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A Framework Guide for the Selection of External Load Metrics in Ice Hockey

Steven Nightingale[1]*, Jonathan Hughes[2], Mark De Ste Croix[3] and Craig Pfeifer[4]

[1]New Jersey Devils, New Jersey, USA; [2]School of Sport and Health Sciences, Cardiff Metropolitan University, Cardiff, UK; [3]School of Sport and Exercise, University of Gloucestershire, Gloucester, UK; [4]University of South Carolina, USA

*Corresponding Author: snightingale@newjerseydevils.com

ABSTRACT

External workload monitoring has become commonplace in many sports, with staff looking to leverage the information gained to manipulate practice volume and intensity, hoping to maximize player readiness, minimize fatigue, and reduce the risk of injuries. However, with the increase in availability of technology to facilitate this, practitioners are faced with an overwhelming selection of metrics to choose from. Collinearity, contradiction and the accurate quantification of relative metrics risk creating confusion, and therefore it may benefit practitioners to have some guidance to help in the process of metric selection. This framework aims to provide clarity in the underpinning theory, history and development of external workload monitoring practice, a series of questions for reflective practitioners to consider, and evidence-based practical suggestions for its use.

Keywords: workload monitoring, injury reduction, performance optimization

INTRODUCTION

The process of objectively quantifying the work undertaken by athletes can be seen historically by recording sets, reps, and weight lifted in strength training sessions, and tracking distances travelled in running/swimming/cycling sport training. The underpinning rationale goes hand in hand with basic principles of sporting performance, such as progressive overload and periodization. Understanding what stresses an athlete has been subjected to allows coaches, strength coaches, sports scientists and medical staff to make decisions on future training. With advancing technology and understanding, workload monitoring is now utilized in a variety of ways to seek competitive advantage and maximize performance. Understanding the demands of games and practices, longitudinal tracking of loads and exposures, manipulating training to maximize fitness gains and minimize fatigue, and attempting to reduce the risk of injury and illness are some of the ways workload monitoring is currently used (Torres-Ronda et al, 2022; West et al, 2021).

Whilst Global Positioning Systems (GPS) have become the gold standard for quantifying external load in outdoor sports such as soccer, rugby and field hockey, the transmitter/receiving units worn by the athletes need a clear and unobstructed path to the satellites in the sky, meaning GPS cannot be used for indoor sports. Player movements can be recorded and analyzed during indoor events, but they are not coming from a GPS. Instead, the role of satellites can be replicated by using a Local Positioning System (LPS), which uses receiver beacons installed on the perimeter of the playing arena to imitate the role of the satellites.

While LPS use has been proven to be a fairly valid and reliable method of quantifying external workload in indoor sports (Alarifi et al, 2016; Serpiello et al, 2018), and specifically in ice hockey (Gamble et al, 2023) they present practical and logistical problems which must also be considered. As mentioned previously, in an LPS, receiver beacons replace satellites and must be installed around the perimeter of the playing area. Studies have reported using as few as 6 beacons (Bastida-Castillo et al, 2019) and as many as 18 beacons (Serpiello et al, 2018). These beacons require configuration and permanent installation to ensure the reliability of the data, which comes at significant additional cost to a system (Alarifi et al, 2016; Obeidat et al, 2021), and therefore limits the viability of such a system to teams with large operational budgets (Stevens et al, 2017). Additionally, due to these sensors needing to be immovable, data can only be collected at an arena with installed beacons, which has been configured to the individual system. From a practical perspective, this is challenging, as teams may use different facilities for matches and daily training when in their home city, and the collection of data during any matches or practices during periods of away travel will be impossible (Allard et al, 2022). To off-set these problems, teams often turn to a third method of external load monitoring.

Most modern GPS/LPS devices are fitted with micro-electromechanical sensors (MEMS). The inclusion of gyroscopes, accelerometers and magnetometers in the devices allow for the collection of inertial data without the requirement of satellites or pre-installed receiver beacons. These additional sensors allow for the quantification of the magnitude of load on the body, such as acceleration and deceleration, and most brands have a specific metric of quantification of load accumulated across multiple planes of movement (Hennessy and Jeffreys, 2018). This data collected from these tri-axial sensors is commonly referred to as Inertial Measurement Units (IMU).

Whilst there is a limited number of published studies utilizing IMU data collection in both practices and games of ice hockey, this has increased over recent years to include studies on both male and female participants, and junior, international, and professional levels of competition. However, the metrics used to quantify external load varies between studies. A summary of the recent hockey literature which has reported practice and/or game related IMU metrics is outlined in Table 1. Whilst there are several companies providing IMU systems, Catapult™ hold the market share and is the most commonly used system in the literature. Therefore, only studies using Catapult™ are reported, and all metrics subsequently discussed are produced by Catapult™.

As IMU metrics are named to reflect movement characteristics, a deeper explanation of these metrics is warranted for clarity, especially as many metrics are specific to ice hockey. PlayerLoad is a summation of all forces in movements recorded from the anteroposterior, mediolateral and vertical accelerometers and is reported in arbitrary units. The manufacturer computed algorithm can be seen below:

$$PlayerLoad = \sqrt{\frac{\left(a_{y1} - a_{y-1}\right)^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}{100}}$$

On Ice Load is similar to PL, in that it is a summated metric of forces in movements recorded from the anteroposterior, mediolateral and vertical accelerometers. It uses the same formula as PL, however to differentiate it, OIL does not include movements below a threshold of 0.3m.s^{-2}, therefore removing periods of very low activity (for example,

Table 1. A summary of IMU metric reporting in ice hockey

Author	IMU absolute metrics	IMU relative metrics
Allard et al (2020)	On-Ice Load (OIL)	OIL/min
Byrkjedal et al (2022)	PlayerLoad (PL), accelerations, decelerations, change of direction (CoD)	PL/min
Douglas et al (2022)	PL, Explosive Efforts (EE), Skating Load (SL) at various intensities	PL/min, EE/min, SL/min
Douglas et al (2019b)	PL, EE	PL/min
Douglas et al (2019a)	PL, SL, EE, Explosive ratio (ER), % high force strides	n/a
Neeld et al (2021a)	PL, SL, EE, Average Stride Force/lb, number of high force strides	PL/min, SL/min
Neeld et al (2021b)	PL, SL, EE, Average Stride Force/lb, number of high force strides	PL/min, SL/min
Nightingale et al (2024)	PL, SL, OIL, EE, total high force strides	PL/min, SL/min, OIL/min, EE/min
Perez et al (2022)	PL, Accel'Rate (AR)	PL/TOI, AR/TOI
Rago, Mohr and Vigh-Larsen (2023)	Accelerations, Decelerations	Accelerations/min, decelerations/min

when a player is sitting on the bench, or standing waiting for a restart of play).

Skating Load is a summated peak acceleration metric of movements recorded during a skating stride, which is subsequently multiplied by the athlete's mass, calculated using the following formula provided by the manufacturer:

$$Skating\ Load = \left(\sqrt{(a_y)^2 + (a_x)^2 + (a_z)^2} \times Player\ Mass\right)/100$$

Explosive efforts (EE) is a frequency count of actions occurring at a rate greater than 2m.s^{-2} in any plane. Explosive Ratio is calculated by the formula: Explosive Efforts/PlayerLoad. High Force Strides are considered strides taken in the high force band, which according to Catapult™ recommendations, is any stride above 190 au SL for males and 130 au SL for females. Change of direction measures the frequency of changes in on-ice motion direction following a deceleration and prior to an acceleration, and count of impacts measures the frequency of collisions (triggered by a G force >3 g on the sensor) with the ice, boards, or another player. Finally, Average Stride Force/lb is an average skating intensity metric calculated by dividing Skating Load by athlete mass.

With numerous metrics available, practitioners must determine which are most relevant. Bredt et al (2020) reviewed the calculation of PlayerLoad and highlighted its misreporting in recent literature, advising caution when using the PlayerLoad as a general measure of 'load'. This caution is due to discrepancies between Catapult's definition of PlayerLoad – "a modified vector magnitude, expressed as the square root of the sum of the squared instantaneous rate of change in acceleration in each of the three vectors - X, Y and Z axis - and divided by 100" - and the equation presented above. This definition of PlayerLoad involves the rate of change of acceleration (Δacceleration/Δtime), while the mathematical formula sums the changes in acceleration (∑Δacceleration). Furthermore, there have been different interpretations of the definition as it pertains to where the mathematical sum, sigma, should be performed within the formula. This can lead to significantly different results, as a standard data set was used to demonstrate in the Bredt et al (2020) study. Four different calculations to generate PlayerLoad were found in published papers, and the resulting PL values computed were 1.07, 10.76, 107.62, and 10681.84.

Equal criticism could be applied to On-Ice Load (OIL). Firstly, this metric is calculated in a similar way to PlayerLoad, and so the same criticisms can be applied as reported above. The difference between OIL and PL is that whilst PL sums the force of all movements across each plane, OIL excludes any force less than 0.3m.s^{-2}. According to Allard et al (2022), this removes "periods of lower activity, common in this sport (e.g., coasting, standing, and resting on the bench)" and theoretically provides a more accurate reflection of workload for ice hockey. However, positional differences exist in the game of hockey, which includes defensemen completing a greater amount of low intensity work during active gameplay than forwards (standing, gliding; backwards and forwards: 84% and 75% respectively) (Jackson et al, 2016), and Douglas and Kennedy (2020) found that defensemen cover significantly more distance at 'very slow' (1.0km/hr – 10.9km/hr or 0.27m/s – 3.0m/s) speeds than forwards. This leaves the practitioner with a decision to make, as it would appear that PL could be a more appropriate measure to assess game workload for defensemen and OIL could be a more appropriate measure for forwards.

Considering the points discussed, practitioners must contemplate several questions: Why report metrics? Which metrics should be reported? How many metrics are necessary? These questions are complex, with answers influenced by the team's style of play and the practitioner's subjective opinions. To offer some guidance, the authors make the following observations:

Why report metrics?

Discrete external load metrics have been linked to overall success in some sports. In soccer, Andrzejewski et al (2022) found statistically significant correlations between end of season league points and total distance with ball possession (r=0.75, p<0.001), sprint distance with ball possession (r=0.55, p<0.001), and maximum speed (r=0.41, p=0.01), although they noted the importance of technical characteristics. Similarly, Hoppe et al (2015) reported correlations between total distance with ball possession (r=0.77, p<0.01) and high-speed running distance with ball possession (r=0.52, p=0.03) with final points accumulation. In basketball, Lopez-Sierra et al (2021) compared multiple external load metrics with game outcome, concluding mixed results. Although PlayerLoad was not significantly different depending on match outcome, other metrics (high-speed running distance, Explosive Distance, and maximum accelerations) all were significantly higher in games with a winning outcome. In ice hockey, research is limited. Douglas et al (2019a) examined various external load metrics and match outcomes, finding no significant differences in PL, SL and EE for forwards, or PL, SL, EE, ER and %HFS for defenders and match outcomes. Therefore, seemingly no single metric has yet to be found to predict match success definitively, and more research needs to be conducted.

While external load metrics alone may not provide a blueprint for success, they are valuable for guiding and evaluating team practices. Team sport training often focuses on the group rather than the individual, but monitoring training loads can enhance understanding of fitness changes and injury risks. This can help practitioners manage training cycles to better reflect game demands, improving team preparedness (Owen et al., 2017; Weston, 2018).

Which metrics should be reported?

Bishop et al (2022) recently published a valuable framework for selecting metrics in alternative performance tests. Their guidance can be applied in this context. The authors encouraged practitioners to consider three questions when selecting metrics: i) is there a biological basis linking the metric to a favorable performance outcome? ii) is the system/tool feasible to implement? iii) what is the quality of the data obtained?

Douglas et al (2019a) reported that increased ER and %HFS in forwards led to a significant positive change in match outcomes, making these metrics valuable for consideration in IMU reporting. Ice hockey, being a contact sport, benefits from increased momentum (body mass*velocity), an important attribute for collision sport athletes (McMahon et al, 2020). Skating Load incorporates body mass with peak accelerations. Although not directly linked to game success, greater skating momentum likely improves collision outcomes, potentially increasing puck possession and providing competitive advantage. Speed is also crucial for ice hockey players. Bracko (2001) found significant differences in top speed between elite and non-elite female players. Top speed is most common in the neutral zone, where players create space to initiate an "odd-man rush", a situation where the attackers outnumber defenders, leading to high scoring opportunities (Yu et al, 2019), and higher danger attacking zone entries occur at higher speeds (Yu et al, 2019). Therefore, acceleration and speed metrics are logically important for overall game success.

The second question from Bishop et al (2022) must be addressed on a team-by-team basis. External load monitoring systems are costly, and not all teams may have the budget or see a significant return on investment. Additionally, data collection and analysis require specialized practitioners, which may not be feasible for every team. Despite these challenges, the authors recommend considering the use of such monitoring to evaluate practices in the context of games to enhance high-performance models.

Finally, practitioners must assess whether external load monitoring equipment is valid, reliable, and 'fit for purpose'. Whilst reliability studies in ice hockey are rare, Van Iterson et al (2017) found that PlayerLoad demonstrated moderate to good reliability in nine ice hockey-specific tasks. The Coefficient of Variation (CV) ranged from 0-10% for seven of nine tasks, and the Intraclass Correlation Coefficient (ICC) was >0.75 for eight of nine tasks. Additionally, previous studies have shown that IMU data in indoor sports is valid and reliable (Douglas et al, 2019b).

Reporting workload volume

To capture a holistic measure of workload volume in team sports, some studies advocate using multiple metrics (Zurutuza et al., 2020; Owen et al, 2019; Djaoui et al, 2022). Furthermore, Allard et al (2020) identify several key movement strategies unique to ice hockey, and recommend reporting information on skating strides, accelerations, changes of direction and collisions. However, caution is advised to avoid the common pitfall of reporting too many metrics. The metrics ultimately selected should measure different qualities of the sport, yet should also be correlated to enable definitive statements regarding training load. For example, consider metrics X, Y, and Z for measuring volume. If metrics X and Y are highly correlated, but metric Z is not, a discrepancy can arise. If metrics X and Y indicate above-average load while metric Z indicates below-average load, the practitioner must subjectively decide if the session workload is 'above average'. This situation complicates the assessment of training load and the reporting of load monitoring to key stakeholders. Following the advice of Bishop et al (2022), the number of variables selected should be limited to a few key metrics to facilitate informed training decisions.

Principal Component Analysis (PCA) is recommended to reduce redundancy by identifying metrics that provide similar information. This method is ideal for practitioners with statistical expertise, but even without PCA, some ice hockey-specific metrics can be discounted. As noted, the PL and OIL are highly correlated due to their similar computation algorithms. SL, calculated using peak accelerations and body mass, is also highly correlated to PL and OIL. Including more than one of these three metrics adds little additional information about total movement in a session.

Taking all of this into account, we recommend picking one of the following two approaches, with one focussed on simplicity, and the other focussed on a more thorough model. Approach A is to simply report either PlayerLoad or Skating Load as a measure of total work volume. Considering biological validity, we recommend representing external load volume with total Skating Load, however anecdotally, technical coaches may be more familiar and comfortable with PlayerLoad, as this is the most commonly reported Catapult volume metric. Approach B is to report a model of volume represented by Skating Load, instances of explosive speed (the number of Explosive Efforts), and instances (counts) of change of direction. These metrics represent different movement qualities, yet unpublished research has shown good to strong positive correlations (r= 0.77 – 0.94) between them. These could be reported separately, or used in a 'multi-mechanical model' whereby metrics are combined. Originally showcased as a concept in a paper by Owen et al (2017), that multi-modal model came under scrutiny for the application of its' statistical analysis, primarily for not considering the collinearity of individual metrics in the model, thereby skewing the data towards metrics which share common variance (Weaving and Read, 2021). Following open dialogue in the academic/ scientific space, the original authors acknowledged the need for refinement in their model, whilst also highlighting the applied significance of the success of the model in conveying complex ideas in a simple way, improving communication and understanding between performance staff and technical coaches (Owen, 2022).

With an appreciation for both sides of that argument, and in lieu of advanced modelling through PCA, we present our novel suggestion for a multi-modal model of external workload volume for ice hockey below, where zSL is the z-score of the Skating Load for the individual for the session, zEE is the z-score of Explosive Efforts for the individual for the session, and zCoD is the z-score of the sum of IMA CoD counts for the individual for the session.

$$Volume = (zSL * 0.33) + (zEE * 0.33) + (zCoD * 0.33)$$

Considerations for assessing intensity

External load is often reported in two ways: absolute values and time-relative values (absolute value divided by playing time). Absolute values reflect the volume of work completed, while time-relative values are often used to indicate the intensity of work completed (Owen et al, 2019; Urrutia et al, 2024). Examples in team sports include reporting total running distance (absolute) and distance per minute (time-relative) in soccer (Odetoyinbo, 2018), Australian rules football (Garrett et al., 2019), field hockey (Polglaze et al., 2015) and rugby league (Twist et al., 2017). PlayerLoad (PL) and PL/min are reported in basketball (Randell et al., 2019), handball (Kniubaite et al., 2019), Australian rules football (Garrett et al., 2019), and field hockey (Polglaze et al., 2015). In ice hockey, absolute and relative external load metrics reported include PL and PL/min (Douglas et al., 2020; Neeld et al., 2021; Byrkjedal et al., 2022), Skating Load (SL) and SL/min (Douglas et al., 2020; Neeld et al, 2021), Explosive Efforts (EE) and EE/min (Douglas et al., 2020), On-Ice Load (OIL) and OIL/min (Allard et al., 2020), absolute and relative accelerations and decelerations (Rago et al., 2023), and total distance and distance/min (Byrkjedal et al., 2022).

It could be argued that these time-relative values more accurate reflect training density (the amount of work completed in a given time frame) rather than training intensity, although these terms are mostly used interchangeably in literature. However, using time-bound derivatives in ice hockey needs further consideration.

Ice hockey games consist of three 20-minute periods with stopped clocks, resulting in each period lasting approximately 33-37 minutes. Periods are separated by 16-18 minute intermissions, depending on league rules, leading to a total game duration of around 135 minutes, with around 100 minutes of actual gameplay. In sports like soccer, rugby, field hockey and Australian rules football, players generally play most, if not all, of the game., with injuries and substitutions affecting only a minority of players. In contrast, ice hockey teams consist of 18 outfield players (usually 12 forwards and 6 defenders), but only 5 players are on the ice at any given time. The average shift duration is 45-60 seconds (Brocherie et al, 2018) and total playing time for elite male players ranges from approximately 13 to 22 minutes for defenders, and 9 to 19 minutes for forwards (Nightingale et al, 2024).

Current literature employs two methods for calculating relative PL. Douglas et al (2022), Douglas, Rotondi et al (2019) and Neeld et al (2021) used total game time, resulting in PL/min values between 2.1 and 2.3. Conversely, Byrkjedal et al (2022) and Perez et al (2022) used the time on ice (or "active time") method, resulting in PL/min values of around 6.3. Practitioners should be mindful of which method is used to calculate relative metrics when consulting literature.

If utilising time-relative metrics as measures of intensity, practitioners must decide which method to use in their own practice, based on the purpose of the data collection. If the goal is to compare practice and game workloads, the whole game time method may be more appropriate. In games, players typically follow a work:rest ratio of roughly 1:3 to 1:4, completing their shifts before resting on the bench. Similarly, in practice, players perform drills and rest while others complete their repetitions, resulting in comparable work:rest ratio. It is impractical for sports science practitioners to stop wearable devices from accumulating data when players are not actively in drills. Therefore, the time component in the relative metric calculation will be the total duration of practice for all players. A study of players in the elite Russian league (Kontinental Hockey League) using total game time and practice time to calculate relative metrics found PL/min values around 2.5 for both games and practice (Nightingale et al, 2024), consistent with values reported by Douglas et al (2022), Douglas, Rotondi et al (2019) and Neeld et al (2021).

However, if the goal is to obtain an individualised, accurate reflection of the intensity of work completed during a game, the time on ice (or active time) method should be considered. Using total game time to calculate relative metrics can lead to two issues: 1) it will underestimate relative loads for all players, and 2) it will inflate relative metrics for players who play more minutes compared to low-minute players. A hypothetical example of these metrics can be seen in Table 2.

Alternatively, practitioners could choose metrics which reflect the intensity of the session without using time-relative metrics. Catapult™ produces many metrics which could better reflect the intensity of the work completed. As previously discussed, Explosive Ratio (ER) is a ratio of the number of explosive efforts divided by the session total PlayerLoad. A higher ER signifies that there has been a larger proportion of high intensity work for a given amount of 'total work', and it has been suggested that a higher ER may be related to game success (Douglas, Johnston, et al, 2019). However, only one study has found this relationship, and it was only apparent for one position. Furthermore, in unpublished data, ER does not correlate with other metrics that would fall into the category of 'intensity'. The high force stride percentage (%HFS) has been reported in papers, calculated as the number of strides taken in the 'high force' band in relation to the total number of strides taken, and is worth considering. % High Intensity Skating Load (%HISL) is a metric that could also be considered, and this metric is calculated as the amount of skating load accumulated in a 'high' (band 3) in relation to the total amount of SL for a session.

REPORTING WORKLOAD INTENSITY

Similarly to the discussion on volume quantification, we advocate for either a simple or complex method for capturing workload intensity. In the simple approach, practitioners should look to use a time-bound relative derivative of the metric used for volume. If Skating Load or PlayerLoad have been used to quantify volume, then SL/min(toi) or PL/min(toi) should be used to quantify intensity. Whilst

Table 2. Hypothetical example of three activity profiles in ice hockey

	Player A	Player B	Player C
Total PL (au)	200	160	200
Total Game Time (mins)	100	100	100
Time On Ice (mins)	14	9	16
PL/min (total game time)	2.0	1.6	2.0
PL/min (TOI)	14.2	17.8	12.5

it can be argued that these more accurate represent training density, and we remind practitioners to carefully consider their calculations as discussed above, these metrics have been used consistently across a range of sports, and coaches are likely to be familiar and comfortable with them. For the more complex approach, following the model example and principles discussed earlier regarding the multi-modal approach for volume, we advise using two true intensity quantifiers and one density quantifier, resulting in a model presented below, where zSL/min(toi) is the z-score of the Skating Load per minute (time on ice) for the individual for the session, z%HFS is the z-score of the percentage of High Force Strides for the individual for the session, and z%HISL is the z-score of the percentage of High Intensity Skating Load for the individual for the session. In unpublished research, these metrics have demonstrated moderate to strong correlations.

$$Intensity = (zSL/\min(toi) * 0.33) + (z\%HFS * 0.33) + (z\%HISL * 0.33)$$

MULTI-MECHANICAL MODELS: FROM THEORY TO PRACTICE

To demonstrate the effects of multi-mechanical models, consider the data set in Table 3, which is workload data from an unpublished data set of elite ice hockey players in a single game.

This example highlights several pitfalls when assessing workload data in elite ice hockey players. If the practitioner was to only report total PlayerLoad and PL/min (for example, to the coach or medical staff), the conclusion would be that these players accumulated the same volume and intensity of work. This could lead to the players receiving the same recovery strategies, and subsequent loading strategies for the next practice.

When utilising the Time on Ice method for quantifying intensity, the conclusion would be different, as Athlete B has a higher PL/min(toi) than Athlete A. Using this approach, it is possible that Athlete B would be prescribed additional recovery work and potentially have their next practice workload reduced to account for this perceived "harder" game.

However, when utilising the multi-modal approach, which combines metrics for a more holistic overview of load accumulation, and compares an athlete to their season averages, it becomes clear that Athlete A accumulated more workload volume than they are used to, with a significantly higher intensity than they are used to, whereas Athlete 2 accumulated a workload volume just slightly above average, at an intensity below their season average. As a result of this information, Athlete A should likely be prescribed additional recovery work and may potentially need the subsequent practice workload reduced, whereas for Athlete B, no further action is likely to be taken. Understanding what was accumulated in relation to an individual's normative values is crucial to adopting the correct post-game strategies, but simple models have the potential to misrepresent what has happened.

Finally, it has been noted that z-scores can create confusion in populations not familiar with statistical concepts, due to negative values and small ranges (Andrade, 2021). Converting z-scores into T-scores using the formula T=10z+50, where 50 becomes the average score (a *z-score* of 0) (Osadebe, 2014), might be more accessible to technical coaches. In the example in Table 3, Athlete A would have T-scores of 61 (volume) and 65 (intensity), whereas Athlete B would have T-scores of 57 (volume) and 49 (intensity). It should be clear from this snapshot that Athlete A undertook more work in the game than Athlete B.

PRACTICAL APPLICATIONS

Workload monitoring can have several key functions. One reason to monitor workload is inform future practice planning decisions, as proactive workload monitoring attempts to maximize player readiness, minimize fatigue, and reduce the risk of injuries, which can occur when practice does not adequately prepare athletes for the demand of games, or conversely when short-term load accumulation is too high for the preparedness level of the athletes. This goal is complex in a team environment, where one practice is planned for the whole team, but all athletes will have individual responses. While the concept of the 'acute-chronic workload ratio'

Table 3. A comparison of in-game workload values for 2 players

Player ID	Time on Ice	Total PL	PL/min	PL/toi	MMM (volume)	MMM (intensity)
Athlete A	22.0	395	3.76	18.0	+1.05	+1.49
Athlete B	20.5	395	3.76	19.3	+0.65	-0.14

(ACWLR) is a controversial topic, the authors feel that the over-arching theme of encouraging small undulations while avoiding large spikes or drops in volume, is a prudent starting point to appropriately manage an intense season of practice and competition. As professional ice hockey has large day-to-day swings in total workload, from days off to practice days, to days with a "morning skate" and full game, the authors have anecdotally found that utilizing a rolling 5-day team average against a rolling 20-day team average to be a useful guide when planning future practice volume. To further enhance this process, the authors recommend taking an individual approach to player workload assessment, to inform recovery strategies or the need for additional practice. One way this can be performed is by looking at the individual's load for the session, and comparing it to recent (~1 month) or season-long performances, using z-scores or T-scores. Again anecdotally, the authors have seen success in the classifications in Table 4.

Workload monitoring can play a crucial part in the return to play (RTP) process of an injured athlete. By having a comprehensive understanding of what is required of the athlete in practices and games, a 'road map' can be created by working backwards, ensuring that on-ice RTP can follow a safe yet challenging quasi-linear approach to load accumulation.

Finally, it is important to consider how the data will be reported. Multiple stakeholders may have an interest in the data, from coaches, front office, players, medical staff, and strength and conditioning practitioners. Medical and strength and conditioning staff will likely understand the concept of z-scores, but it is unlikely to be understood by other members of the organization. For that reason, the authors recommend presenting data with visualizations, such as using colors and/or arrows to accompany the underlying numbers, alongside a key to what the numbers represent.

CONCLUSION

The purpose of this guide is to highlight the complexities that exist in workload monitoring, and to attempt to guide practitioners when considering which external load metrics can provide a comprehensive overview of volume and intensity in ice hockey. Metrics should be selected to reduce redundancy, ensure ecological validity, and measure different yet correlated aspects of the sport. Practitioners should also be mindful of the issues in calculating absolute and relative metrics when developing their load monitoring strategies.

Table 4. Post-game recommendations based on in-game workload

Classification	Z-Score	T-Score	Recommendation
Very easy session	<-1.5	<35	Advise top up work
Easy session	-1.5 to -0.8	35-42	Could consider top-up work
Normal session	-0.8 to 0.8	42-58	n/a
Hard session	0.8 to 1.5	58-65	Discuss recovery strategies with athlete
Very hard session	>1.5	>65	Implement recovery strategies and discuss subsequent session alterations with coaching team

Table 5. Summary of recommended external workload metrics for ice hockey, categorized by volume and intensity

Category	Metric	Approach	Rationale
Volume	Player Load (PL)	Simple	Most reported in literature, likely to be accepted by coaching staff
Volume	Skating Load (PL)	Simple	Biologically and ecologically valid, incorporates body mass
Volume	Multi-modal (SL, Explosive Efforts, Change of Direction)	Complex	Holistic representation of different movement qualities, provides a more complete workload profile
Intensity	PL/min or SL/min	Simple	Consistent across sports; reflects work rate or density; choice should match the selected volume metric
Intensity	Multi-modal (SL/min, %High Force Stride, %High Intensity Skating Load)	Complex	Holistic representation of intensity-related qualities, provides a more complete picture of work rate and high-intensity demands

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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REFERENCES

1. Alarifi A, Al-Salman A, Alsaleh M, Alnafessah A, Al-Hadhrami S, Al-Ammar MA, Al-Khalifa HS. Ultra wideband indoor positioning technologies: Analysis and recent advances. Sensors (Basel) 16(5); 707, 2016
2. Allard P, Martinez R, Deguire S, Tremblay J. In-season session training load relative to match load in professional ice hockey. J Strength Cond Res 36(2); 486-492, 2022
3. Andrade, C. Z scores, standard scores, and composite test scores explained. Indian J Psychol Med, 43(6); 555-557, 2021
4. Andrzejewski M, Oliva-Lozano JM, Chmura P, Chmura J, Czarniecki S, Kowalczuk E, Rokita A, Muyor JM, Konefał M. Analysis of team success based on match technical and running performance in a professional soccer league. BMC Sports Sci Med Rehabil 14(1); 82, 2022
5. Bastida-Castillo A, Gómez-Carmona CD, De la Cruz-Sánchez E, Reche-Royo X, Ibáñez SJ, Pino Ortega J. Accuracy and inter-unit reliability of ultra-wide-band tracking system in indoor exercise. Appl Sci 9(5); 939, 2019
6. Bishop C, Turner A, Jordan M, Harry J, Loturco I, Lake J, Comfort P. A framework to guide practitioners for selecting metrics during the countermovement and drop jump tests. Strength Cond J 44(4); 95-103, 2022
7. Bracko MR. On-ice performance characteristics of elite and non-elite women's ice hockey players. J Strength Cond Res 15(1); 42-47, 2001
8. Brocherie F, Girard O, Millet GP. Updated analysis of changes in locomotor activities across periods in an international ice hockey game. Biol Sport 35(3); 261-267, 2018
9. Bredt SDGT, Chagas MH, Peixoto GH, Menzel HJ, de Andrade AGP. Understanding player load: Meanings and limitations. J Hum Kinet 71(1); 5-9, 2020
10. Byrkjedal PT, Luteberget LS, Bjørnsen T, Ivarsson A, Spencer M. Simulated game-based ice hockey match design (scrimmage) elicits greater intensity in external load parameters compared with official matches. Front Sports Act Living, 4; 822127, 2022
11. Djaoui, L., Owen, A., Newton, M., Nikolaidis, P. T., Dellal, A., & Chamari, K. (2022). Effects of congested match periods on acceleration and deceleration profiles in professional soccer. Biology of Sport, 39(2), 307-317.
12. Douglas A, Johnston K, Baker J, Rotondi MA, Jamnik VK, Macpherson AK. On-ice measures of external load in relation to match outcome in elite female ice hockey. Sports, 7(7); 173, 2019
13. Douglas A, Rotondi MA, Baker J, Jamnik VK, Macpherson AK. On-ice physical demands of world-class women's ice hockey: from training to competition. Int J Sports Physiol Perform 14(9); 1227-1232, 2019
14. Douglas, AS, Rotondi MA, Baker J, Jamnik VK, Macpherson AK. A comparison of on-ice external load measures between subelite and elite female ice hockey players. J Strength Cond Res 36(7); 1978-1983, 2022
15. Douglas AS, Kennedy CR. Tracking in-match movement demands using local positioning system in world-class men's ice hockey. J Strength Cond Res 34(3); 639-646, 2020
16. Garrett J, Graham SR, Eston RG, Burgess DJ, Garrett LJ, Jakeman J, Norton K. A novel method of assessment for monitoring neuromuscular fatigue in Australian rules football players. Int J Sports Physiol Perform 14(5); 598-605, 2019
17. Gamble, A. S., Bigg, J. L., Pignanelli, C., Nyman, D. L., Burr, J. F., & Spriet, L. L. (2023). Reliability and validity of an indoor local positioning system for measuring external load in ice hockey players. European journal of sport science, 23(3), 311-318.
18. Hennessy L, Jeffreys I. The current use of GPS, its potential, and limitations in soccer. Strength Cond J 40(3); 83-94, 2018
19. Hoppe MW, Slomka M, Baumgart C, Weber H, Freiwald J. Match running performance and success across a season in German Bundesliga soccer teams. Int J Sports Med 36(07); 563-566, 2015
20. Jackson J, Snydmiller G, Game A, Gervais P, Bell G. Movement characteristics and heart rate profiles displayed by female university ice hockey players. Int J Kinesiol Sports Sci 4(1); 43-54, 2016
21. Kniubaite A, Skarbalius A, Clemente FM, Conte D. Quantification of external and internal match loads in elite female team handball. Biol Sport 36(4); 311-316, 2019
22. Lopez-Sierra, P.A.B.L.O., Arenas-Pareja, M.D.L.Á., Ibanez, S.J., & Antunes, A. (2024, January). Load differences in basketball according to the final outcome. In Atividade Física (International Congress of Physical Activity), 28, 29, 30 of September 2023, Castelo Branco, Portugal (p. 299)
23. McMahon JJ, Lake JP, Ripley NJ, Comfort, P. Vertical jump testing in rugby league: A rationale for calculating take-off momentum. J Appl Biomech 36(6); 370-374, 2020
24. Neeld K, Peterson B, Dietz C, Cappaert T, Alvar B. Differences in external workload demand between session types and positions in collegiate men's ice hockey. Int J Kinesiol Sports Sci 9(1); 36-44, 2021
25. Neeld KL, Peterson BJ, Dietz CC, Cappaert TA, Alvar BA. Impact of preceding workload on team performance in collegiate men's ice hockey. J Strength Cond Res 35(8); 2272-2278, 2021
26. Nightingale, S., Hughes, J., Croix, M. D. S., & Pfeifer, C. (2024). Practice and Match Workload Characteristics of Elite Men's Ice Hockey. International Journal of Strength

and Conditioning, 4(1).

27. Obeidat H, Shuaieb W, Obeidat O, Abd-Alhameed R. A review of indoor localization techniques and wireless technologies. Wirel Pers Commun 119; 289-327, 2021
28. Odetoyinbo K, Wooster B and Lane A. The effect of a succession of matches on the activity profiles of professional soccer players. In: Science and football VI: the proceedings of the Sixth World Congress on Science and Football. Reilly T, Korkusuz F, eds. Oxfordshire: Routledge, 2008. pp. 31-136.
29. Osadebe, P.U. Standardization of Test for Assessment and Comparing of Students' Measurement. Int Educ Stud, 7(5); 94-103, 2014
30. Owen AL, Djaoui L, Newton M, Malone S, Mendes B. A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer. Sci Med Footb 1(3); 216-221, 2017
31. Owen, A. L., Djaoui, L., Newton, M., Malone, S., Ates, O., & Mendes, B. (2019). A contemporary positional multi modal assessment approach to training monitoring in elite professional soccer. J. Complement. Med. Altern. Healthc, 10, 1-10.
32. Owen, A. (2022). Author reply to Weaving et al.: comment on: 'A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer: a mathematical problem?'. Science and Medicine in Football, 6(2), 270-271.
33. Perez J, Brocherie F, Couturier A, Guilhem G. International matches elicit stable mechanical workload in high-level female ice hockey. Biol Sport 39(4); 857-864, 2022
34. Polglaze T, Dawson B, Hiscock DJ, Peeling P. A comparative analysis of accelerometer and time–motion data in elite men's hockey training and competition. Int J Sports Physiol Perform 10(4); 446-451, 2015
35. Rago V, Mohr M, Vigh-Larsen J. Quantifying training load and intensity in elite male ice hockey according to game-related contextual variables. Biol Sport 40(1); 283-289, 2023
36. Serpiello FR, Hopkins WG, Barnes S, Tavrou J, Duthie GM, Aughey RJ, Ball K. Validity of an ultra-wideband local positioning system to measure locomotion in indoor sports. J Sports Sci 36(15); 1727-1733, 2018
37. Stevens TG, de Ruiter CJ, Twisk JW, Savelsbergh GJ, Beek PJ. Quantification of in-season training load relative to match load in professional Dutch Eredivisie football players. Sci Med Footb 1(2); 117-125, 2017
38. Torres-Ronda L, Beanland E, Whitehead S, Sweeting A, Clubb J. Tracking systems in team sports: a narrative review of applications of the data and sport specific analysis. Sports Med Open 8(1); 15, 2022
39. Twist C, Highton J, Daniels M, Mill N, Close G. Player responses to match and training demands during an intensified fixture schedule in professional rugby league: a case study. Int J Sports Physiol Perform 12(8); 1093-1099, 2017
40. Urrutia, S., Cappuccio, Á., & Ramírez, A. G. (2024). Equation for player load control of training with GPS in a high-performance soccer. Retos: nuevas tendencias en educación física, deporte y recreación, (58), 913-918.
41. Van Iterson EH, Fitzgerald JS, Dietz CC, Snyder EM, Peterson BJ. Reliability of triaxial accelerometry for measuring load in men's collegiate ice hockey. J Strength Cond Res 31(5); 1305-1312, 2017
42. Weaving, D., & Read, D. B. (2022). Re: A contemporary multi-modal mechanical approach to training monitoring in elite professional soccer: a statistical problem?. Science and Medicine in Football, 6(2), 268-269
43. West SW, Clubb J, Torres-Ronda L, Howells D, Leng E, Vescovi JD, Carmody S, Posthumus, Dalen-Lorentsen T, Windt J. More than a metric: how training load is used in elite sport for athlete management. Int J Sports Med 42(04); 300-306, 2021
44. Weston M. Training load monitoring in elite English soccer: a comparison of practices and perceptions between coaches and practitioners. Sci Med Footb 2(3); 216-224, 2018
45. Yu D, Boucher C, Bornn L, Javan M. Playing Fast Not Loose: Evaluating team-level pace of play in ice hockey using spatio-temporal possession data. arXiv preprint arXiv:1902.02020, 2019
46. Zurutuza U, Castellano J, Echeazarra I, Guridi I, Casamichana D. Selecting training-load measures to explain variability in football training games. Front Psychol 10; 2897, 2020