As shown in Figure 4, the individual fluctuations in the relationship between motivation and performance were clearly distinct from the group-level fluctuations. This illustrates that the dynamic patterns observed at the individual level are not directly comparable to those at the group level, further highlighting the limitations of relying on aggregated group data to understand individual processes.

Figure 2

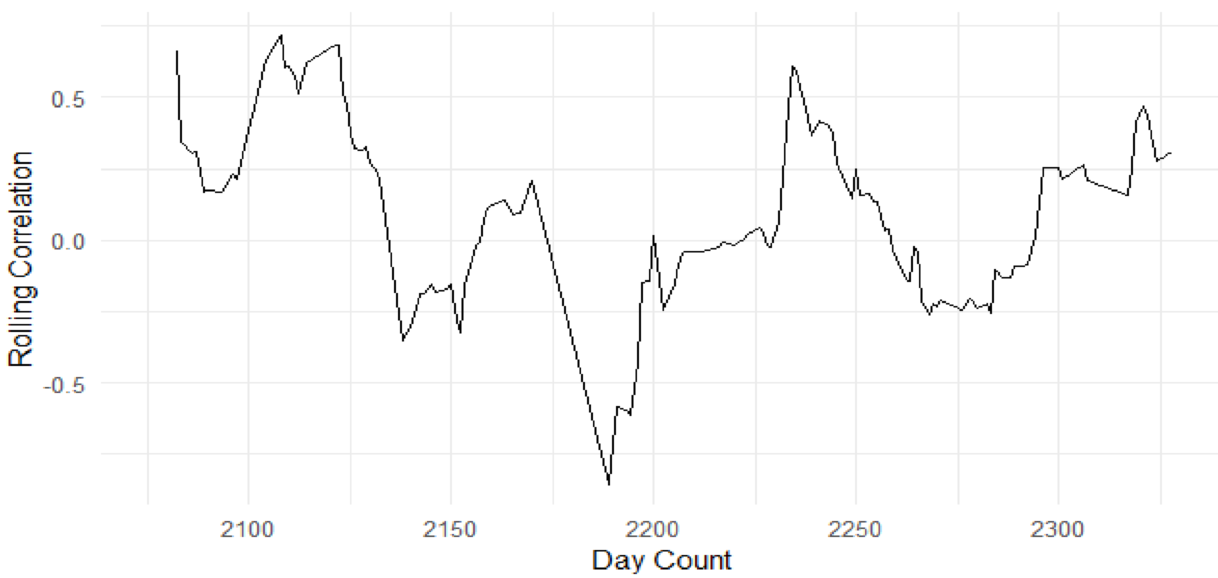
30-Day Window Correlation Player 1



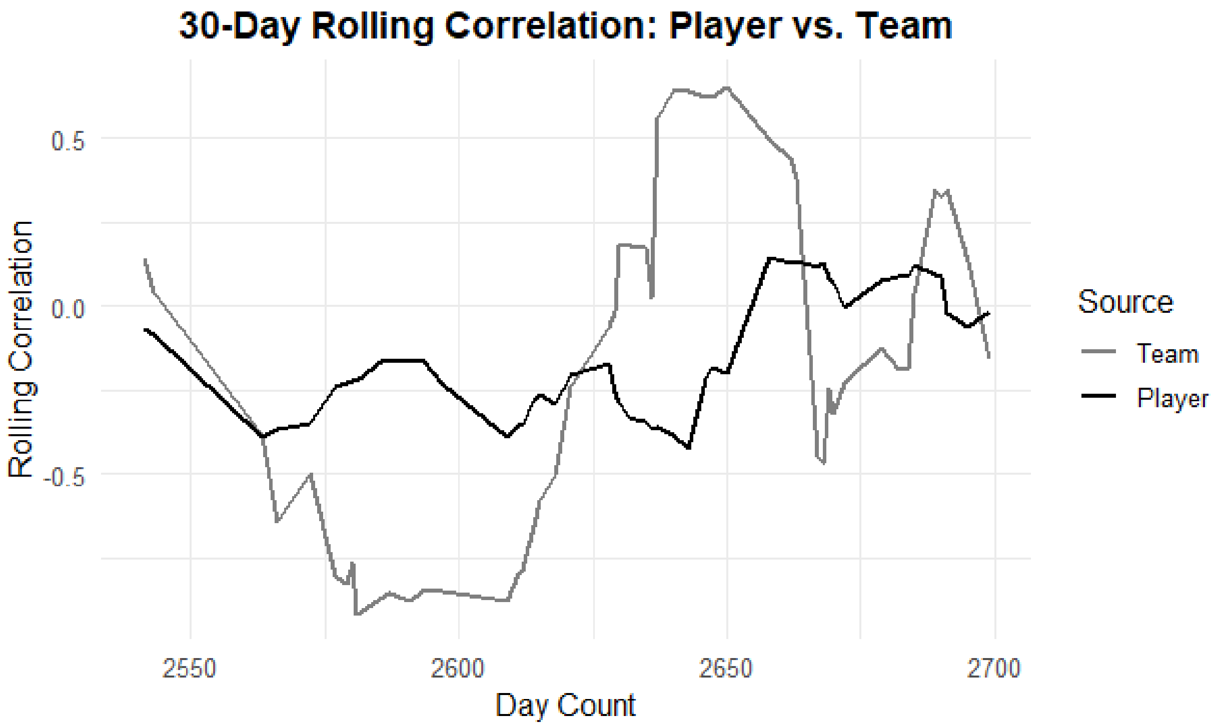
Note: Rolling Pearson correlation coefficients between motivation and performance, computed using a 30-day sliding window across the observation period. Each point represents the correlation for that window. Variability in the correlation reflects changes in the relationship over time.

Figure 3

30-Day Window Correlation Player 2



Note: Rolling Pearson correlation coefficients between motivation and performance, computed using a 30-day sliding window across the observation period. Each point represents the correlation for that window. Variability in the correlation reflects changes in the relationship over time.



Note. The plot displays the 30-day rolling correlations between motivation and performance for Player 1 (black line) and their team (grey line).

Discussion

The aim of this study was to investigate whether motivation and performance in youth football athletes meet the conditions of ergodicity. Specifically, we tested the homogeneity and stationarity assumptions to assess whether group-level statistics can validly generalize to individual athletes over time (Fisher et al., 2018; Molenaar & Campbell, 2009). As hypothesized, our data did not satisfy these assumptions: the group-level statistics differed substantially from individual-level statistics, and relationships between motivation and performance fluctuated considerably over time. These findings are consistent with prior work highlighting the nonergodic nature of psychological processes in sport and related fields (Fisher et al., 2018; Neumann et al., 2021).

Homogeneity of Motivation and Performance

Our analyses revealed that although group- and individual-level means of motivation and performance were comparable, the variability at the individual level was consistently greater. For example, in Team 2, the individual-level standard deviation (SD) for performance (10.98) was more than double the group-level SD (4.85), with non-overlapping confidence intervals (CIs), indicating substantial homogeneity violations in individual variability. These results were not only observed in the main dataset but were even more pronounced in the symmetrical subset. In this subset, designed to control for unequal data contributions, the individual-level SDs were up to nearly four times higher than group-level SDs (e.g., Team 3 motivation SD: individual 13.1, group 3.4; individual-to-group ratio = 3.88).

The bivariate correlations also highlighted important discrepancies. While the main dataset suggested overlapping CIs between group- and individual-level correlations, the symmetrical subset revealed inconsistent patterns, including differences in correlation direction. For instance, in Team 1, the group-level correlation between motivation and performance was negative ($r = -.07$), whereas the individual-level correlation was positive and moderate ($r = .33$). Such inconsistencies suggest that group-level correlations may mask or misrepresent individual-level dynamics (Neumann et al., 2020; Fisher et al., 2018).

These findings provide a clear example of what the *Cattell Data Box* (**figure 1**; Cattell, 1952) conceptually illustrates: the statistical structure of data at the group level (vertical slice) does not necessarily reflect the patterns found at the individual level (horizontal slice). By comparing these slices, our study highlights how relying on aggregated group data may obscure the variability and dynamic relationships present within individuals.

Stationarity of Motivation–Performance Relations

The stationarity assumption was also not supported. The 30-day rolling window analyses showed that within-player correlations between motivation and performance varied markedly across time. For example, Player 1's correlations ranged from approximately −.10 to .65, while Player 2's correlations fluctuated between about .05 and .55. These results demonstrate that the relationship between motivation and performance was not stable but dynamic and context dependent. This variability further reinforces the inadequacy of group-level averages for capturing the true nature of individual-level processes.

Theoretical and Practical Implications

Our findings extend previous research by demonstrating nonergodicity in a large, longitudinal dataset of youth athletes, supplemented with a symmetrical subset that strengthens the validity of our conclusions. (Orie et al., 2020; Hill et al., 2020). The dynamic and highly individual nature of motivation–performance relationships underscores the need for person-specific analyses in sport psychology. Coaches and practitioners should be cautious about basing training and performance decisions solely on group-derived data (Neumann et al., 2021). Instead, individualized assessments and interventions are necessary to optimize athlete development and performance.

A relevant example of this individualized approach is provided by Orie et al. (2020), who conducted a case study monitoring an Olympic champion over four years to determine which types of training most effectively enhanced performance. By analyzing time-series data, the researchers were able to identify specific training conditions that yielded the best results. This highlights the practical value of individualized monitoring, aligning with our findings that group-level statistics do not generalize reliably to the individual. As a next step, researchers and practitioners should work toward developing analytic tools that translate such individualized data into actionable information for coaches and support staff.

Although we did not distinguish between intrinsic and extrinsic motivation, our finding that motivation-performance relations were dynamic and individual-specific aligns with SDT’s assertion that motivation is shaped by personal needs and contexts. Future research could explore whether shifts between intrinsic and extrinsic motivation contribute to these fluctuations.

Limitations and Future Directions

Our study had several limitations. First, the dataset contained missing data, which reduced the number of usable observations and may have limited the representativeness of the findings. We addressed this by applying inclusion criteria (e.g., requiring days with both motivation and performance data) and by creating a symmetrical subset. This subset helped control for unequal data contributions and observation windows, allowing for unbiased comparisons between group-level and individual-level statistics. We recommend that future research adopt similar approaches to minimize bias from unbalanced datasets and strive for more complete data collection through rigorous monitoring protocols or, where appropriate, the use of imputation techniques.

Second, the use of single-item self-report measures for motivation may have introduced biases such as social desirability. However, in our case, these measures were justified. Coaches emphasized the importance of minimizing participant burden to ensure that data collection supported, rather than disrupted, athletes’ well-being and training routines. Additionally, athletes were assured that their responses would not affect selection decisions, which likely reduced selfpresentation bias. Future research could strengthen validity by combining subjective ratings with objective performance measures (e.g., GPS tracking, heart rate monitoring) and incorporating implicit assessments of motivation.

Despite these precautions, the use of self-report data means that biases such as social desirability and response fatigue cannot be fully ruled out (De Mortel, 2008; Scollon et al., 2003; Saw et al., 2015). Response fatigue, in particular, may have affected data quality given the repeated nature of the assessments over two seasons (Scollon et al., 2003; Saw et al., 2015). Future research should explore strategies to monitor or mitigate such biases, for example through periodic data quality checks or mixed-methods designs.

Future research could also extend our findings by incorporating distinctions between different types of motivation as proposed in Self-Determination Theory (SDT). Specifically, examining how intrinsic and extrinsic motivation fluctuate over time in relation to performance could provide valuable insights into the dynamic processes underlying athletic achievement. This could help identify whether certain types of motivation are more predictive of sustained performance at the individual level, and inform the development of more targeted, person-specific interventions.

While we focused on descriptive and correlational analyses, future studies could apply more advanced methods—such as time-varying vector autoregressive (VAR) models or recurrence network analysis (Haslbeck et al., 2020; Hasselman & Bosman, 2020)—to gain deeper insights into the dynamic interplay between motivation and performance over time. Additionally, researchers should explicitly test for ergodicity before aggregating data across individuals to ensure that the level of analysis aligns with the research question. Although group-level analyses are valuable for understanding population trends, they are insufficient for capturing individual dynamics or informing personalized interventions.

Conclusion

This study provides clear evidence that group-level statistics on motivation and performance do not reliably generalize to the individual level. Both the homogeneity and stationarity assumptions of ergodicity were violated, highlighting the importance of adopting individualized approaches in sport psychology research and practice. By doing so, we move closer to truly personalized training and performance optimization for athletes.

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Author Note

Use of Artificial Intelligence Tools

I acknowledge that I have made use of artificial intelligence tools (e.g., ChatGPT) to support my thesis work, specifically for purposes such as language editing, text improvement, and generating inspiration for phrasing. These tools were not used to carry out the substantive research work itself, including hypothesis formulation, data analysis, or interpretation of results. All use of AI was in accordance with good scientific practice, as described by the Bachelor Thesis guidelines of the Faculty of Behavioural and Social Sciences, University of Groningen. I take full responsibility for verifying the accuracy and integrity of any AI-assisted content included in this thesis.