Module 2. Load Control and Monitoring for Injury Prevention. Application of Microtechnology

BARÇA INNOVATION HUB Universitas

1. Module 2. Load Control and Monitoring for Injury Prevention. Application of Microtechnology

This module provides a scientific framework for developing strategies and practical tools to reduce injury risk in indoor team sports.

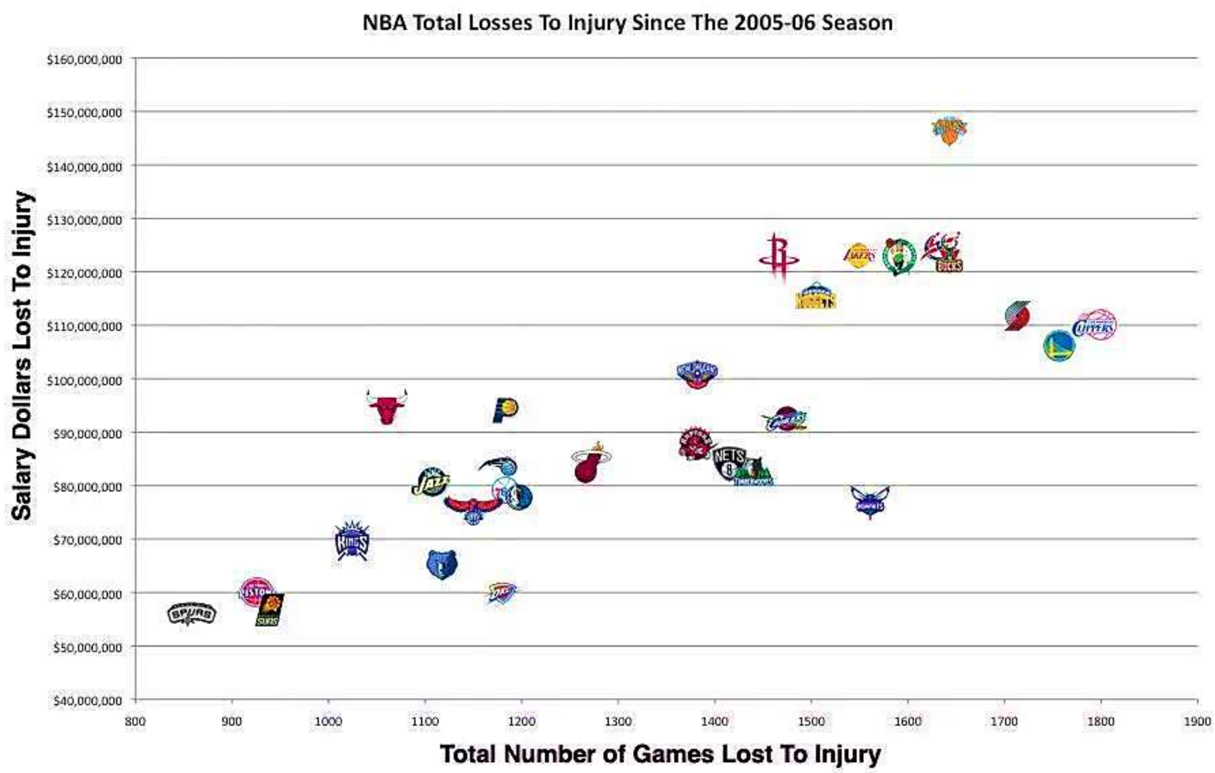
First, we must understand the relationship between training or competition load and injury risk. This insight is crucial for understanding the connection between training and injury occurrences. On the one hand, injuries can lead to significant financial losses for both clubs and, in some cases, the players themselves.

For instance, the Premier League paid out €243 million in player salaries for injured athletes during the 2017-2018 season. That figure marked a 21% increase compared to the previous season. Arsenal experienced the highest number of injuries that season, totaling 54. However, Manchester City incurred the highest costs, spending approximately €23 million, based on player salaries. Additionally, while players were unable to train or compete, the average cost per injury amounted to €362,000 per player. The most frequent injuries involved knee and muscle issues.

Another way to assess the impact of injuries on teams is to track the number of games lost due to player injuries. In the NBA, data from the 1998-1999 to 2017-2018 seasons show that the percentage of games lost to player injuries ranged from 15% to 22%, which is a substantial number.

Analyzing the total number of games lost due to injury, and correlating it with the salary of injured players during their absence, provides another valuable indicator (see figure 1). For example, during the 2005-2006 NBA season, the Phoenix Suns and San Antonio Spurs had the lowest injury-related expenses.

Figure 1: NBA: Total Losses To Injury Since The 2005-06 Season



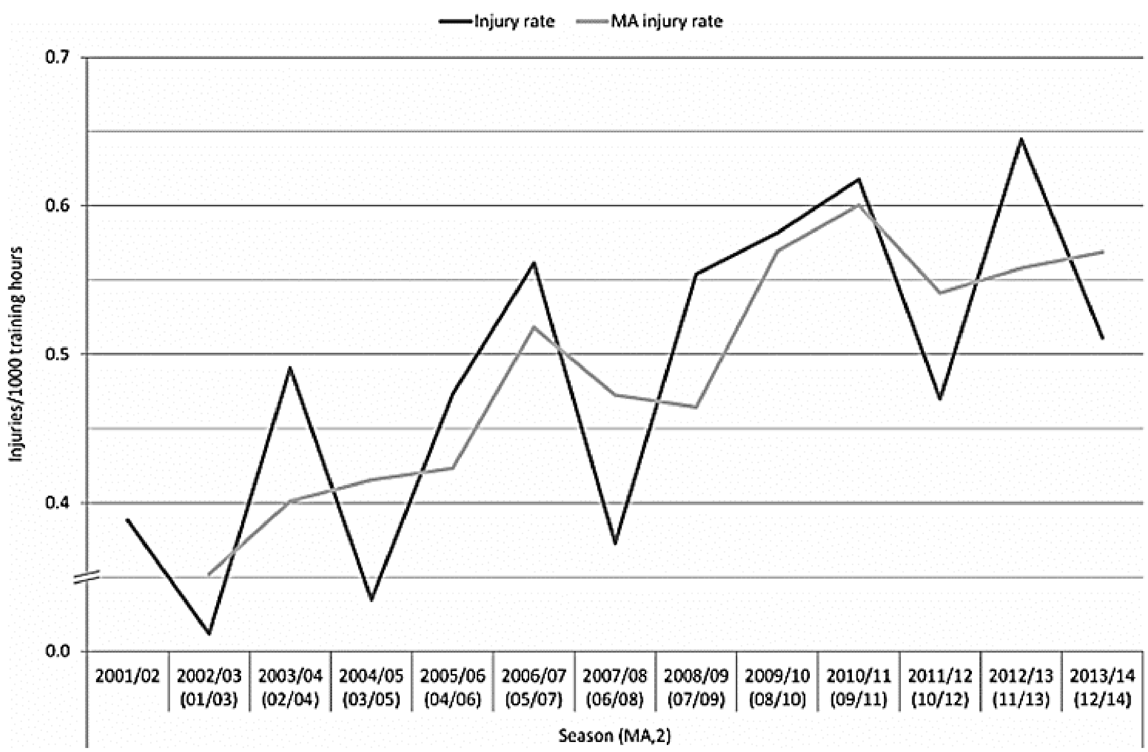
Source: Moreno, 2015, https://goo.su/lkiwxC

Similarly, the Golden State Warriors paid nearly €24 million in salary to Stephen Curry while he was injured during 2022.

Although this certificate primarily covers indoor team sports, it is useful to examine football-related data as well. One of the most common injuries in football is hamstring strain, which is less frequent in indoor sports like basketball, handball, or rink hockey.

This type of muscle injury results in an average of 17 days of absence from both training and competition. Additionally, athletes who face this injury often experience a subsequent decline in performance, and their recovery costs average €280,000. To better understand injuries and prevention strategies, we can analyze the data in figure 2. The figure highlights how hamstring injuries during training increased by 4% annually between the 2001 and 2013-2014 football seasons (Ekstrand et al., 2016). These figures underscore the importance of implementing a structured approach to reduce injury rates.

Figure 2: Annual increase in hamstring injuries in professional football training

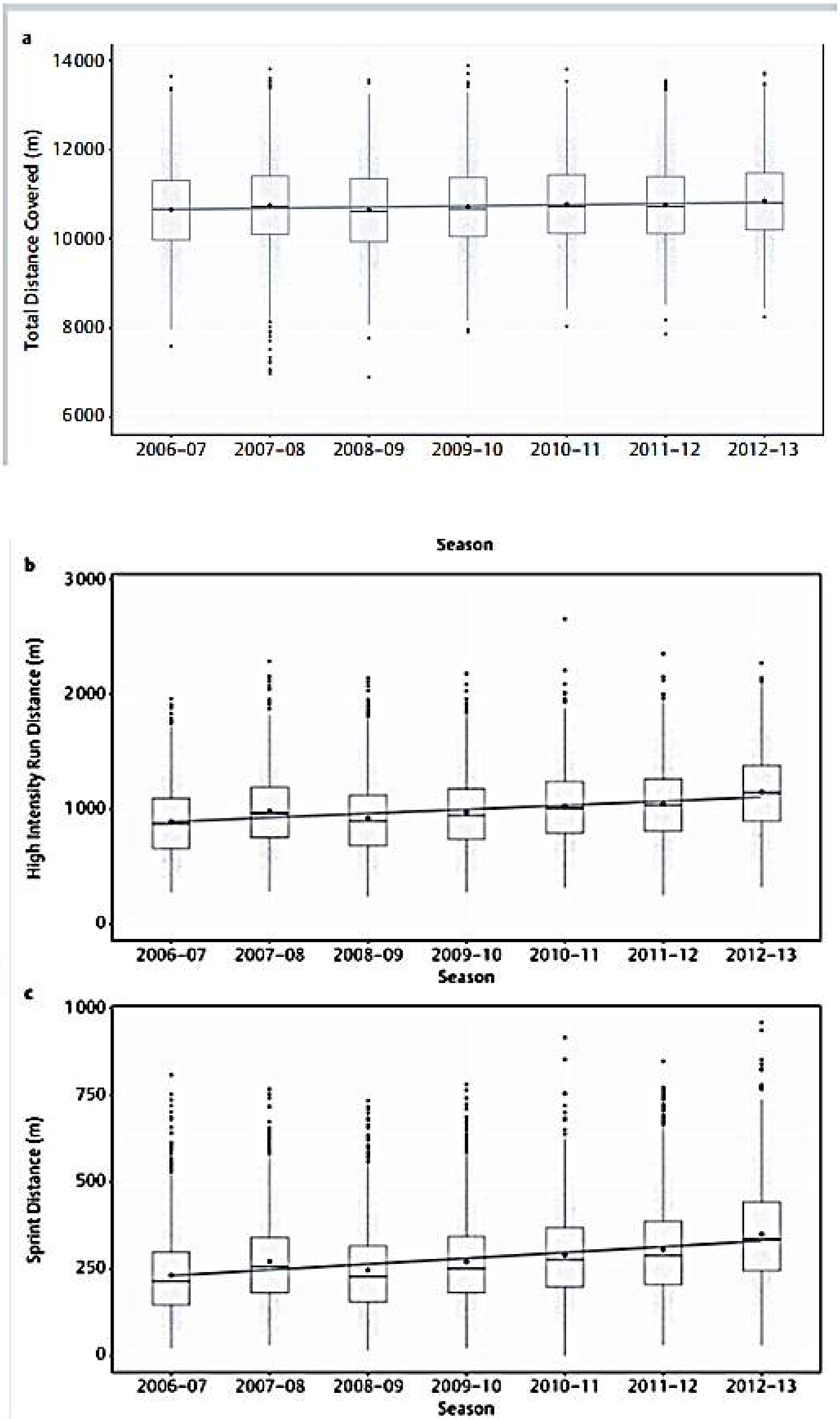


Source: Ekstrand et al., 2016, https://goo.su/dwlSeo

Further injury prevention research is shown in a study by Barnes et al. (2014), where technical and physical demands in the Premier League over multiple seasons were quantified using GNSS (Global Navigation Satellite Systems). The study tracked variables like total distance covered (as a volume indicator) and found little variation.

However, when analyzing high-intensity running and sprint distances, there was a sharp upward trend. This data covers the 2006-2007 through 2012-2013 seasons.

Figure 3: Quantifying technical and physical demands in the Premier League from the 2006-2007 to the 2012-2013 seasons


a
Total Distance Covered (m)
14000
12000
10000
8000
6000
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
Season
b
High Intensity Run Distance (m)
3000
2000
1000
0
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
Season
c
Sprint Distance (m)
1000
750
500
250
0
2006-07
2007-08
2008-09
2009-10
2010-11
2011-12
2012-13
Season

Source: Barnes et al., 2014, https://goo.su/Rjzqh

The general trend in football, which shows rising physical demands in competition, can be linked to trends in indoor sports like basketball, particularly in the NBA. From 2014, the NBA saw an increase in the number of possessions per game, which correlates with the pace of the game and increased physical demands. Possessions rose from 91 or 92 per game in the 2000/2002 seasons to 100 per game in the 2018-2020 seasons.

A study by Nassis et al. (2019) revealed that only 22% of football players met the sprint demands of competition during small-sided games. This may suggest a higher risk of injury, as players may not be fully prepared to meet the physical demands of actual competition.

Conversely, in the same study, 89% of players performed more technical touches (technical gestures) in small-sided games than they did in matches.

Moreover, only 22% of the players analyzed were able to meet both the sprint and technical touch demands required during a match. This suggests that while small-sided games are valuable, they need to be supplemented with other drills that replicate the physical demands of competition, particularly sprinting and distance covered at high speeds.

It is recommended to assess these elements in other types of indoor team sports to specifically evaluate the physical demands. In some cases, where the coach spends a lot of time training preferential simulation situations (tasks) with an emphasis on the cognitive structure (tactics) in a reduced space, we may find a situation similar to the one previously described in football.

In Barnes et al.'s (2014) study on physical and technical demands in the Premier League, which type of system was used to gather the data?

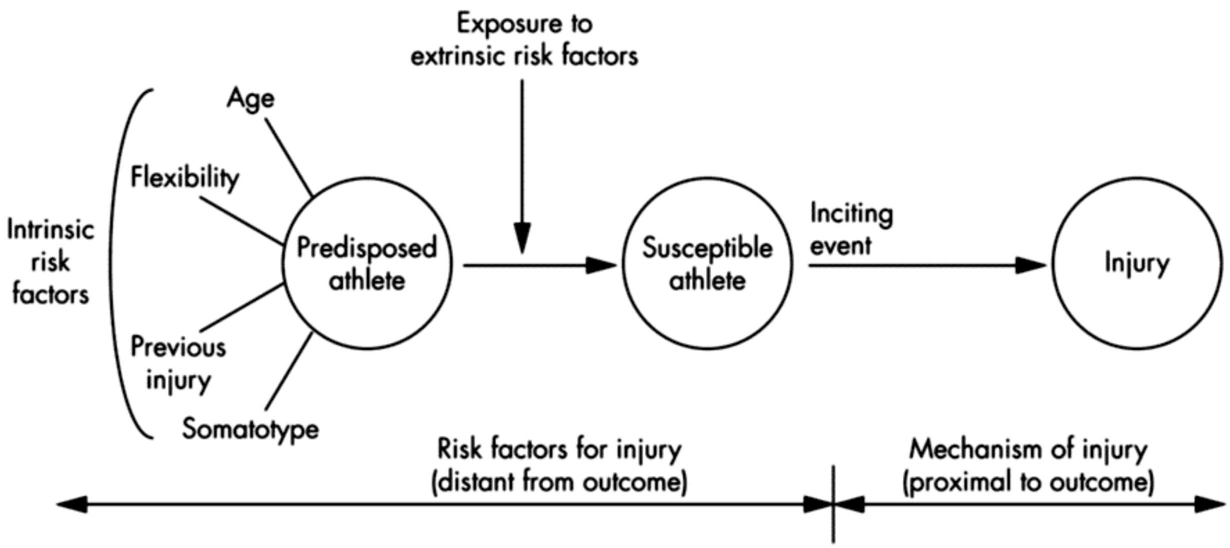
- ◯ Satellite alternation system
- ◯ Entropy tracking system
- ◯ Global Navigation Satellite System
- ◯ Advanced Artificial Intelligence system

SUBMIT

When discussing injury prevention, it’s essential to also consider injury etiology models. Meeuwisse’s (1994) study shifted from focusing on a single factor causing injuries to a multifactorial analysis, recognizing that multiple factors may increase injury risk (multifactorial analysis). He proposed using multivariate analyses to better understand the complexity of injury causality.

The following figure outlines the key factors that contribute to injury risk. On the one hand, internal factors specific to the player (such as age, flexibility, previous injuries, and body type) are evaluated. On the other hand, external risk factors from the player’s environment are considered, which increase susceptibility to injury. Essentially, injury risks can be broken down into individual risk factors, exposure to external factors, and the mechanisms that lead to injury.

Figure 4: Multifactorial model of sports injury etiology



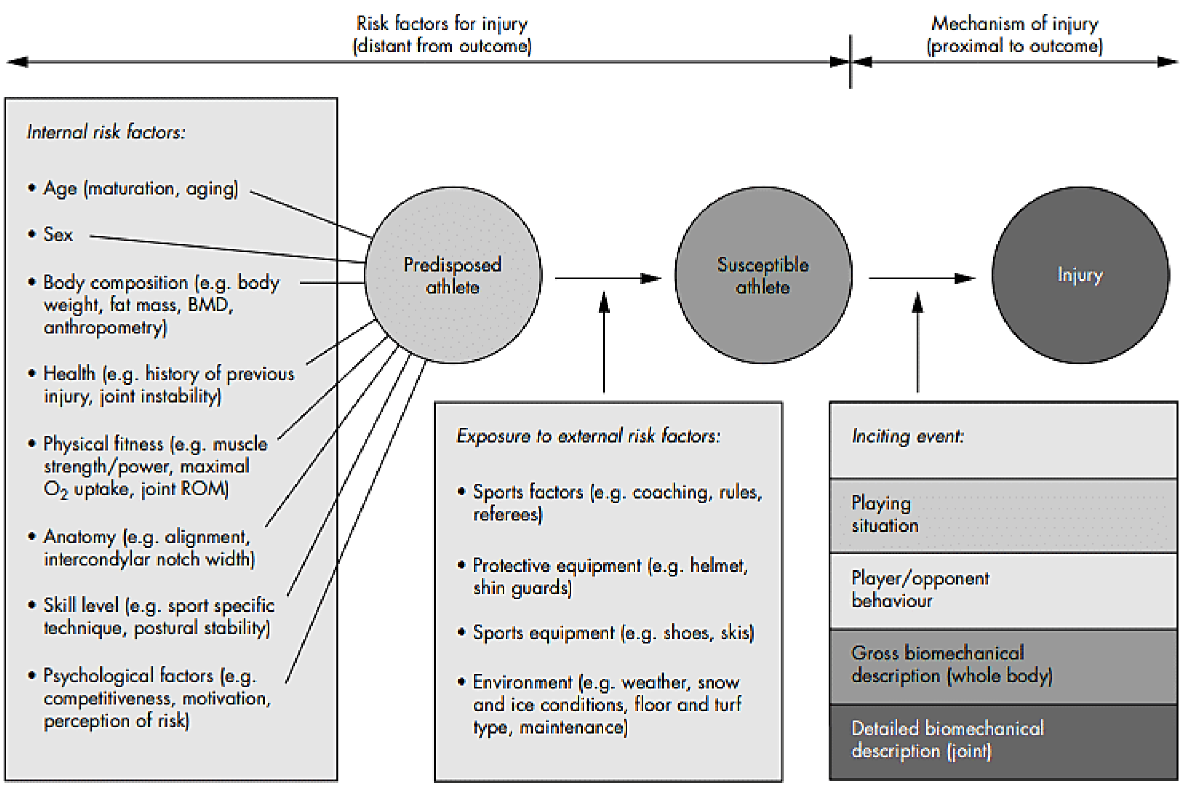
Source: Meeuwisse, 1994, https://goo.su/b3RqlKu

Meeuwisse's (1994) work was further developed by Bahr and Krosshaug (2005). Building on the earlier model, they detailed intrinsic factors like age, gender, body composition, health, skill level, and psychological aspects such as competitiveness, motivation, and stress. They also analyzed joint instability and physical conditioning, including oxygen consumption, range of motion, and joint alignment.

Additionally, they expanded on external environmental factors that had not been taken into consideration. External risks included sports-related factors (rules and referees), player protection (helmets or surface type), equipment (footwear), and weather conditions (rain or snow for outdoor sports). However, weather impacts are minimal in the indoor sports discussed in this module.

Finally, the injury mechanisms were examined in greater detail, including the game situation in which the injury occurred, the behavior of both the player and their opponent, as well as a comprehensive biomechanical analysis of the movement (at both global and local levels of the body). This provided a more comprehensive understanding of how injuries occur.

Figure 5: Comprehensive model of injury causality

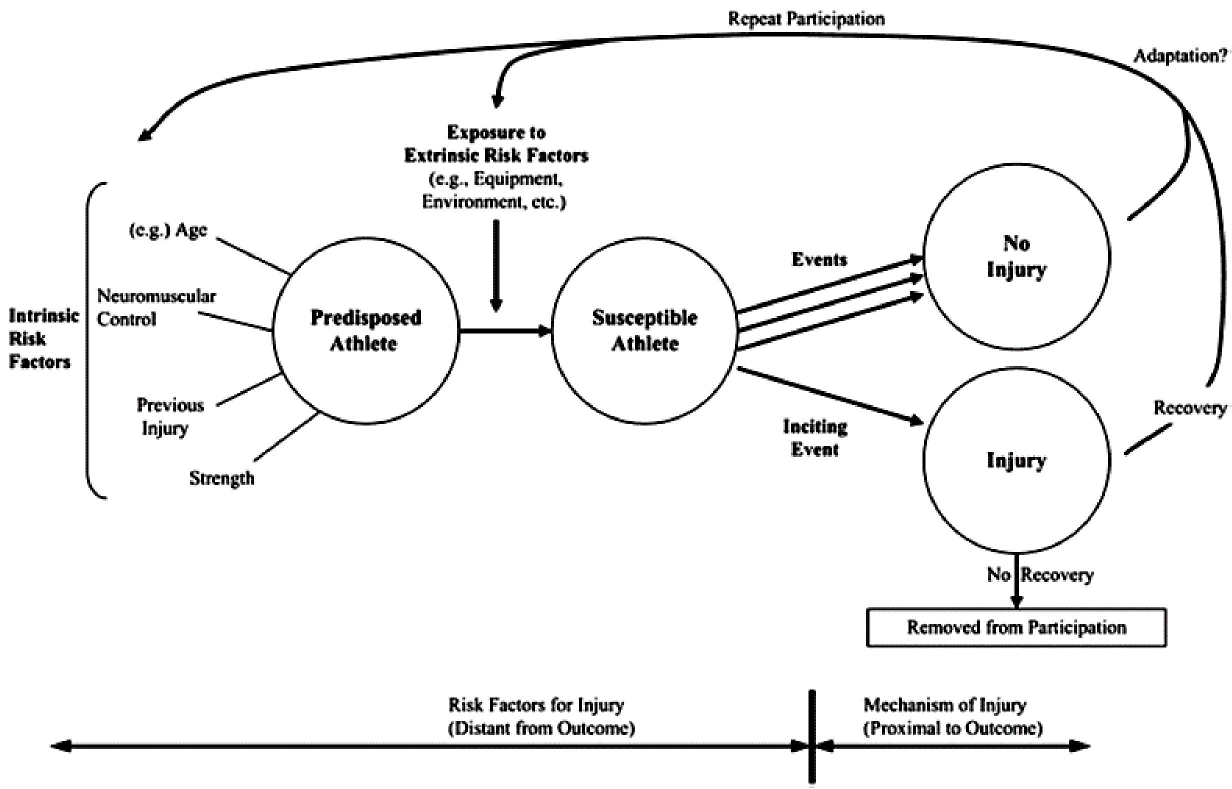


Source: Bahr y Krosshaug, 2005, https://goo.su/gTFi6q

Meeuwisse et al. (2007)(2007) introduced a dynamic approach to injury causality. Previously, the focus was on internal and external risk factors, injury mechanisms, and injuries themselves. This article introduces the idea that every training or competition stimulus can either cause or prevent an injury. If no injury occurs, the stimulus can positively impact the player's internal risk factors through training adaptations. For example, a training session might enhance the player’s neuromuscular control, producing beneficial effects from the training process.

However, if an injury does occur, recovery will be necessary, which directly affects intrinsic risk factors, increasing the risk due to the history of the injury.

Figure 6: Dynamic and recursive model of injury etiology in sports injuries



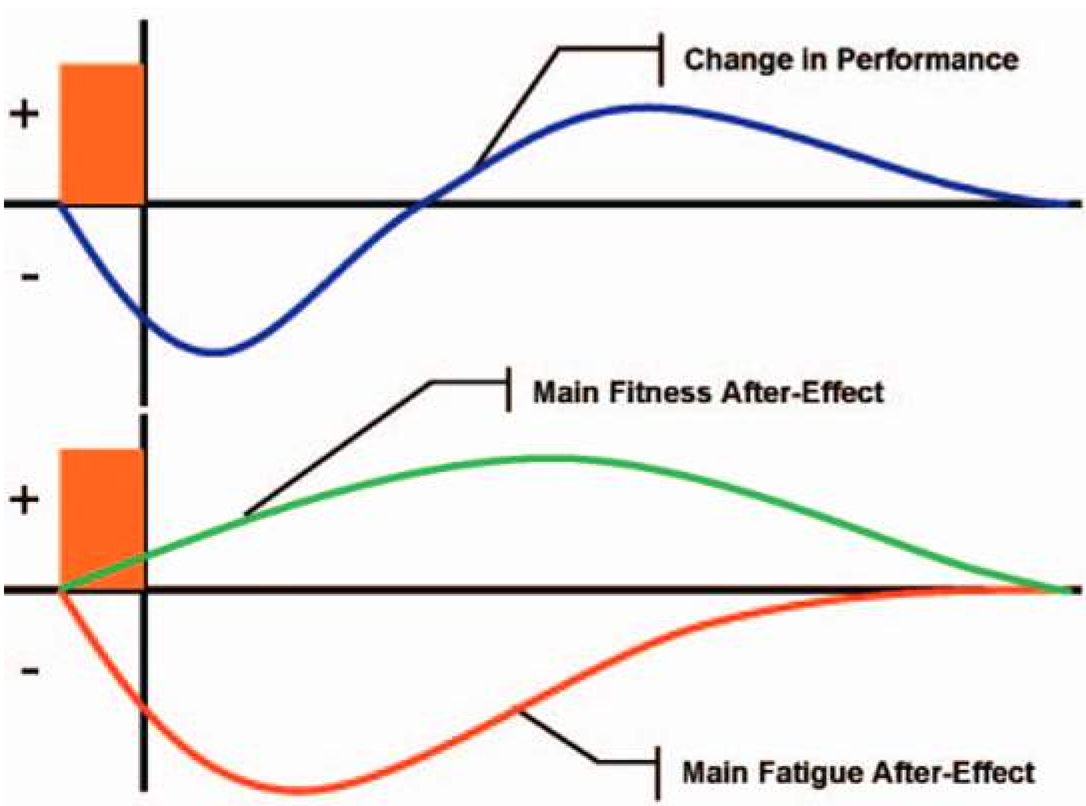
Source: Meeuwisse et al., 2007, https://goo.su/EWBcfCN

After reviewing various models of injury etiology, we now turn our attention to training or competition loads. A study by Chiu and Bradford (2003) revisited Banister's analysis of the dose-response relationship of training loads. This model, however, focused solely on performance, without considering its potential effects on injury likelihood.

The following figure illustrates how, based on the load, stress is generated from that training (or competitive) stimulus according to bifactorial theory. This stress leads to a series of negative effects manifested as fatigue, along with a set of positive effects related to fitness, which can result in overcompensation, allowing the player to exceed their pre-stimulus conditioning level.

There is a point at which the positive effects of training outweigh the negative ones, resulting in what Banister described as "overcompensation" in performance.

Figure 7: Fitness-fatigue theory



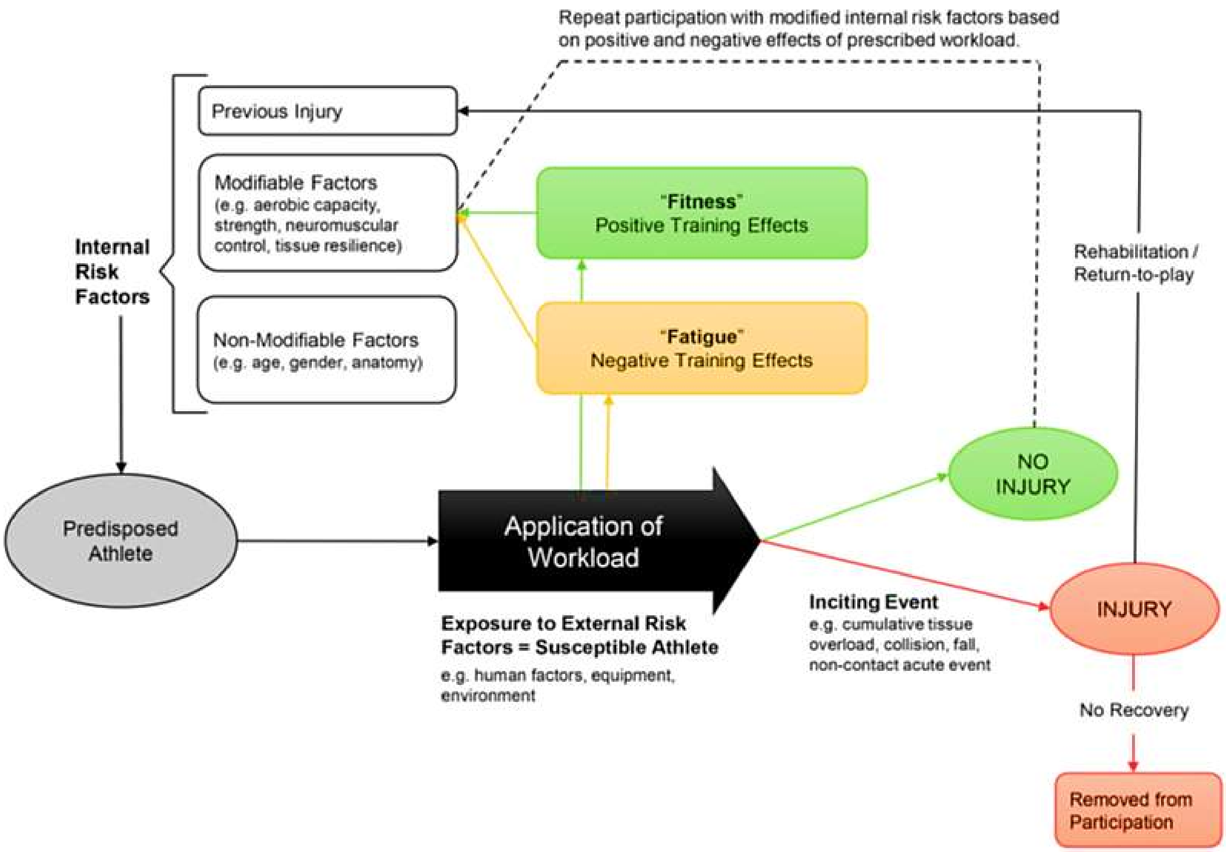
Source: Chiu y Bradford, 2003, https://goo.su/F2RUxZr

However, this approach did not initially address injury risks related to training load. Yet, it’s possible that training loads do play a role in injury occurrence.

Windt and Gabbett (2017) proposed including training and competition loads in models of sports injury etiology, as seen in the figure below. These authors also distinguish between intrinsic and extrinsic risk factors, along with the positive and negative effects of training loads on athletes. If no injury occurs, the load will still influence internal risk factors in various ways. If an injury occurs, as in the Meeuwisse model (2007), there is a consequence, as the athlete becomes more vulnerable to future injuries due to their injury history.

Therefore, training load should not be viewed as just another risk factor but rather as the mechanism through which sports injuries may occur.

Figure 8: Model of sports injury etiology



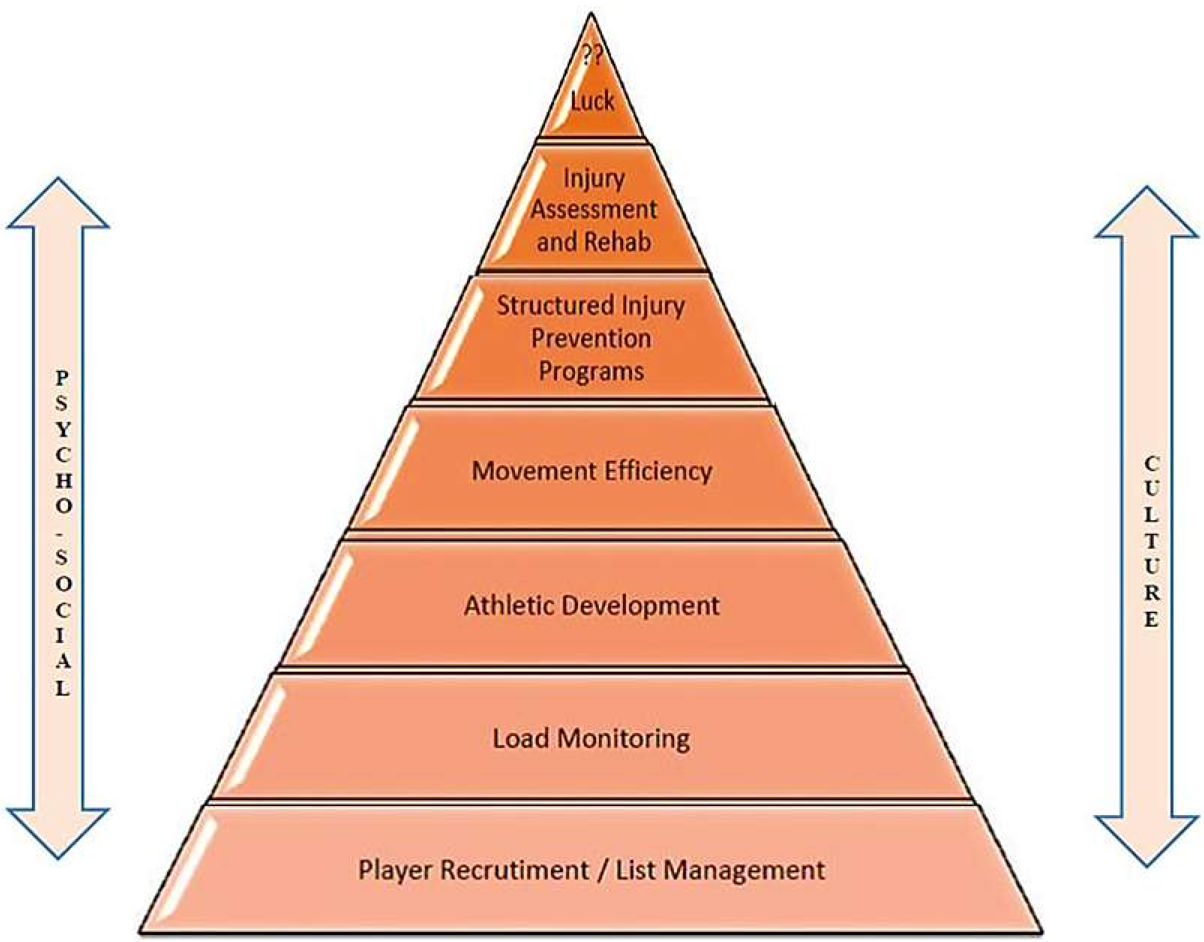
Source: Windt y Gabbett, 2017, https://goo.su/6KV7M

It's clear that appropriate physical conditioning can lead to positive adaptations in a player's physical state. These adaptations can improve modifiable internal risk factors, such as aerobic capacity and body composition. The negative effects of training load are mainly manifested as fatigue, which is influenced by modifiable risk factors. This fatigue can reduce neuromuscular control, increasing vulnerability to injury.

Therefore, according to Windt and Gabbett's (2017) injury etiology model, training load must be considered an essential factor in injury prevention strategies or programs.

Various models use pyramids to illustrate hierarchical concepts that reduce injury risk, such as monitoring load and improving strength, among others. To our knowledge, however, no model had previously included all the elements shown in Figure 9 (Coles, 2018).

Figure 9: Injury prevention pyramid



Source: Coles, 2018, https://goo.su/zIcHf3

The base of this model's pyramid is player recruitment, meaning the players available. For example, the probability of injury for a 40-year-old handball, basketball, or futsal team differs significantly from that of a team with an average age of 23. Since age is an intrinsic risk factor, the younger team will initially face a lower injury risk (though other risk factors must also be considered). Therefore, team composition is a key factor in injury prevention. This factor had not previously been presented as clearly as it is in this article.

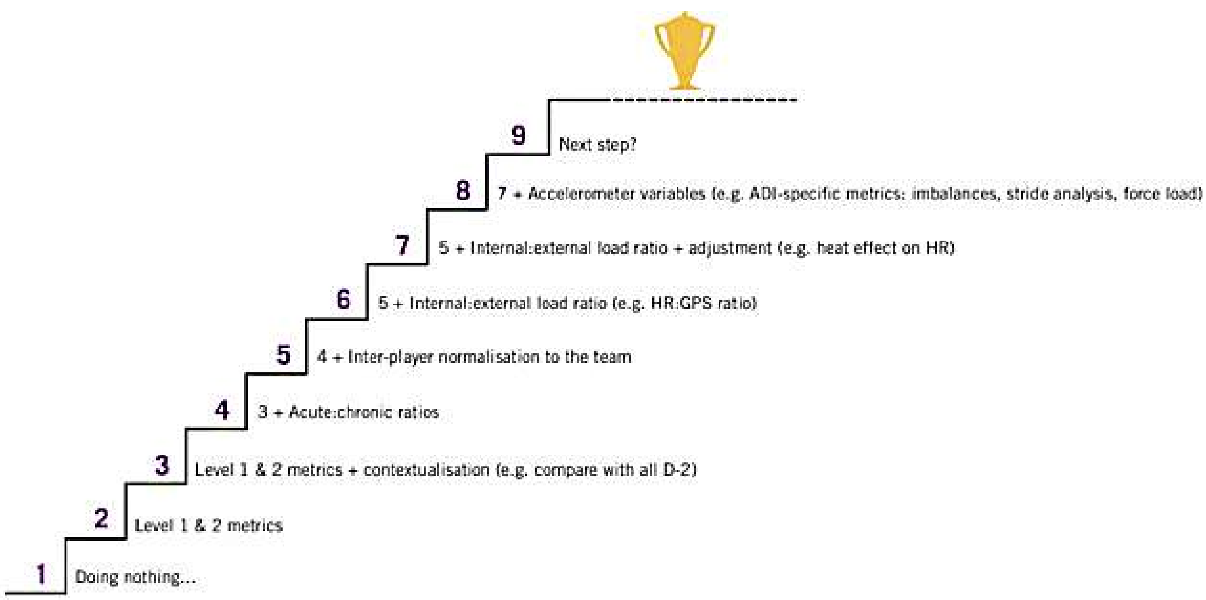
The pyramid builds upward from other factors like load monitoring, athletic development, optimizing movement efficiency, implementing structured injury prevention programs, rehabbing injuries, and even including a bit of luck.

According to this model, fitness coaches have a significant impact on injury prevention by contributing to prevention programs, developing strength, improving movement efficiency, and monitoring training or competition loads.

A thorough injury prevention strategy requires the collaboration of the coach, medical team, fitness coach, and the player, who must take an active role in the process. The teamwork and interaction between these individuals will result in a better approach to reducing injury risk.

The figure below provides examples of actions aimed at monitoring training and competition loads to lower injury risk and improve athletic performance (Lacome et al., 2018).

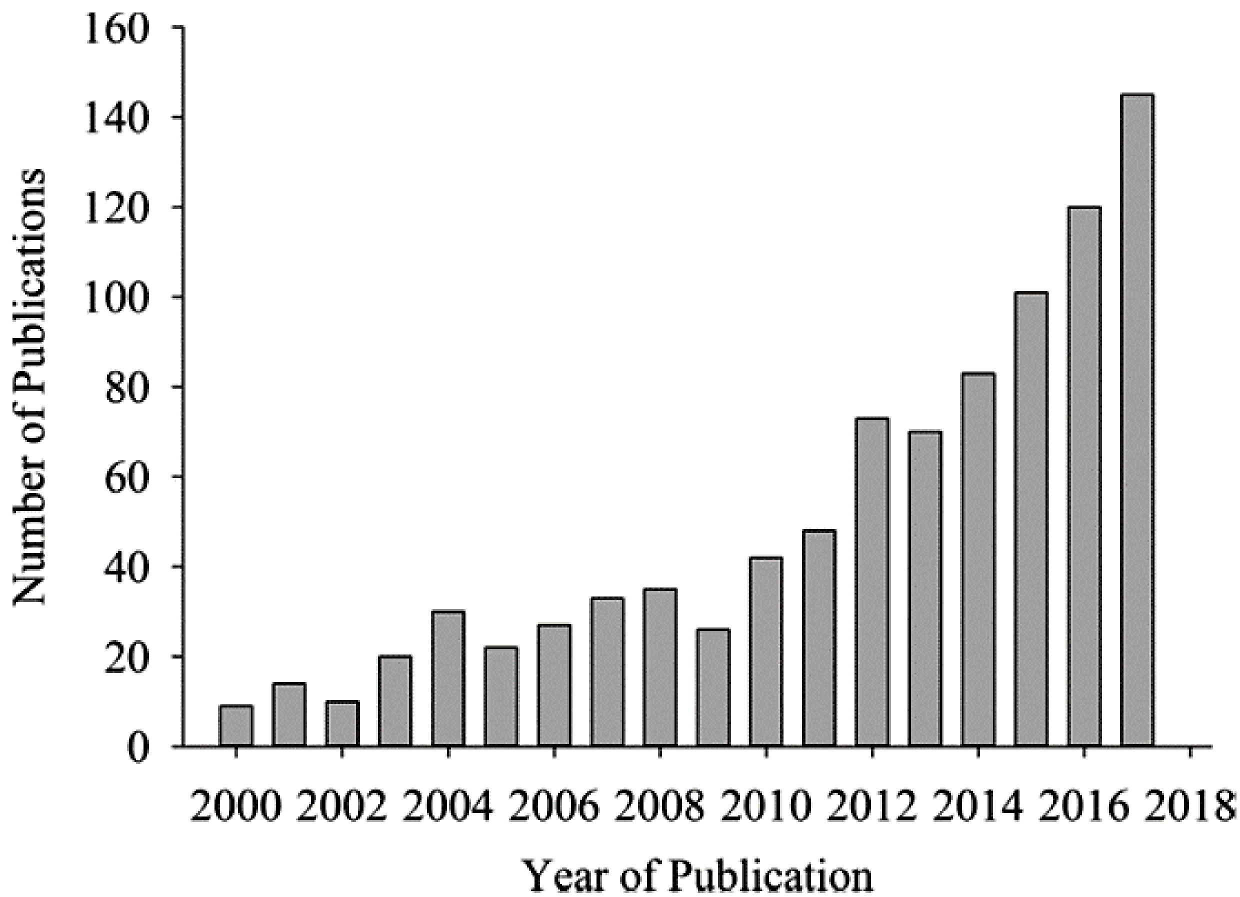
Figure 10: Possible actions for monitoring training and competition loads to reduce injury risk and optimize performance



Source: Lacome et al., 2018, https://goo.su/OEXLm

Scientific research on IMU, LPS, and GNSS systems has expanded significantly, along with studies on performance and injury risk since 2000. The growth in injury-related research appears likely to continue.

Figure 11: Growth in research on "training" and "injury" since 2000



Source: Gabbett, 2018, https://goo.su/lH5ZEL

To effectively reduce injury risk, it is important to find the optimal training load that produces the desired performance effects with minimal fatigue.

In elite sports, the goal of training is always to optimize performance and achieve victories. While optimizing performance to win, we must also determine the optimal load dose, as too much load increases injury risk, as discussed in previous modules. Therefore, finding this optimal dose is a practical application of training and competition load monitoring.

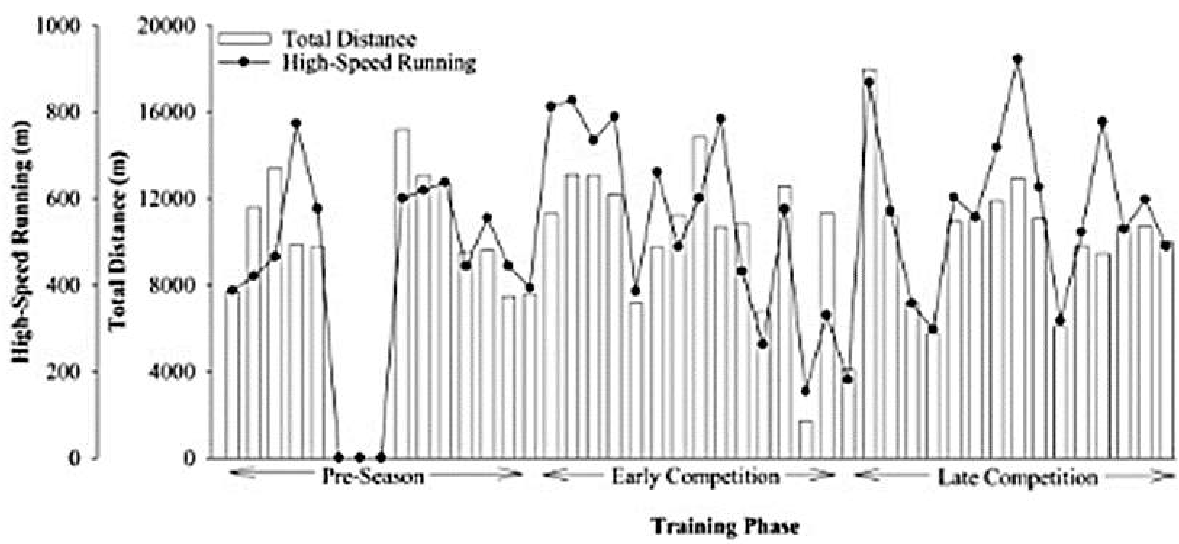
According to Windt and Gabbett's (2017) injury etiology model, how should load be considered?

- ◯ As a rigid, external strategy
- ◯ As a key element in injury prevention strategies or programs
- ◯ As an associated but not determining factor
- ◯ Load is not considered relevant in the model

SUBMIT

In continuing with load monitoring, Gabbett et al. (2012) examined the total and high-intensity distances rugby players covered during different microcycles throughout a season. They found that when players ran just nine extra meters per session at speeds over 25 km/h, their risk of non-contact soft tissue injuries increased by 2.7 times. Thus, controlling high-intensity demands is especially important in indoor sports to mitigate injury risks. When it comes to speed, since this module focuses on indoor team sports, we recommend lowering the high-speed threshold from 25 km/h to around 18-20 km/h.

Figure 12: Total weekly training distance and high-speed distance covered during a professional rugby league season



Source: Gabbett et al., 2012, https://goo.su/aKOz2

A similar study by Colby et al. (2014) on Australian football found that when players accumulated greater distances over three weeks in the preseason, their risk of injury increased by 5.5 times. The risk was

3.7 times higher with increased sprint distances. During the season, the likelihood of injury doubled when there was a high force load (measured through IMU technology) over three weeks, and it doubled again when there was a sharp increase in speed changes over four weeks. This introduces another factor to consider in load monitoring for indoor sports, aimed at reducing injury risks.

Figure 13: Australian football loads during different phases of the season

	Preseason	In-season	Whole-season
Distance (m)			
1–2 y	350,674 (313,731–387,616)	344,088 (299,321–388,855)	694,762 (629,839–759,685)
3–6 y	375,136 (339,277–410,995)	373,924 (354,243–393,605)	749,060 (705,808–792,312)
>7 y	356,431 (316,662–396,200)	‡320,417 (262,034–378,800)	676,848 (597,150–756,547)
V1 distance (m)			
1–2 y	§‖99,883 (90,090–109,676)	99,574 (81,572–117,577)	199,458 (180,025–218,890)
3–6 y	§120,903 (111,984–129,822)	106,281 (96,846–115,716)	227,184 (211,123–243,245)
>7 y	§113,757 (100,480–127,034)	92,534 (78,612–106,457)	206,292 (182,857–229,727)
Sprint distance (m)			
1–2 y	‖4,322 (2,756–5,888)	5,753 (3,770–7,735)	10,075 (6,645–13,506)
3–6 y	7,480 (6,048–8,930)	7,170 (6,330–8,010)	14,660 (12,649–16,671)
>7 y	5,848 (4,900–6,796)	¶4,076 (2,819–5,332)	9,924 (8,393–11,454)
Force load (AU)			
1–2 y	26,890 (23,474–30,307)	26,787 (23,090–30,483)	53,677 (47,792–59,563)
3–6 y	28,043 (25,370–30,716)	29,814 (27,067–32,560)	57,857 (53,445–62,269)
>7 y	27,613 (23,322–31,904)	26,798 (20,973–32,622)	54,411 (45,668–63,154)
Velocity load (AU)			
1–2 y	31,608 (27,192–36,025)	31,446 (27,078–35,814)	63,055 (56,000–70,109)
3–6 y	36,475 (33,386–39,565)	36,117 (34,011–38,224)	72,593 (68,545–76,641)
>7 y	35,898 (31,536–40,260)	32,281 (26,404–38,159)	68,180 (59,331–77,029)
RVC (AU)			
1–2 y	365 (324–407)	385 (321–450)	751 (663–839)
3–6 y	386 (321–452)	440 (396–384)	827 (733–920)
>7 y	345 (290–399)	¶347 (251–443)	692 (567–817)

*AU = arbitrary units; RVC = relative velocity change.
†Data are expressed as mean (95% confidence intervals).
§Preseason load significantly greater than in-season ($p \leq 0.05$).
‖1–2 y significantly lower load than 3–6 y ($p \leq 0.05$).
¶>7 years significantly lower load than 3–6 y ($p \leq 0.05$).

Source: Colby et al., 2014, https://goo.su/29Ea22b

Injury prevention also requires understanding the demands of competition and preparing players to handle them appropriately.

The following figure shows load data from a top-tier basketball team during different sessions within a season. The first column indicates the average distance covered per minute by the team, while the second shows the same data for an individual player in that session.

The third column shows the minimum detectable change across selected sessions to identify significant changes in the distance covered per minute.

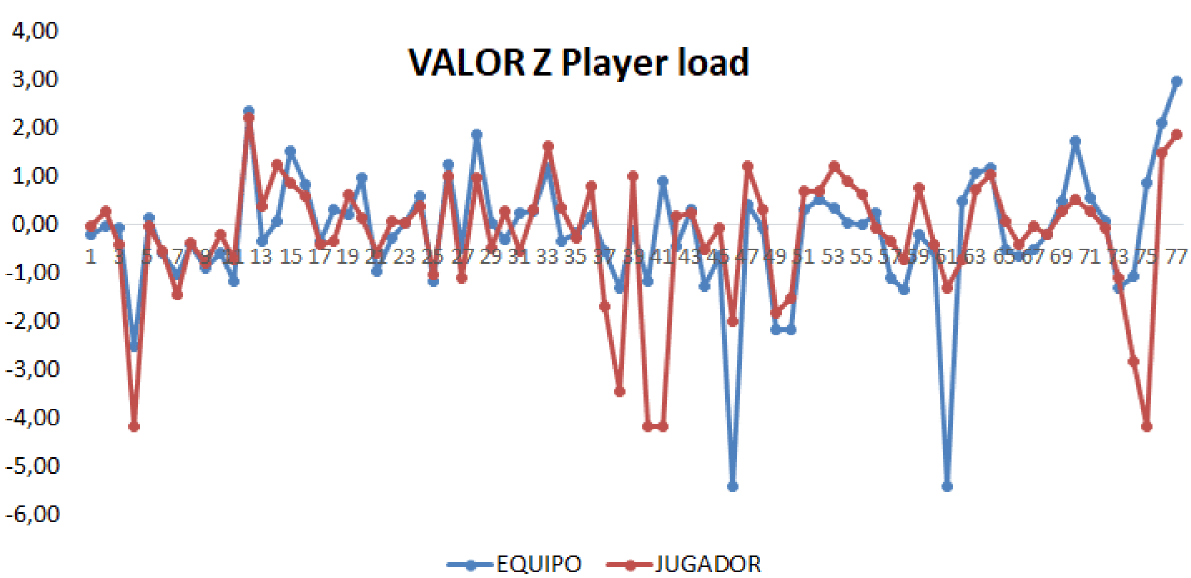
However, calculating the minimum detectable change alone is not enough. We also need to assess the magnitude of that change. To do this, the Z score for the team is calculated in the fourth column. For example, values range from 0.62 to 1.08, sometimes reaching 2.24. The sixth column displays the Z value for the player selected in the example. Finally, the last column corresponds to the calculation of the coefficient of variation (CV), which represents the relationship between the mean size and the variability of the variable. For interpretation purposes, it can be expressed as a percentage, understanding that it can exceed 100%.

Figure 14: Comparison of team data with that of an individual player

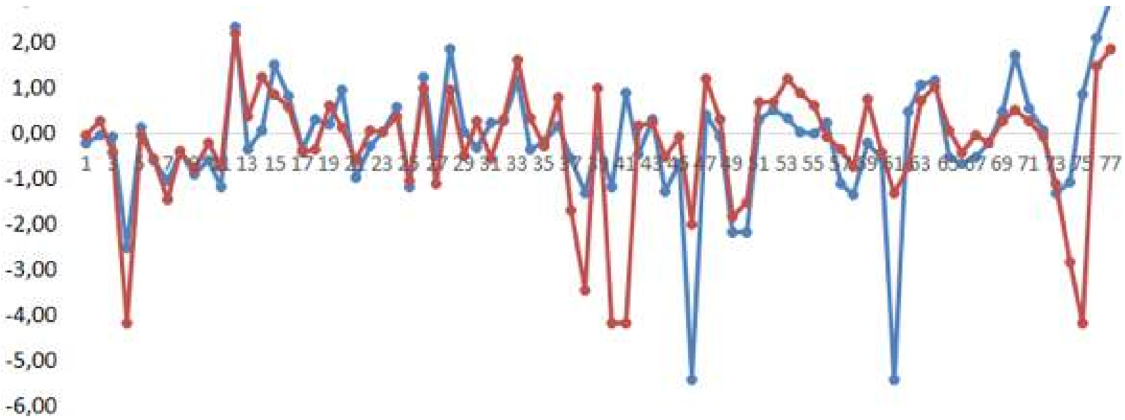
04/11/2016	35,93	34,39	-1	-0,62	-1	-0,75	-4%
05/11/2016	32,41	32,57	-1	-1,08	-1	-0,96	0%
08/11/2016	37,26	42,49	-1	-0,45	0	0,16	14%
09/11/2016	33,45	34,79	-1	-0,95	-1	-0,71	4%
14/11/2016	35,97	34,99	-1	-0,62	-1	-0,68	-3%
15/11/2016	31,55	34,65	-1	-1,20	-1	-0,72	10%
22/11/2016	57,78	49,97	1	2,24	1	0,99	-14%
23/11/2016	37,63	33,65	-1	-0,40	-1	-0,83	-11%
29/11/2016	40,84	38,57	0	0,02	-1	-0,28	-6%
30/11/2016	51,51	55,36	1	1,42	1	1,60	7%
01/12/2016	46,48	37,4	1	0,76	-1	-0,41	-20%
06/12/2016	37,58	32,12	-1	-0,41	-1	-1,01	-15%
07/12/2016	42,62	22,89	1	0,25	-1	-2,04	-46%
13/12/2016	41,88	37,75	0	0,16	-1	-0,38	-10%
14/12/2016	47,45	43,36	1	0,89	1	0,25	-9%
15/12/2016	32,94	30,23	-1	-1,01	-1	-1,22	-8%
20/12/2016	38,28	36,02	-1	-0,31	-1	-0,57	-6%
25/12/2016	40,47	41,42	0	-0,03	0	0,04	2%
26/12/2016	44,71	40,43	1	0,53	0	-0,07	-10%
29/12/2016	31.39	27.29	-1	-1.22	-1	-1.55	-13%

Source: Original work

Figure 15: Analysis of the Z value across different sessions for a player and for the team average



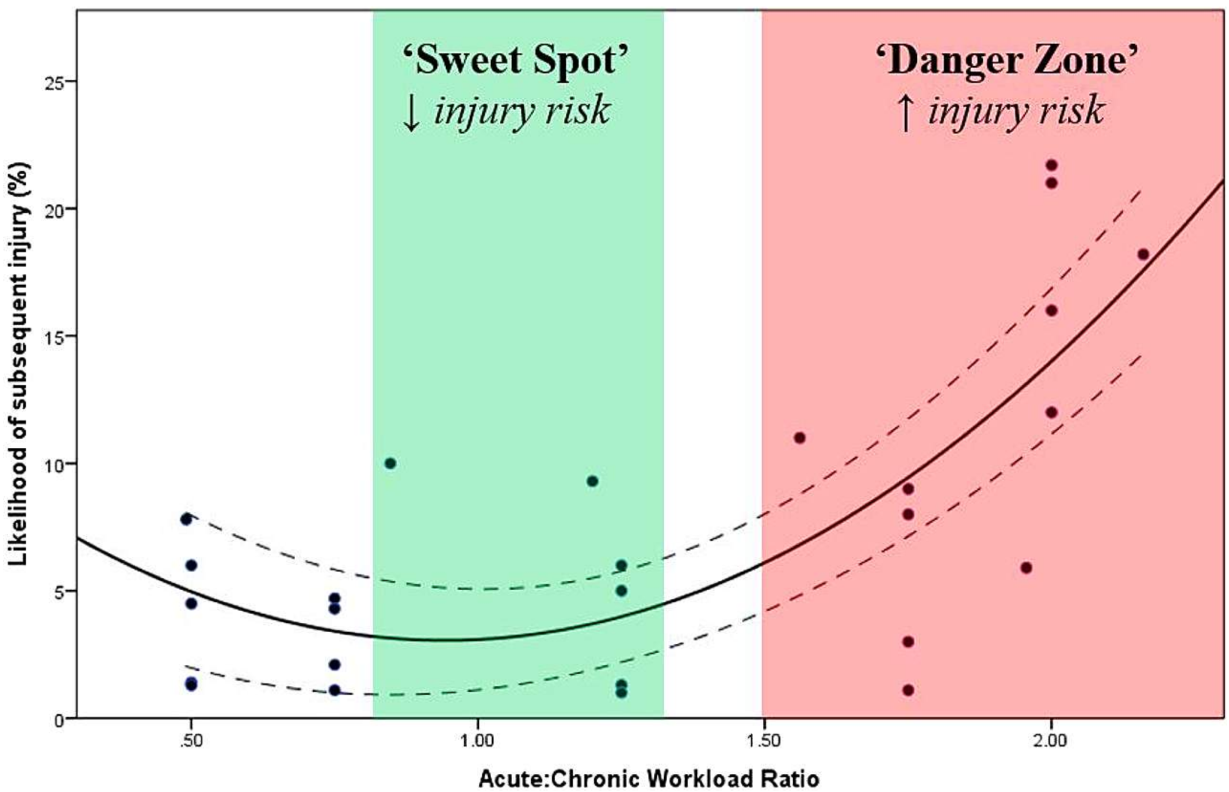
Z VALUE – Player Load



Source: Original work

Other key concepts to consider in the process of minimizing injury risk include the acute load accumulated over a short period and the chronic workload accumulated over a longer period. The relationship between these two concepts, acute and chronic load, through their quotient, provides the acute-chronic load ratio as described in scientific literature (Gabbett, 2016). In this way, we can define a zone based on a certain ratio (Figure 16), distinguishing a lower-risk zone for injury (green zone). On the other hand, exceeding this ratio indicates a zone associated with a higher likelihood of injury (red zone).

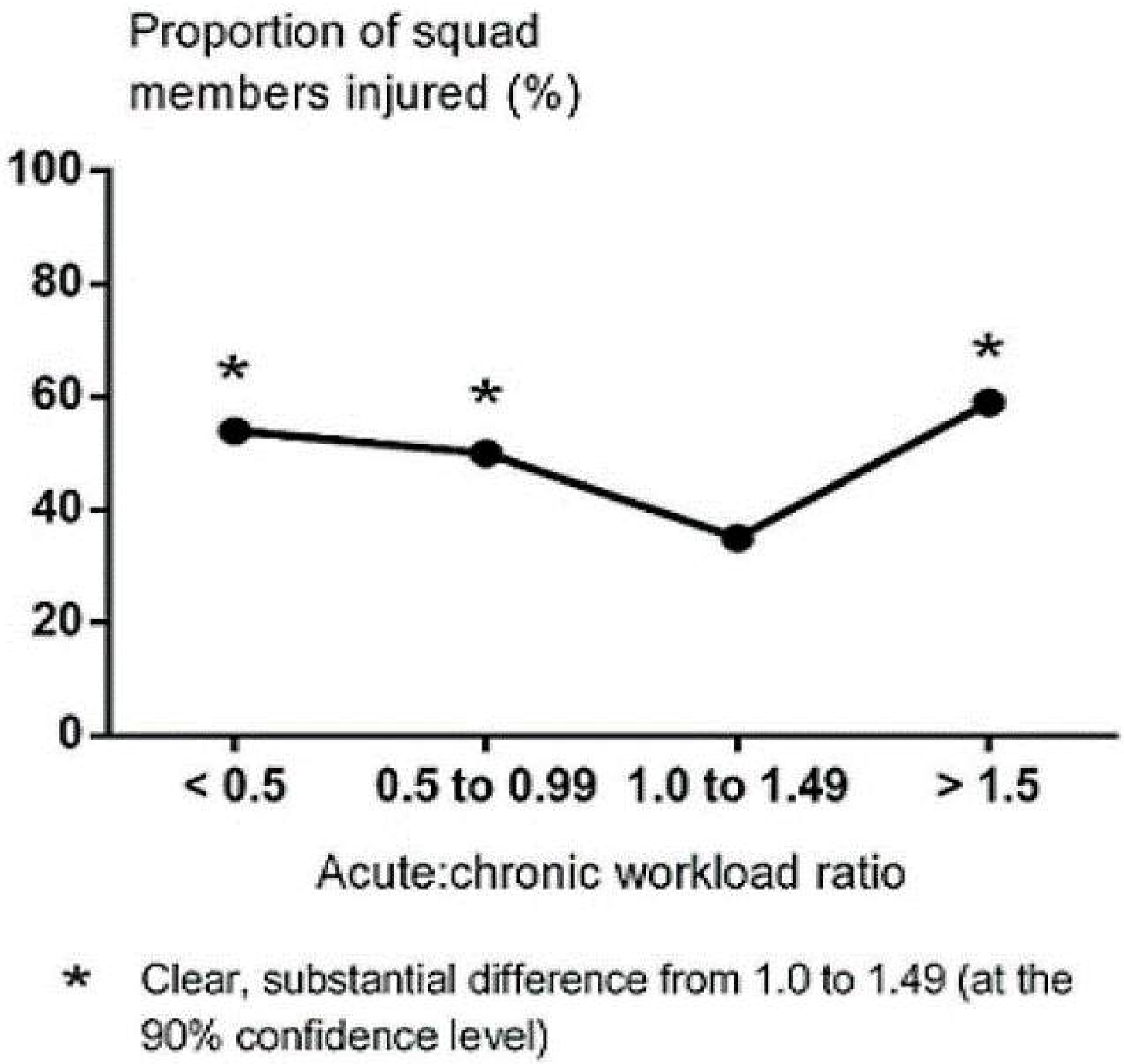
Figure 16: Guide to interpreting and applying acute and chronic load data



Source: Gabbett, 2016, https://goo.su/walG

If we want to analyze this relationship in an indoor sport like basketball, we can consider the publication by Weiss et al. (2017). In this study, the authors reported that the percentage of injured players in the analyzed squad varied as the load ratios changed. This resulted in higher-risk zones for injury compared to an optimal zone, which was established between a ratio of 1 and 1.49.

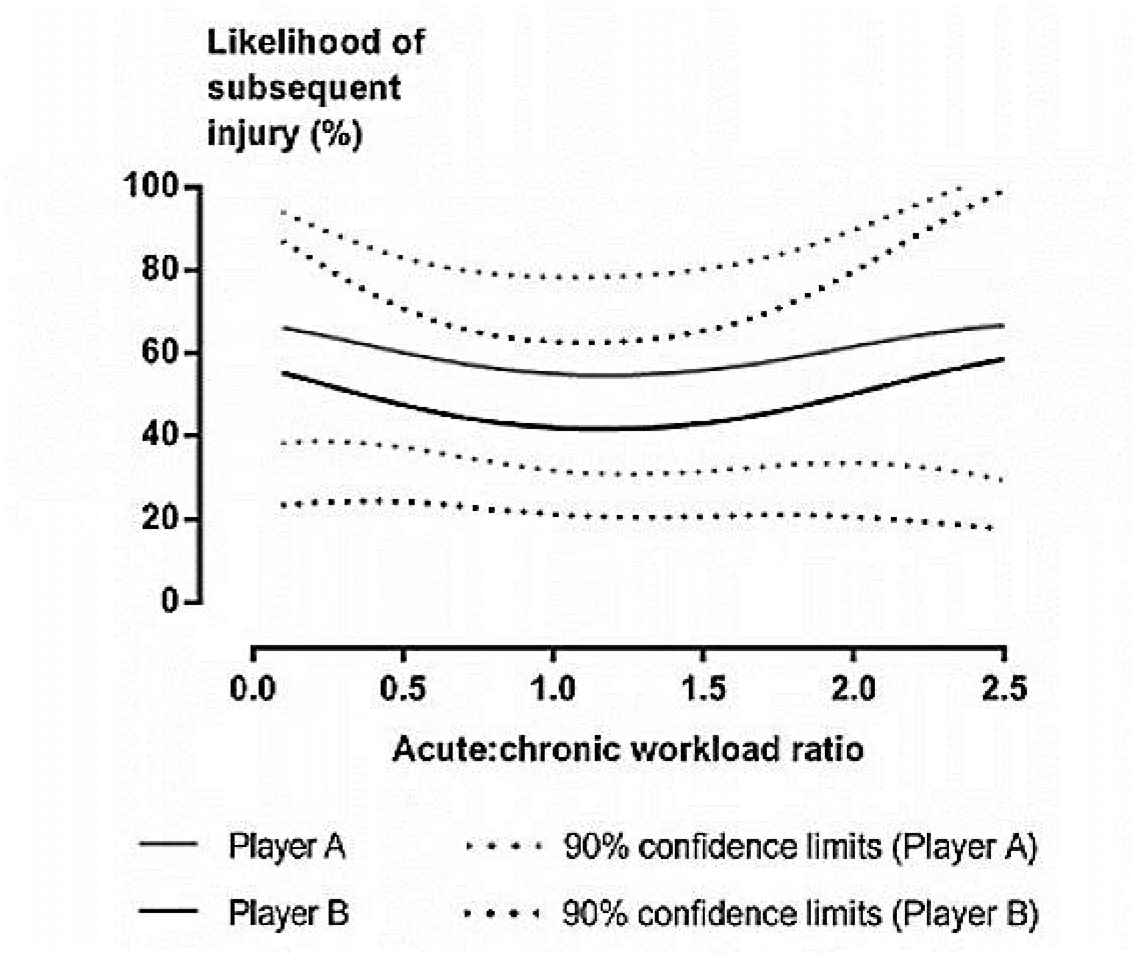
Figure 17: Acute:chronic workload ratio in basketball players



Source: Weiss et al., 2017, https://goo.su/Ktf7oK

Moreover, it is essential to pay close attention to the concept of individualization in this context. The following figure illustrates how two players from the same team show different injury likelihood with the same acute-chronic load ratio (Weiss et al., 2017).

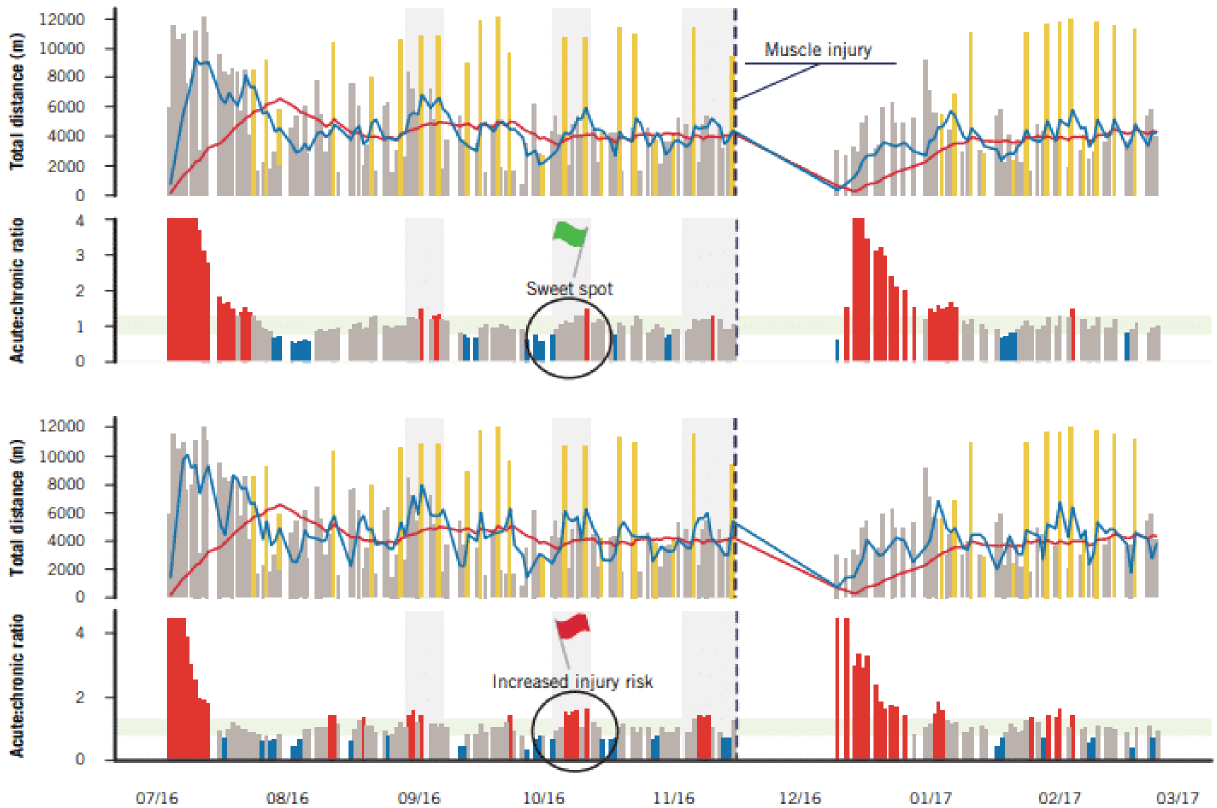
Figure 18: Comparison of acute and chronic load ratios between two basketball players and their injury likelihood percentages



Source: Weiss et al., 2017, https://goo.su/Ktf7oK

Therefore, we can state that the acute-chronic load ratio is also individual. But do the chosen ratios matter? What difference does it make if we set the acute load over four days or a week and the chronic load over three, four, or five weeks? The publication by Lacome et al. (2018) shows that an acute load over four days and a chronic load over eighteen days were more sensitive to predicting higher injury risk than using seven days for acute load and twenty-eight days for chronic load. Consequently, this tool related to acute and chronic load could be used as a new strategy for injury prevention (Figure 19).

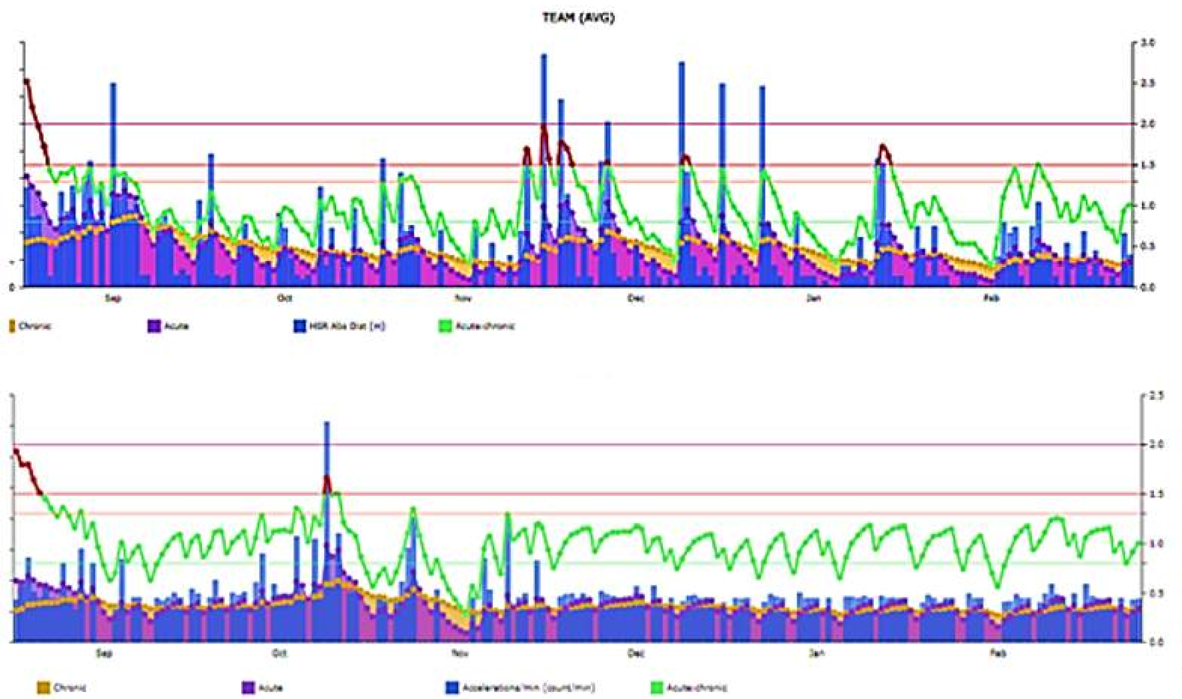
Figure 19: Changes in total distance (in meters) and other variables for an elite athlete over seven months



Source: Lacome et al., 2018, https://goo.su/OEXLm

The next figure shows further examples of how this ratio behaves in a basketball team in terms of distance covered >18 km/h and the number of accelerations over several months of the season.

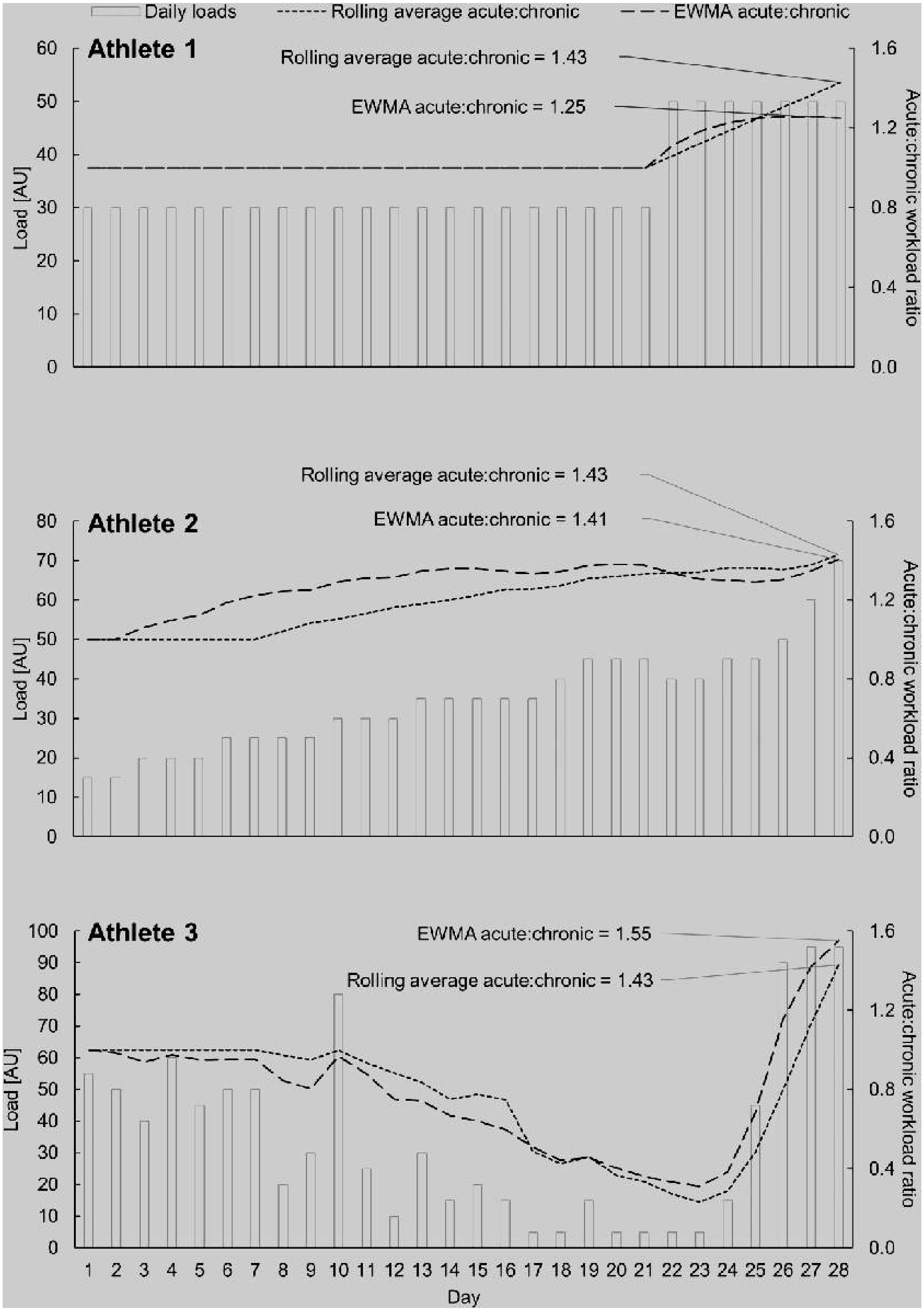
Figure 20: Load control and acute-chronic load ratio in an elite basketball team



Source: Original work

Another aspect to consider regarding this ratio is the mathematical calculation used to obtain it. In this case, the calculation is done using rolling averages or moving averages. However, this is not the only method for calculating the acute-chronic load ratio. It can also be calculated using an exponentially weighted moving average analysis. This second method gives more weight to recent load data, meaning that more recent training sessions are given greater importance. The next figure shows the evolution of the ratio for three athletes, comparing simple average analysis (rolling average) and exponentially weighted moving averages (EWMA) (Williams, West, et al., 2017).

Figure 21: Different acute-chronic workload ratio values produced using exponentially weighted moving averages and simple moving averages



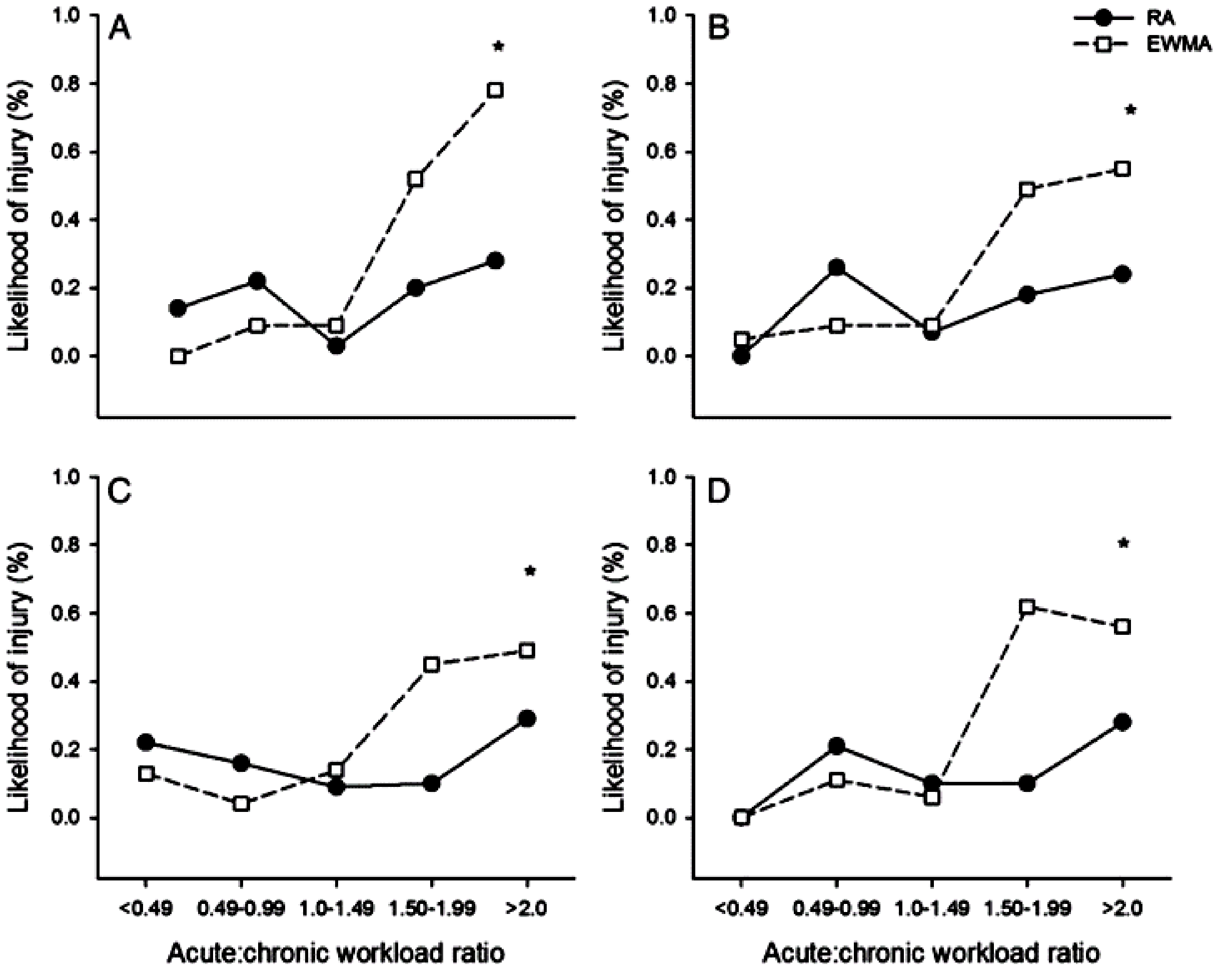
Daily loads
Rolling average acute:chronic
EWMA acute:chronic
Athlete 1
Rolling average acute:chronic = 1.43
EWMA acute:chronic = 1.25
Load [AU]
Acute:chronic workload ratio
Athlete 2
Rolling average acute:chronic = 1.43
EWMA acute:chronic = 1.41
Athlete 3
EWMA acute:chronic = 1.55
Rolling average acute:chronic = 1.43
Day

Source: Williams et al., 2017, https://goo.su/j0mU

The previous figure highlights the difference between the two analyses. Athlete 1 reaches ratio values of 1.25 and 1.43. Athlete 2's data shows ratios of 1.41 and 1.43. Lastly, the workload dynamics for Athlete 3 reveal significant fluctuations between the initial and most recent data analyzed, with the exponential analysis producing a ratio of 1.55, higher than previously recorded. This suggests that the exponentially weighted moving average analysis is more sensitive, especially with high ratios.

Murray et al. (2017) calculated the acute-chronic load ratio across different variables. The study found significant differences between the two methods across the four variables studied, especially when the ratio was high (Figure 22). These data correspond to the preseason, and the same trend was observed during the competitive season.

Figure 22: Likelihood of injury in each ACWR range during preseason



Source: Murray et al., 2017, https://goo.su/YZPkwm

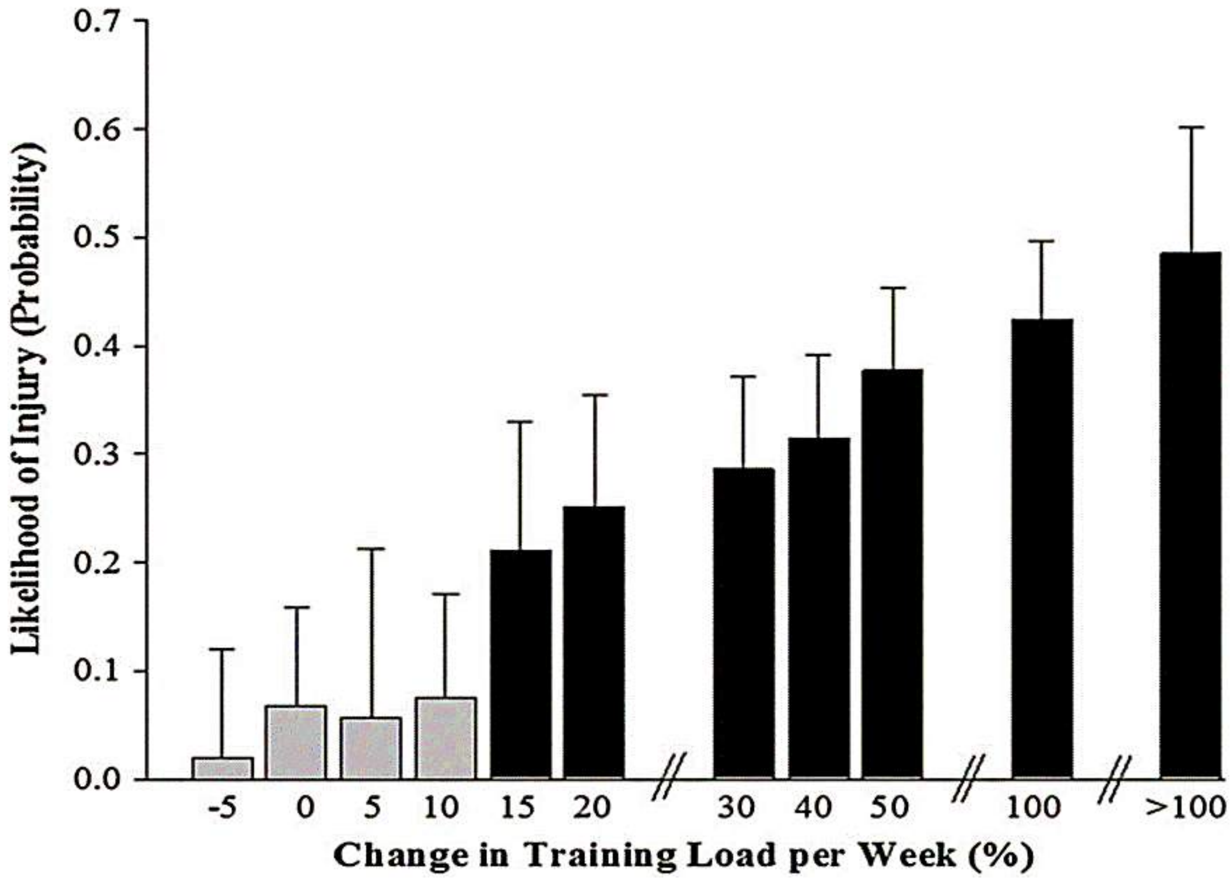
A third method for calculating this ratio is the coupled and uncoupled method. In coupled analysis, for example, over four weeks, the chronic load includes all four weeks, and the acute load only includes the last week. However, in the uncoupled method, the chronic load covers the first three weeks, and the acute load covers the last week, excluding the last week from the chronic load analysis.

In general, we can establish that acute peaks in training or competitive load across multiple variables should be avoided (or controlled) as they are associated with an increased injury risk. The exponentially weighted moving average model appears to be more sensitive in detecting increased injury risk at higher acute-chronic ratios.

These studies suggest that higher chronic loads (within certain limits) allow athletes better preparedness to handle some acute training peaks, partly due to sufficient physical conditioning that enables them to cope better with training and competition demands. Therefore, good physical conditioning (understood as a moderating factor) can help "digest" loads better, thereby reducing injury risk. From our perspective (complexity), it is important to note that these guidelines should be considered but always evaluated and interpreted appropriately and relatively, given the multifactorial nature of injuries.

Another useful tool or concept for minimizing injury risk is monitoring the percentage of load changes between different weeks. For example, we can measure the percentage increase in load between two consecutive microcycles and its relationship to injury probability, following the guidelines in the next figure: greater injury probability corresponds with a higher percentage of load increase (Gabbett, 2016).

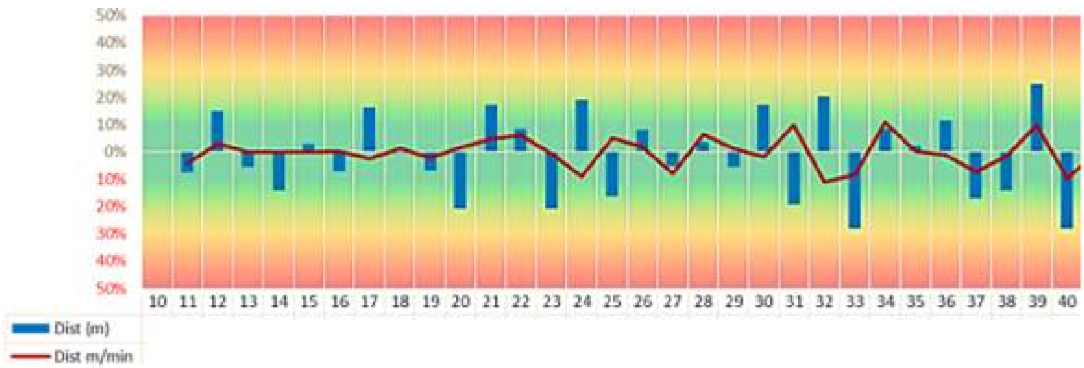
Figure 23: Likelihood of injury with different load changes between two microcycles



Source: Gabbett, 2016, https://goo.su/walG

The next figure shows the application of percentage load changes in the total distance covered by an elite basketball team. Different thresholds are indicated according to the percentage increase and color-coded: green for lower risk, red for higher risk.

Figure 24: Example of percentage load changes between weeks in an elite basketball team



Source: Original work

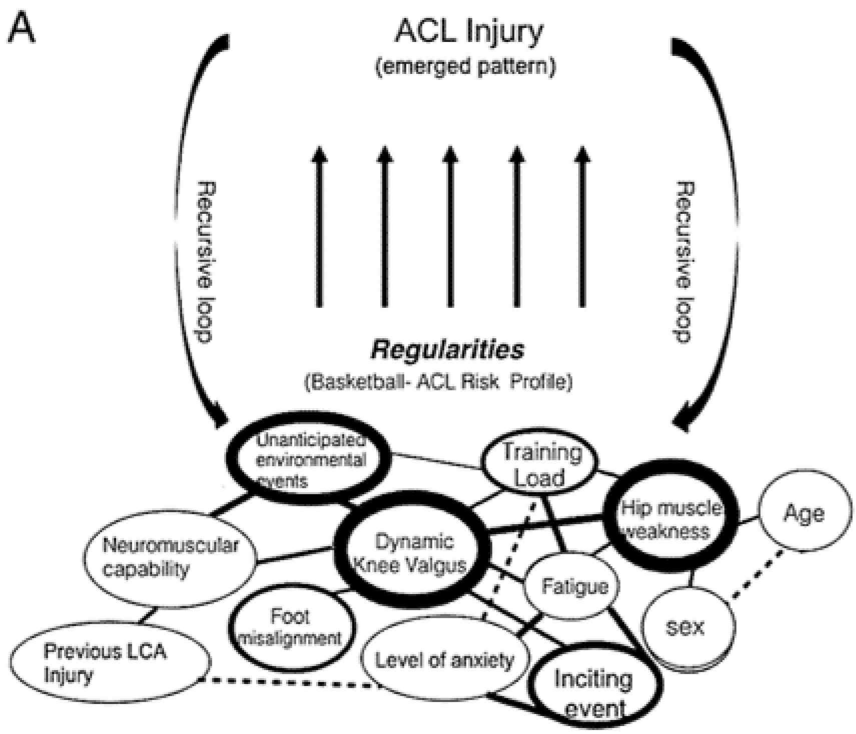
Before concluding this module, we must emphasize the growing role of machine learning or artificial intelligence, which can offer a better understanding and potentially improve the success of injury prevention processes in indoor team sports.

Additionally, although this module has focused primarily on monitoring external load to aid in injury prevention, we must not overlook the internal—and individual—responses (e.g., heart rate and heart rate variability) of each player to training or competitive stimuli.

Moreover, it will be important to approach this issue from the perspective of complex dynamic systems and the complexity paradigm to better understand strategies for injury prevention in indoor team sports. As mentioned in the previous module on performance optimization, a holistic approach to reducing injury risk will support this goal, as proposed in scientific literature (Bittencourt et al., 2016).

The following figure shows how various parameters interact, including training load and fatigue, along with others like strength values, neuromuscular capacity, age, sex, etc.; elements and interactions that influence injury risk (Bittencourt et al., 2016).

Figure 25: Holistic approach to reducing injury risk. Example of ACL injury in basketball



Source: Bittencourt et al., 2016, https://goo.su/kKKCY

Therefore, all the information presented in this module, along with other possible factors and methods related to injury prevention, should be considered in the challenging but achievable goal of reducing injury risk in indoor team sports.

What parameters are proposed by et al., 2016 in their interaction network?

- Strength, range of motion, and speed
- External load and endurance
- Primarily neuromuscular variables
- Training load, fatigue, strength values, neuromuscular capacity, age, sex, etc.

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