Research Square

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External Load Volume and Variability Differentially Relate to Internal Load in Soccer

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Abstract

PURPOSE

To compare how derivatives of external training load (TL) metrics relate to perceptual and physiological internal TL in semi-professional soccer players.

METHODS

Thirty-five male semi-professional soccer players were monitored across two consecutive eight-week competitive seasons using 10-Hz GPS units with integrated heart-rate monitoring. External TL metrics, including total distance (TD), acceleration count (AccNumber), deceleration count (DeccNumber), and high-speed distance (HSD), were expressed as weekly accumulated volume (acc), training monotony (m), and week-to-week percent change (P_). Internal TL was assessed using weekly accumulated session rating of perceived exertion (accsRPE) and training impulse (accTRIMP). Linear mixed-effects models examined associations between standardized external TL derivatives and internal TL outcomes.

RESULTS

accTD was significantly associated with both accsRPE and accTRIMP ($p < 0.001$). accsRPE was associated with variability-related metrics, including mHSD ($p < 0.01$), mDeccNumber ($p < 0.05$), as well as P_TD ($p < 0.01$). accTRIMP was associated with accDeccNumber ($p < 0.01$) and mDeccNumber ($p < 0.05$), with no significant percent-change associations.

CONCLUSION

sRPE reflects both cumulative volume and monotony of mechanical demands, while TRIMP reflects accumulated distance and both the cumulative volume and within-week consistency of braking exposure. These findings highlight how distinct external load expressions relate to perceptual and physiological internal load.

INTRODUCTION

Training load (TL) reflects the aggregate stress placed on athletes due to training stimuli and is the catalyst manipulated to elicit notable adaptations in sport performance, health, and injury resistance (Calvert et al., 1976; Impellizzeri et al. 2019; Impellizzeri et al. 2005). However, athlete responses to TL are inherently variable, influenced by intensity, duration, frequency, and modality of the exercise bout, as well as athletes' perception and ability to cope with load (Impellizzeri et al. 2019). Despite these challenges, advanced techniques that track an athlete's real-time movements and responses, such as global positioning system (GPS) and heart rate (HR) monitoring, have enabled significant progress in effective monitoring and TL analysis (Bertschy et al., 2021; Cummins et al., 2013; Malone et al., 2017; Buchheit, 2014).

A major advancement in TL research is the distinction between external and internal domains (Impellizzeri et al. 2019; Impellizzeri et al. 2005). External load represents objective physical demands of an athlete, encompassing a wide range of metrics such as total distance covered (TD), the number of accelerations (AccNumber), decelerations (DeccNumber), and high-speed distance (HSD) (Impellizzeri et al. 2019; Bourdon et al., 2017). Internal load reflects individual perceptual and physiological responses to this external stimulus (Impellizzeri et al. 2019; Drew & Finch, 2016; Teixeira et al., 2021; Askow et al., 2021). The session rating of perceived exertion (sRPE), a well-validated internal load that reflects how athletes discern the difficulty of a training session multiplied by that session's duration (Liu et al., 2023), represents an athlete's perceptual effort (Lovell et al., 2013; Owen et al., 2016). To capture physiological training intensity and volume in internal load, HR-based training impulse (TRIMP) condenses continuous cardiovascular responses into a single value by integrating heart rate over time with an exponential weighting that emphasizes higher-intensity effort (Impellizzeri et al. 2005; Askow et al., 2021; Stagno et al., 2007). Recognizing external load as the applied stimulus and internal load as the individual response, integrating measures within and across these domains provides a more comprehensive representation of athlete demands (Gabbett et al., 2016; Williams et al., 2017).

When multiple TL metrics are examined concurrently, relationships between external and internal load are often assessed using linear correlations. However, these approaches evaluate metric-to-metric associations without accounting for how load is accumulated or structured over time (Marynowicz et al., 2020; Bartlett et al., 2017). Emerging evidence has therefore proposed new derivatives of TL metrics to provide perspectives into this distribution of load across training periods (Oliveira et al., 2021; Clemente et al., 2019; Nobari et al., 2021). For instance, cumulative totals represent weekly micro-cycles, while within-week variation can be observed through training monotony (Oliveira et al., 2021; Clemente et al., 2019; Delecroix et al., 2019). Additionally, examining week-to-week percent changes in external load provides an index of load progression, allowing practitioners to assess whether internal load responses are sensitive to recent increases or decreases in training stress, rather than absolute workload alone [31, 20, 19] (Clemente et al., 2020; Nobari et al., 2020; Clemente et al., 2019). While cumulative external load reflects overall workload exposure, variation-based measures characterize the consistency and fluctuations in load exposure over time, which may affect acute internal load responses. Together, by capturing fluctuations in load and cumulative totals, these measures offer a critical insight for refining the internal-external load interaction.

Despite the emergence of these derivative measures, a key challenge in TL research is determining which metrics provide both physiologically meaningful and practically interpretable insights in applied settings (Williams et al., 2017). While cumulative and variation-based measures offer additional context to load distribution, the expanding number of derived variables may introduce potential redundancy and interpretive complexity for practitioners (Williams et al., 2017; Coyne et al., 2018; Lago-Fuentes et al., 2020). Therefore, a more balanced approach is necessary to reduce the amount of TL interpretations to an optimal set that consolidates the numerous, potentially redundant load metrics (Coutts, 2014).

Therefore, the purpose of this study was to determine which external-load derivatives meaningfully correspond to internal-load responses by comparing volume- and variation-based expressions of load. It was hypothesized that volume-based interpretations and their measures would align more closely with the perceptual effort measure, sRPE. In contrast, heart-rate-derived TRIMP would have stronger associations with variation-based external load expressions, reflecting its responsiveness to acute cardiovascular responses arising from fluctuations in workload exposure.

MATERIALS AND METHODS

Experimental Approach

This study employed a cohort design to examine (a) weekly accumulation and variation in training demands across two consecutive eight-week summer soccer seasons, and (b) associations between multiple interpretations of external workload and weekly accumulated internal responses.

Subjects

A total of thirty-five male semi-professional players (Mean ± SD; age: 23 ± 2 years, height: 186.6 ± 4.9 cm, and weight: 77.2 ± 10.3 kg) participated in this study over two competitive years, with only three players contributing data in both years. Players competed across five positions: central defender (CD = 5), external defender (ED = 10), central midfielder (CM = 8), and forward (F = 12). Goalkeepers were omitted from this study due to their unique playing position that substantially differs from outfield positions.

Each season spanned an identical eight-week summer competitive period from May to July. Inclusion criteria required players to (i) be rostered for the full 8-week period, (ii) were not injured for longer than 1 week, (iii) for each analyzed week, participate in all training sessions, along with playing at least 45 minutes of every match that occurred in such week. Players meeting these criteria were classified as starters (Fields et al., 2021).

Training Load Monitoring

HR and positional data were collected using a 10-Hz GPS unit with integrated heart-rate monitoring (Polar Team Pro, Polar Electro, Lake Success, NY) during all training sessions and matches. The 10-Hz tracking device has reported acceptable inter-unit reliability in total distance, low speed running (LSR) (0.00–13.99 $km \times h^{-1}$), high speed running (HSR) (14.00-19.99 $km \times h^{-1}$), and very high speed running (VHSR) (> 20.0$km \times h^{-1}$) with high interclass correlation coefficients (ICCs) (0.63, 0.99, 0.99, 0.99, respectively) and low typical error of measurement (4.64, 5.05, 1.06, 2.89, respectively) (Akyildiz et al., 2022). Regarding accuracy, ICCs were classified as extremely high for LSR and HSR (0.99 and 0.92, respectively), and high for TD and VHSR (0.63 and 0.65, respectively) (Akyildiz et al., 2022).

Players were instructed on the desired fitting of the wearable module and were thoroughly checked before each session. To reduce inter-unit errors, players wore the same module for every monitored session. Data collection commenced 10 minutes before each session to allow for proper calibration of both the GPS signal and the HR sensor, as well as verification of device functionality. Data processing was completed with manufacturer-specific data sources and filtering algorithms.

The following external load measurements were gathered for every training and match session: total distance (TD; kilometers), acceleration count (AccNumber; ≥2 $m \cdot s^{-2}$), deceleration count (DeccNumber; ≤−2 $m \cdot s^{-2}$), and high-speed distance (HSD; ≥19.8 $km \cdot h^{-1}$),). HR data were used to calculate Banister's TRIMP using sex-specific equation below. Weekly accumulated TRIMP (accTRIMP) was calculated as the sum of session TRIMP values across each week.

$$W = \Sigma \int_{0}^{} \frac{HR_{(t)} - HR_{(rest)}}{HR_{(max)} - HR_{(rest)}} \times 0.64 \times e^{1.92t} \frac{HR_{(t)} - HR_{(rest)}}{HR_{(max)} - HR_{(rest)}}$$

Banister's Training Impulse (TRIMP) for Males: Reillustration from Polar Training Load Pro White Paper (Polar Research and Technology, 2019). HR(t): Heart Rate at a given time, HR (rest): Resting Heart Rate (from user settings), HR (max): Maximal Heart Rate (from user settings), Equation for males shown above.

The Borg CR-10 Rating of Perceived Exertion (RPE) scale was used approximately 5 minutes after each training or match session, responding to the question "How hard was the training session?", with a rating of 1 on the scale corresponding to very light activity, and a 10 rating corresponding to very, very hard or maximal exertion (Foster et al., 2001). The same researcher provided the scale at every training and match session. Players were previously informed and understood the scale to ensure accuracy. To ensure unbiased, accurate reporting, players recorded their scores without other players present. Weekly accumulated sRPE (accsRPE) was calculated by multiplying session RPE by session duration (min) and summing values across each week.

Training Load Modeling

For each external load metric, three different interpretations were calculated. The weekly accumulated sum was determined by summing the TL metric from all training sessions completed during a given week. Training monotony was defined as the average of the TL metric over all training days in the week, divided by the standard deviation of the same TL metric over those training days. Week-to-week percent change was calculated as the difference between the total TL metric for the specified week and the total TL metric for the previous week, divided by the total TL metric for the previous week, then multiplied by 100. Weekly accumulated variables were given a "acc" prefix (e.g accTD), training monotony metrics were given a "m" prefix (e.g mTD), and week-to-week percent change metrics were given a "P_" prefix (e.g P_TD). Associations between these external load derivatives and weekly internal load measures (accsRPE and accTRIMP) were examined.

Statistical Procedures

Descriptive statistics are presented as mean ± SD. In the primary analysis, linear mixed-effects models were fitted to examine the associations between the weekly accumulated total, training monotony, and week-to-week percent change of each external load variable and internal load responses (accsRPE and accTRIMP). External-load derivatives were z-standardized across all observations (overall mean centered and scaled by the overall sample SD) prior to modeling. For each model, standardized regression coefficients and 90% confidence intervals were calculated. Because each external-load derivative possesses a unique distribution and variance structure, a one–standard deviation (SD) increase reflects a variable-specific magnitude of change (e.g., kilometers for TD, number of AccNumber and DeccNumber). Thus, although standardization enables comparison of relative effect sizes across predictors, the absolute physiological or mechanical meaning of a one-SD change differs between variables. This approach prioritizes comparability of effect magnitudes across heterogeneous predictors but reduces direct interpretability in original units, requiring effect estimates to be interpreted as relative (standardized) rather than absolute changes. Global standardization was selected to preserve between-player differences in exposure and variability, aligning with the study's aim of identifying

population-level associations rather than isolating within-player responses. Significance was assessed using p-values, with coefficients having $p < 0.05$ annotated. Players were included as random intercept to account for individual variability. All statistical analyses were completed in R, within the integrated development environment (IDE) RStudio Version 2024.09.0 + 360 (c2009- 2013RStudio, Inc.).

RESULTS

In total, 59 training sessions and 20 matches across two competitive seasons were included in the analyses, yielding 596 individual player-session observations. Of these, 458 training sessions (Year 1: 223; Year 2: 235) and 138 match observations (Year 1: 71; Year 2: 67) met inclusion criteria and were retained for analysis.

Across all observations, weekly mean accsRPE was 2069 ± 582 a.u, while weekly mean TRIMP was 543 ± 137 a.u. accsRPE and accTRIMP were highest in week 1 (2672 A.U., 756 A.U., respectively) and lowest in week 5 (1593 A.U., 426 A.U., respectively). The largest week-to-week increases in internal load occurred between Weeks 2 and 3 for both accsRPE (69%) and accTRIMP (67%). Descriptive statistics for other load variables are observed in Tables 1 and 2. Week-to-week change variables were not calculated for Week 1 due to the absence of a preceding week. accsRPE and accTRIMP correspond to the subsequent week (Week 2 onward), representing the internal load outcome associated with the preceding week's external load changes.

Table 1
Descriptive statistics for weekly accumulated and monotony external load variables. Values are Mean ± SD.

Measure	W1	W2	W3	W4	W5	W6	W7	W8	All Weeks	Global SD
accsRPE (a.u.)	2668 ± 702	2602 ± 430	1804 ± 337	2304 ± 778	1600 ± 325	2310 ± 1174	1671 ± 486	1786 ± 324	2093 ± 569	--
accTRIMP (a.u.)	769 ± 151	695 ± 138	471 ± 129	659 ± 141	428 ± 79	518 ± 134	456 ± 228	397 ± 123	549 ± 140	--
accTD (km)	32.4 ± 4.8	33.3 ± 6.0	20.9 ± 3.4	29.0 ± 4.2	21.1 ± 3.2	24.8 ± 6.8	21.4 ± 8.5	18.5 ± 5.1	25.1 ± 5.3	7.4
accDeccNumber	387 ± 97	330 ± 80	216 ± 49	328 ± 74	233 ± 59	270 ± 92	223 ± 126	194 ± 71	273 ± 81	103
accAccNumber	416 ± 110	356 ± 84	240 ± 57	367 ± 73	263 ± 60	301 ± 103	234 ± 129	218 ± 71	299 ± 86	110
accHSD (m)	1179 ± 840	1031 ± 480	732 ± 270	759 ± 258	634 ± 282	850 ± 416	813 ± 599	774 ± 452	847 ± 450	489
mTD	2.3 ± 0.3	1.5 ± 0.3	1.4 ± 0.2	2.2 ± 0.5	1.6 ± 0.3	1.5 ± 0.5	1.4 ± 0.2	1.1 ± 0.2	1.6 ± 0.3	0.5
mDeccNumber	2.2 ± 0.4	1.3 ± 0.3	1.2 ± 0.3	2.3 ± 0.5	1.4 ± 0.2	1.4 ± 0.5	1.4 ± 0.4	1.0 ± 0.1	1.5 ± 0.3	0.5
mAccNumber	2.6 ± 0.5	1.5 ± 0.4	1.4 ± 0.3	2.5 ± 0.6	1.8 ± 0.4	1.5 ± 0.5	1.6 ± 0.5	1.2 ± 0.2	1.7 ± 0.4	0.7
mHSD	1.0 ± 0.3	0.7 ± 0.1	0.7 ± 0.2	0.8 ± 0.1	0.6 ± 0.1	0.6 ± 0.1	0.7 ± 0.1	0.5 ± 0.0	0.7 ± 0.1	0.2

Table 2
Descriptive statistics for week-to-week percent (%) change external load variables. Values are Mean ± SD.

Measure	W1to2	W2to3	W3to4	W4to5	W5to6	W6to7	W7to8	All Weeks	Global SD
accsRPE (a.u)	2497 ± 545	1872 ± 313	2753 ± 853	1650 ± 222	2441 ± 1355	1784 ± 486	1760 ± 340	2108 ± 588	--
accTRIMP (a.u)	631 ± 147	425 ± 81	691 ± 129	458 ± 96	473 ± 106	494 ± 243	403 ± 130	511 ± 133	--
P_TD (%)	-6.2 ± 29.7	-71.6 ± 38.6	31.0 ± 20.0	-40.1 ± 39.6	13.1 ± 31.6	-49.2 ± 71.3	-3.6 ± 12.6	-18.1 ± 34.8	53.0
P_DeccNumber (%)	-33.4 ± 39.0	-68.7 ± 48.3	37.5 ± 25.2	-38.7 ± 38.4	12.9 ± 34.1	-66.2 ± 92.7	-10.2 ± 20.6	-23.8 ± 42.6	62.9
P_AccNumber (%)	-33.5 ± 42.1	-68.4 ± 50.8	38.7 ± 24.5	-47.7 ± 40.1	13.5 ± 34.3	-75.6 ± 96.9	-6.0 ± 20.4	-25.6 ± 44.2	66.4
P_HSD (%)	-33.5 ± 163.6	-48.8 ± 57.0	-3.1 ± 46.9	-47.3 ± 86.1	19.7 ± 50.9	-92.3 ± 160.6	6.2 ± 25.1	-28.4 ± 84.3	102

Standardized fixed-effect estimates from the linear mixed-effects models are presented in Fig. 1. Points represent coefficient estimates for each predictor across different models, with error bars indicating confidence intervals. Asterisks denote coefficients with $p < 0.05$. Different colors and shapes distinguish model types. All coefficients represent the expected change in internal load per one–standard deviation (SD) increase in the respective external-load derivative, allowing comparison across predictors despite variable-specific scales (global SD's shown in Tables 1 and 2). For example, the SD of accTD was ~ 7.4 km (Table 1), such that the reported effect reflects the change in internal load (accsRPE or accTRIMP) associated with a 1-SD increase in weekly total distance (i.e., approximately + 7.4 km relative to the sample mean). Each SD represents the typical magnitude of variation for that variable across all players and weeks.

Examining external load derivatives as predictors of accumulated sRPE (accsRPE), both weekly percent change in total distance (P_TD; estimate = 1032, p = .0034) and accumulated total distance (accTD; estimate = 447, p = .0001) demonstrated significant positive associations with accsRPE. Additionally, significant monotony-related associations were observed for deceleration and high-speed distance metrics, including mDeccNumber (estimate = 328, p = .0402) and mHSD (estimate = 200, p = .0079). No other derivatives of the weekly percent change in external load were significantly correlated with accsRPE.

For accTRIMP, accumulated total distance (accTD) demonstrated a significant positive association (estimate = 106, p < .001), with accumulated deceleration count (accDeccNumber; estimate = 79.5, p = .0099) and monotony of deceleration count (mDeccNumber; estimate = 71.7, p = .0241) also significantly associated. No other monotony or percent-change derivatives reached statistical significance.

Figure 1: Standardized regression coefficients for predictors of weekly accumulated session-RPE (accsRPE) and weekly accumulated TRIMP (accTRIMP).

DISCUSSION

This study examined whether distinct expressions of external load, specifically weekly accumulated volume, within-week training monotony, and week-to-week percentage change, exhibit unique associations with internal load in semi-professional soccer players. Importantly, because all predictors were standardized, the reported associations reflect relative effect magnitudes rather than absolute changes in external load and thus should be interpreted as the magnitude of impact per typical variation within each metric rather than per fixed unit of exposure.

Consistent with our hypothesis, accumulated total distance (accTD) emerged with a significant association to accsRPE. This finding compares with the majority view of the literature describing sRPE as a global index of training load, correlating to volume and even intensity-related training load measures (Bartlett et al., 2017). Notably, no other accumulated external load measures were significant predictors of accsRPE, indicating that perceptual exertion was more closely related to total distance volume than to the accumulation of specific mechanical actions. Although sRPE is recognized as a multipurpose metric that reflects both work completed and internal physiological stress, its calculation inherently places greater weight on volume-based exposure (Askow et al., 2021). Specifically, sRPE is calculated as the product of session duration and perceived exertion, such that longer exposure times proportionally increase the resulting load, even when perceived intensity is similar (Askow et al. 2021). This duration-intensity formulation aligns sRPE more closely with total external workload than discrete intensity characteristics (Askow et al., 2021). Consequently, sRPE demonstrated associations with accumulated volume metrics, such as TD, which are similarly scaled with time spent under load.

Despite the primary influence of volume-based predictors, variability and change-derived metrics also demonstrated associations with accsRPE. Specifically, mDeccNumber and mHSD were positively associated with accsRPE. While it was hypothesized that derivatives reflecting variation in workload would relate more strongly to accTRIMP than to accsRPE, the descriptive data indicated that external load was distributed with moderate to low variability within each week across the season, as evidenced by monotony values consistently near 1.0 A.U. This suggests that when braking actions and high-speed running are distributed with relatively low within-week variability, these demands contribute to sustained perceptual strain independent of their total weekly volume.

Accumulated high-speed running and mechanical load variables, including accelerations and decelerations, have previously demonstrated associations with sRPE in soccer populations (Clemente et al., 2020; Casamichana et al., 2013; Scott et al., 2013). However, these relationships are not consistently observed across contexts and may depend on the magnitude of exposure. In the present study, the relatively low accumulation of high-speed running likely limited their contribution to accsRPE, which is primarily driven by total exposure. For instance, professional soccer data have shown weekly high-speed running distances of up to 2,417 m (Clemente et al., 2020), whereas we observed our highest week of HSD at 1,179 m. When absolute intensity and volume are lower, monotony may represent a more sensitive driver of internal load, as reduced cumulative exposure increases the relative influence of load distribution across the week, where limited day-to-day variability may sustain perceptual strain despite modest total workloads. This interpretation is supported by literature indicating that training responses cannot be fully explained by accumulated load alone and that the distribution of load across the microcycle provides additional explanatory value (Clemente et al., 2019).

P_TD further demonstrated a significant association with accsRPE. Weeks characterized by abrupt week-to-week increases in TD (notably Weeks 3–4 and 5–6) coincided with subsequent elevations in accsRPE, indicating that sRPE is particularly responsive to sudden increases in workload magnitude. This finding aligns with the broader training load literature demonstrating that rapid increases in workload relative to recent exposure are associated with injury risk (Gabbett, 2016). While these studies have primarily focused on injury outcomes, they consistently demonstrate that rapid increases in workload relative to recent exposure, particularly when loads exceed those to which the athlete is prepared, are associated with adverse outcomes (Gabbett et al., 2016). Overall, our results emphasize the sensitivity of sRPE to workload increases relative to recent exposure.

The findings of this study demonstrate that accTD, accDeccNumber, and mDeccNumber exhibited significant positive associations with accTRIMP. Although TRIMP is often conceptualized as an intensity-based metric (Desgorces et al., 2020), the present findings suggest that, in team-sport environments, TRIMP primarily reflects cumulative cardiovascular load (Borresen et al., 2009). The accTD association is best explained by the structure of Banister's TRIMP equation, which integrates weighted heart-rate responses across the full duration of training sessions and therefore scales with total exposure time (Falk Neto et al., 2020). As a result, external load variables that reflect overall exposure (accTD) exert a greater influence on TRIMP than metrics describing short-term workload variability. Consequently, accTD may function as a primary driver of TRIMP in prolonged, intermittent sports.

Beyond cumulative volume, both accDeccNumber and mDeccNumber refined the interpretation of TRIMP responses. Decelerations capture high mechanical-load actions with substantial eccentric braking demand (Harper et al., 2019) and have been identified as meaningful contributors to cardiovascular strain through repeated mechanical loading (Silva et al., 2018), imposing notable metabolic demand even at low speeds (Osgnach et al., 2010; Gaudino et al., 2014). The mDeccNumber association is particularly notable as the only variability-based predictor of accTRIMP, indicating that the within-week consistency of braking actions, beyond their cumulative count, contributes to physiological internal load. Overall, this aligns with frameworks distinguishing biomechanical from physiological load-adaptation pathways while recognizing their interaction across the microcycle (Vanrenterghem et al., 2017). Decelerations therefore stand out as the only external-load action in this study whose accumulated volume and within-week consistency both relate to internal load, predicting accTRIMP through accDeccNumber and mDeccNumber, and accsRPE through mDeccNumber.

Neither accAccNumber nor accHSD emerged as a significant predictor of accTRIMP in the present study, suggesting that not all mechanical actions contribute equally to HR-based internal load. Although accelerations often occur frequently through training and matches, they often comprise lower magnitude efforts compared to decelerations that may not sustain elevated HRs long enough to meaningfully contribute to time-integrated cardiovascular load (Harper et al., 2019). Conversely, decelerations, despite their lower frequency in this study, impose greater mechanical stress and repeated biomechanical demands that contribute more consistently to elevated HR responses (Harper et al., 2019; Dalen et al., 2016). This distinction between different forms of mechanical demand has been further highlighted in comparative studies of acceleration and deceleration load in team sports, supporting the interpretation that deceleration counts may be more noticeable predictors of cumulative HR-based internal load (Silva et al., 2018; Dalen et al., 2016). Practically, this indicates that coaches should consider not only weekly training volume but also the density and consistency of high-intensity braking

actions when interpreting cardiovascular internal load responses in environments with frequent stop-start demands.

Limitations

Despite the beneficial findings of this study, it is not without its limitations. Data were collected from a single semi-professional soccer team, which may limit the generalizability of findings to other competitive levels or sporting contexts. To mitigate this, analyses were intentionally restricted to players who consistently completed all training sessions and accumulated substantial match time, improving exposure consistency and strengthening external validity. However, this focus on consistent participation may also mask positional differences in loading profiles that were not examined directly, and that may further influence the internal–external TL relationship. Accordingly, future research should examine whether these associations differ across positional roles and competitive environments.

While the global z-standardization approach enabled direct comparison of effect magnitudes across predictors expressed in different units, the absolute meaning of a 1-SD change differed across variables depending on their underlying distributions. Consequently, standardized coefficients reflect relative associations rather than equal absolute changes in mechanical or locomotor demand. While standardization improves comparability of variables and conceptualizes findings, it may obscure practical considerations.

Week-to-week percent-change metrics were unavailable for the first week of each season, resulting in fewer observations for weekly change-based analyses. Additionally, the limited influence of monotony- and fluctuation-based metrics likely reflects the relatively stable weekly training structure observed in this cohort, as indicated by consistently moderate to low monotony values. In training environments characterized by homogeneous microcycles, variability-derived metrics may provide limited additional explanatory value beyond accumulated volume, despite their potential relevance in contexts with greater workload instability.

CONCLUSION

These findings highlight the importance of distinguishing between volume- and variability-based interpretations of training load when monitoring athletes. Weekly accumulated total distance appears to be the most informative external load metric for interpreting both perceptual (sRPE) and physiological (TRIMP) internal load responses in semi-professional soccer players. Additionally, the accumulation and monotony of deceleration actions provide valuable insights into internal load beyond total running volume. Practitioners should be cautious when relying solely on variability-based metrics, as their relevance may depend on the stability of the weekly training structure. In applied settings characterized by consistent microcycles, monitoring accumulated volume, along with the volume and variation of mechanically demanding actions, namely decelerations, may offer the most practical and interpretable indicators of internal load.

Declarations

Ethics approval and consent to participate

All procedures conformed to the Declaration of Helsinki and were approved by the Institutional Review Board (IRB2022-440). Semi-professional male soccer players competing in the National Premier Soccer League (NPSL) were recruited from a single club.

Consent for publication

Not applicable.

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Author Contribution

TM and YS contributed to the conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, validation, visualization, and writing of the original draft as well as the review and editing of the manuscript, with TM serving as the primary author and YS as the corresponding author. YS additionally provided supervision throughout the project. AB assisted with data curation, project administration, visualization, and writing - review and editing. MK and RD contributed to writing - review and editing.

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Data Availability

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

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Figures

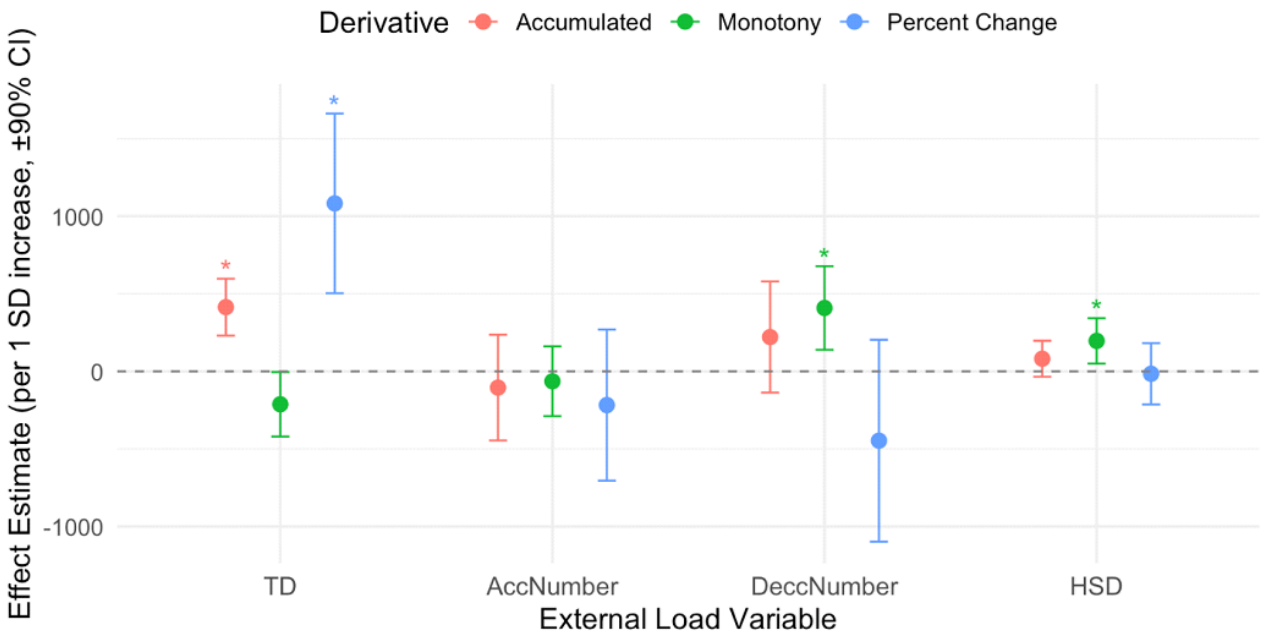


Figure 1.1

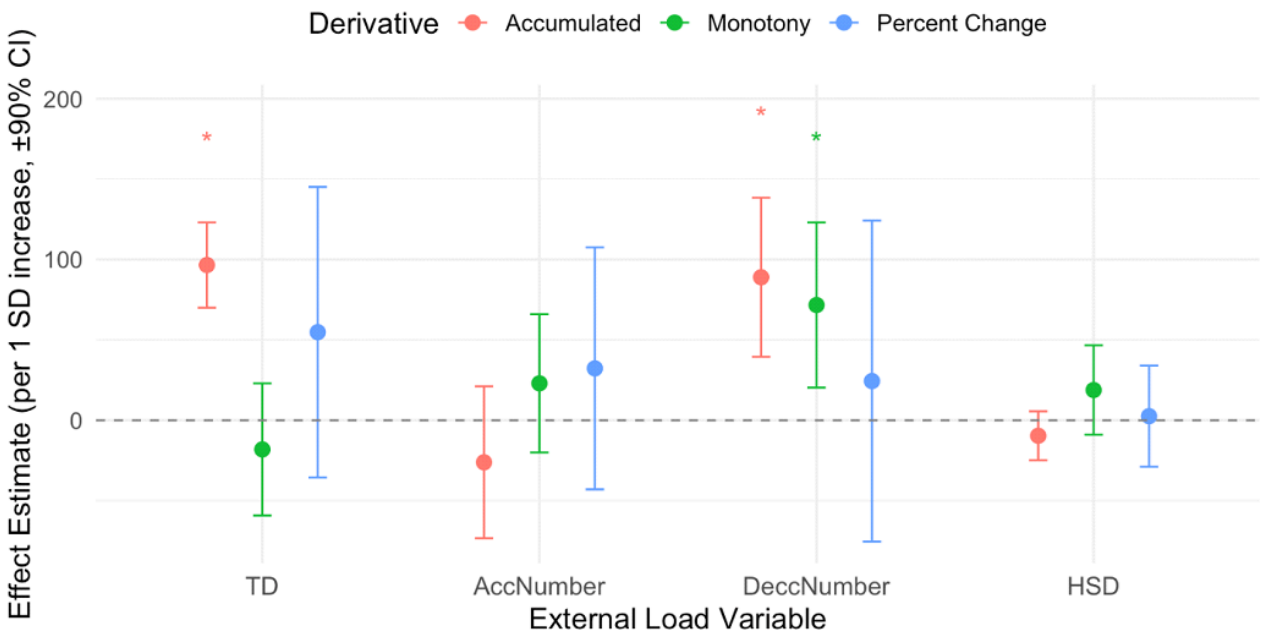


Figure 1.2

Figure 1

Standardized regression coefficients for predictors of weekly accumulated session-RPE (accsRPE) and weekly accumulated TRIMP (accTRIMP).