

Implementing the Reverse Acute to Chronic Workload Ratio Model to Improve Movement Capacity and Roster Availability: An Example Using Data from the NFL

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ABSTRACT

American football athletes require the development of workload capacity for repeated high-intensity efforts, and successful athletes are adept at accelerating, decelerating, and changing directions. The prescription of appropriate training volume stimulus can be difficult to determine, as there are few guidelines for prescribing sport-specific acceleration, deceleration, and maximum velocity efforts. Preparatory training stimulus should closely match in-game demands, however, practitioners need to avoid excessive workloads and undertraining to mitigate workload progression-related injuries and maximize roster availability. The acute-to-chronic workload ratio (ACWR) approach is based upon the fitness: fatigue ratio, which allows practitioners to monitor workloads. New technology allows for in-game positional tracking and these advancements are accessible to the public. By measuring in-game movement, coaches can quantify key metrics like the number of accelerations and average distance covered. These metrics provide a snapshot of in-game demands and performance requirements. Using a reverse engineering approach, coaches can utilize ACWRs

to calculate predefined targets to ensure athletes are adequately prepared for gameplay. The authors of the present article use the ACWR concept and previously reported in-game data derived from the National Football League to show how to reverse engineer the targeted number of efforts and distances to assist in preparatory pre-season training program design. This approach, which the authors of the present article term the Reverse ACWR Method, can be used to set guidelines for training volumes and workload progressions and provides a systematic, quantitative approach that complements periodization. As such, the Reverse ACWR Method allows practitioners to calculate target sport-specific workloads and training progressions derived from scientific-grounded methodology, which may enhance performance, readiness, and roster availability. Although this paper presents an example of how to use positional in-game data to prescribe American football training workloads, this model can be applied to any sport and team that has access to positional in-game movement data.

Keywords: Workload Progression, peak athletic performance, readiness, injury, American Football,

fitness fatigue model.

INTRODUCTION

The pursuit of peak athletic performance requires a comprehensive assessment of in-game demands, which allows for sport-specific and position-specific training interventions.¹⁹ Improvements in player-tracking data technology and data processing allow for the quantification of movement demands during gameplay such as acceleration, deceleration, and maximum velocities.⁵ In 2015, the National Football League (NFL) launched a league-wide initiative (Next Gen Stats) to use global and local positioning systems (GPS and LPS, respectively) to capture athletes' movement demands.¹⁸ With player-tracking data technology becoming standard practice in high-performance sport, practitioners are now tasked with interpreting this data to create data-driven strength and conditioning programs to optimize on-field performance, enhance readiness, and maximize roster availability. With regard to advancements in the field, very few guidelines or theoretical concepts have been made available to sports scientists on how best to utilize the new technology. One way to harness player tracking data technology is to use the on-field positional data to aid in exercise prescription. Specifically, a practitioner may prescribe workload efforts and distances for accelerations, decelerations, and maximum velocities that closely match in-game demands. Thus, GPS data allows for sport-specific, team-specific, and individual-specific prescriptions. Data derived from wearable technology in sports can be used to generate training volume guidelines and develop the workload capacity required for gameplay.⁴

American football is a dynamic intermittent field-based team sport characterized by repeated high-intensity accelerations, decelerations, changes of direction, and high-velocity sprints.^{17,23} When compared to other team sports, American football players are at an increased risk of injury,²³ with a single-season lower extremity injury risk of 41%.¹⁴ Specifically, hamstring strains were the most common lower extremity injury.¹⁴ Thus, the high-performance team needs to minimize the risk of lower extremity injury to maximize player availability.¹⁸ Although injury occurrence is multifactorial and cannot be predicted, a relationship between American Football players' acute-to-chronic workload ratios (ACWR) and soft tissue injuries has been observed.¹³ Thus, to

potentially reduce the risk of soft tissue injuries, practitioners may consider progressing the volume of preparatory training stimulus at a rate below the observed ACWR associated with increased injury risk. To optimize training stimuli, careful consideration during planning should be given with the end goal in mind. One way to achieve this is by implementing backward design to enhance sport-related injury rehabilitation approaches.⁴ Advancements in movement tracking technologies and the widespread availability of data on in-game demands increase the accessibility to the implementation of backward design. Overall, by reverse engineering ACWR, practitioners can develop a foundation to build training programs. The authors term this systematic approach the Reverse ACWR Method, a tool that systematically prescribes training volumes for accelerations, decelerations, and maximum velocity efforts, which are derived from sport/team/individual specific data that may reduce soft tissue injury risk and maximize roster availability.

Athletic performance is shaped by the interaction of two training after-effects: fitness, or the positive, chronic adaptation resulting from a training stimulus, and fatigue, a negative response that occurs immediately after training.^{1,3} This relationship is known as the fitness-fatigue model.^{1,3} The athlete monitoring cycle that allows for the observation of the fitness fatigue model includes data collection on the workload the athlete performs (external workload; e.g. high-speed yards), the response to the workload (internal workload; e.g. measuring creatine kinase to assess muscle damage), workload tolerance (subjective athlete monitoring, perception), and recovery (readiness to perform another training session).¹⁰ ACWR may be calculated using external workloads derived from player-tracking technology metrics (e.g. player load, high-velocity distance). Once external workload data is collected over time (generally ~1 month), workload progression (ACWR) may be calculated. The coupled traditional ACWR calculates workload by using a ratio that compares the external, recent training load (which relates closely to fatigue and is averaged over 1 week) with the external training load performed over a longer period (which relates to fitness, and is averaged over 1 month).²² Essentially, the coupled traditional ACWR provides insights into the volume of external work done by an athlete in the previous week, compared to the previous month. For example, if an athlete has accumulated 130% more high-velocity distance in the previous week, compared to the previous month, the athlete's

ACWR would equal 1.3. However, it is critical to note that there are different ways in which training load progression can be calculated. In the current paper, the Reverse ACWR was calculated using the coupled ACWR. However, practitioners need to be aware that there are different ways that ACWR can be implemented (i.e., coupled traditional ACWR, uncoupled traditional ACWR, week-to-week ACWR, exponentially weighted moving average ACWR) and each method has its own set of limitations. For instance, applying the exponentially weighted ACWR method requires complex calculations and the week-to-week ACWR may be too rapid of a progression, and not allow enough time for athletes to adapt to training stimuli. The Reverse ACWR Method is meant to provide practitioners with a guideline for exercise prescription, where utilizing the coupled or uncoupled ACWR may be the best approach based on the general applicability of these methods. To learn more about the nuances and implications of different ACWR models, practitioners are directed to Windt and Gabbett.²⁴

Several authors have recommended that as workload increases, injury risk also increases.^{6-8,12} Within the sport of American football, current literature implies that an ACWR greater than 1.6 is associated with a greater proportion of injuries.¹³ In contrast, it can be argued that high ACWR protects against soft tissue injuries (i.e., injury to muscles, tendons, and ligaments) in elite rugby league players.¹¹ Thus, an 'optimal' range of workload progression that protects against soft tissue injury likely exists, which limits exposure to increased workloads exceeding the upper ACWR limit associated with increased injury risk. Within the scope of American Football, the optimal range of workload progression is likely 1.0 to 1.6. However, it is critical to note that this workload progression may not be appropriate for all athletes. Specifically, athletes that are new to a training program, have a young training age, are acclimating to the environment, are injured, or returning to play from injury may not respond well to workload progressions of 1.0 to 1.6. Also, since the Reverse ACWR Method is just a guideline, practitioners would still need to adapt programs on an individual level and in response to acute changes in athlete health (e.g., illness, travel-related fatigue) or performance (e.g., neuromuscular status monitoring) based upon data derived from the athlete monitoring process.

Foundational research on ACWR by Gabbett⁹ suggests that to minimize injury risk, practitioners should aim to maintain the ACWR within the range

of 0.8 to 1.3, which he termed the 'sweet spot'. Initial work on the training-injury paradox considered that a 'danger zone' existed above an ACWR of 1.3, as workload spikes may be associated with injury risk.⁹ However, these initial methods that consider workload spikes alone lack the multifactorial context to determine injury etiology. Thus, practitioners have shifted to believe there is no magic number or threshold, due to the complex interactions of mediators and moderators.²⁵ Rather, ACWR should be contextualized with other information (e.g., readiness) to paint the picture of an athlete's status and injury risk.^{2,15,16,25} As such, a major limitation of the Reverse ACWR Method is that pre-planned exercise volumes and progressions may not appropriately match the needs of the team or individual athlete's response to the training stimulus. Thus, the Reverse ACWR Method is designed to be a complementary tool that does not replace athlete monitoring practices. With this approach, situations will arise when workload spikes are warranted and intentionally prescribed by practitioners. The addition of information such as readiness can provide practitioners with a systematic approach to intentional workload spikes.^{2,15,16,25} For example, if training in the off-season and the athletes' readiness to train is high, a workload spike may be warranted. In contrast, if the athlete's training readiness is low, a workload spike may not be warranted. Thus, it's critical to consider the mediators and moderators involved in the cyclical process of loading the athletes.²⁵ Regardless, monitoring the ACWR provides immense value to contextualizing the training process, and can be reverse-engineered to guide exercise prescription.

The current article aims to provide practitioners with a novel, systematic approach that utilizes the concept of the ACWR to create training programs. By utilizing positional-specific data derived from a season, practitioners can quantify the physical demands of each position, and in turn, calculate the workload capacity that an athlete should achieve during preparatory training. To illustrate this model, player-tracking data collected from 768 regular season games from the National Football League (NFL)¹⁸ and an ACWR of 1.3 was used to systematically create a data-informed 3-month pre-season training program for the NFL. Metrics included in this case study are derived from Sanchez et al.¹⁸ and include total distance, maximum velocity, positional maximum velocity, high-velocity effort, high velocity, distance, acceleration (deceleration) effort, and acceleration (deceleration) distance (see appendix for functional definitions). The following

model is presented to provide a guideline to assist practitioners in creating quantitatively based sport and team-specific preparatory training programs. It is critical to note that periodization is a dynamic construct,²¹ and the present model is not designed to replace the modern workload management and monitoring process but to support practitioners in the early stages of planning by providing training milestones.

UTILIZING THE REVERSE ACWR MODEL FOR PROGRAM DESIGN

The objective of a pre-season preparatory training program is to prepare athletes for in-game demands. Utilizing positional movement demands derived from player tracking data during the competitive season and an ACWR of 1.3 allows for the back calculation of training progression. Since position-specific in-game distances and efforts can be quantified, player tracking data can be further utilized to personalize training programs. Consideration of the standard deviation is important when developing the capacity to perform in-game demands. If the mean metric is used as the objective capacity, it is plausible that athletes may be under-trained to perform in-game demands, since they may be exposed to more than average distances and efforts during gameplay. Thus, practitioners should carefully examine player tracking data when determining training goals. In the current case study, +1 standard deviation of the mean is used as the objective for developing in-game demands, which ensures that athletes develop greater than average movement capacity. For example, the average number of high-velocity efforts and high-velocity distance for NFL wide receivers is 4.6 ± 3.8 efforts and 80.3 ± 85.0 meters, respectively.¹⁸ Thus, the objective of a pre-season preparatory training program for wide receivers would be to achieve the capacity to perform 8.4 ($4.6 + 3.8$) high-velocity efforts and 165.3 m ($80.3 \text{ m} + 85 \text{ m}$) high-velocity meters. These values represent the calculated objective training capacity obtained in the final month of the preparatory training period. The reverse ACWR model can then be applied to calculate the workload requirements of the preceding months, using an ACWR of 1.3. First, determine the total number of months athletes have to train (i.e., 3 months). Then, divide the target outcome (effort, distance) by 1.3 to calculate the target efforts and distance for the previous month (i.e., month 2). Repeat the calculation using the resulting quotient by 1.3 again to determine the training goal of month 1. The calculations are

outlined below:

$$\text{Month 3 High Velocity Effort (Target)} = \text{Mean} + 1 \text{ SD} = 4.6 + 3.8 = 8.4 \text{ Efforts}$$

$$\text{Month 2 High Velocity Efforts} = 8.4 \text{ efforts} / 1.3 = 6.46 \text{ efforts}$$

$$\text{Month 1 High Velocity Efforts} = 6.46 \text{ efforts} / 1.3 = 4.97 \text{ efforts}$$

$$\text{Month 3 High Velocity Distance (m)} = \text{Mean} + 1 \text{ SD} = 80.3 \text{ m} + 85 \text{ m} = 165.3 \text{ m}$$

$$\text{Month 2 High Velocity Distance (m)} = 165.3 \text{ m} / 1.3 = 127.15 \text{ m}$$

$$\text{Month 1 High Velocity Distance (m)} = 127.15 \text{ m} / 1.3 = 97.81 \text{ m}$$

Thus, the Reverse ACWR Model suggests that NFL wide receivers preparing for the competitive season should perform 5, 6, and 8 high-velocity efforts with a respective high-velocity distance of 98, 127, and 165 meters over three months, respectively. Operationalizing this information (Table 2) suggests that athletes should complete five 19.6-meter sprints (98 m/5 efforts), six 21.2-meter sprints (127 m/6 efforts), and eight 20.7-meter sprints (165 m/8 efforts) during months 1, 2, and 3 of preparatory training, respectively. To achieve the 19.6 m sprint in practice, practitioners are directed to utilize an acceleratory build-up phase, with a 20-meter segment for achieving high velocity. This approach is commonly known as “flying 20’s.” The aforementioned process can then be applied to the number of acceleration/deceleration efforts and distances for all positions. Using the positional-specific data that was collected across all teams over 768 regular season games¹⁸, the reverse ACWR model was applied to the number of high-velocity efforts, acceleration and deceleration efforts, high-velocity distance, and acceleration and deceleration distances (Table 1). Table 2 provides practitioners with scientifically derived training programs targeting acceleration, deceleration, and high-velocity efforts.

Table 1. Application of the Reverse Acute to Chronic Workload Ratio Model to Develop Movement Capacity for the Demands of an NFL Game

| Position | Plays | | | Distance (m) | | | High Velocity Efforts | | | High Velocity Distance (m) | | | Acceleration Efforts | | | Acceleration Distance (m) | | | Deceleration Efforts | | | Deceleration Distance (m) | | |
|----------|-------|----|----|--------------|------|------|-----------------------|---|---|----------------------------|-----|-----|----------------------|----|-----|---------------------------|-----|-----|----------------------|----|----|---------------------------|----|----|
| Month | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| CB | 39 | 51 | 66 | 2749 | 3573 | 4645 | 5 | 6 | 8 | 101 | 131 | 170 | 37 | 48 | 62 | 50 | 65 | 85 | 20 | 27 | 35 | 37 | 48 | 63 |
| S | 41 | 53 | 69 | 2808 | 3651 | 4746 | 5 | 6 | 8 | 96 | 125 | 163 | 34 | 44 | 57 | 49 | 64 | 83 | 22 | 28 | 37 | 39 | 51 | 66 |
| LB | 36 | 46 | 60 | 2265 | 2945 | 3828 | 6 | 7 | 9 | 118 | 153 | 200 | 35 | 46 | 60 | 45 | 58 | 76 | 19 | 25 | 32 | 32 | 41 | 53 |
| DL | 31 | 40 | 52 | 1720 | 2236 | 2907 | 3 | 4 | 5 | 55 | 72 | 93 | 18 | 23 | 31 | 23 | 30 | 39 | 7 | 9 | 12 | 10 | 13 | 16 |
| OL | 45 | 58 | 76 | 1830 | 2378 | 3092 | 2 | 2 | 3 | 20 | 26 | 34 | 17 | 22 | 29 | 14 | 18 | 24 | 4 | 5 | 7 | 4 | 5 | 7 |
| QB | 44 | 58 | 75 | 2313 | 3007 | 3909 | 3 | 4 | 5 | 64 | 84 | 109 | 33 | 43 | 56 | 31 | 41 | 53 | 13 | 17 | 22 | 18 | 23 | 30 |
| RB | 24 | 31 | 40 | 1814 | 2358 | 3065 | 4 | 6 | 7 | 97 | 126 | 163 | 32 | 42 | 55 | 42 | 55 | 71 | 13 | 18 | 23 | 24 | 31 | 41 |
| TE | 31 | 40 | 52 | 2249 | 2924 | 3801 | 4 | 5 | 7 | 83 | 107 | 140 | 44 | 58 | 75 | 51 | 66 | 85 | 14 | 18 | 23 | 24 | 31 | 40 |
| WR | 33 | 43 | 56 | 2672 | 3474 | 4516 | 5 | 6 | 8 | 98 | 127 | 165 | 60 | 78 | 101 | 78 | 101 | 131 | 20 | 26 | 34 | 40 | 52 | 68 |

Note: NFL = National Football League, CB = Cornerback, S = Safety, LB = Linebacker, DL = Defensive Line, OL = Offensive Line, QB = Quarterback, RB = Running Back, TE = Tight End, WR = Wide Receiver, The target training capacity (Month 3) is derived from Sanchez et al.¹⁸ calculated as Mean + SD, Month 2 is calculated as month 3/1.3, month 1 is calculated as month 2/1.3.

Table 2. Operationalizing the Reverse Acute to Chronic Workload Ratio Model for Developing Movement Capacity in NFL Athletes

| Position | Plays | | | Distance (m) per play | | | High Velocity Efforts | | | Distance Per High Velocity Effort | | | Acceleration Efforts | | | Distance (m) Per Acceleration | | | Deceleration Efforts | | | Distance (m) per Deceleration | | |
|----------|-------|----|----|-----------------------|----|----|-----------------------|---|---|-----------------------------------|------|------|----------------------|----|-----|-------------------------------|-----|-----|----------------------|----|----|-------------------------------|-----|-----|
| Month | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| CB | 39 | 51 | 66 | 70 | 70 | 70 | 5 | 6 | 8 | 21.0 | 21.0 | 21.0 | 37 | 48 | 62 | 1.4 | 1.4 | 1.4 | 20 | 27 | 35 | 1.8 | 1.8 | 1.8 |
| S | 41 | 53 | 69 | 69 | 69 | 69 | 5 | 6 | 8 | 20.3 | 20.3 | 20.3 | 34 | 44 | 57 | 1.4 | 1.4 | 1.4 | 22 | 28 | 37 | 1.8 | 1.8 | 1.8 |
| LB | 36 | 46 | 60 | 64 | 64 | 64 | 6 | 7 | 9 | 21.2 | 21.2 | 21.2 | 35 | 46 | 60 | 1.3 | 1.3 | 1.3 | 19 | 25 | 32 | 1.7 | 1.7 | 1.7 |
| DL | 31 | 40 | 52 | 56 | 56 | 56 | 3 | 4 | 5 | 19.0 | 19.0 | 19.0 | 18 | 23 | 31 | 1.3 | 1.3 | 1.3 | 7 | 9 | 12 | 1.3 | 1.3 | 1.3 |
| OL | 45 | 58 | 76 | 41 | 41 | 41 | 2 | 2 | 3 | 10.8 | 10.8 | 10.8 | 17 | 22 | 29 | 0.8 | 0.8 | 0.8 | 4 | 5 | 7 | 1.1 | 1.1 | 1.1 |
| QB | 44 | 58 | 75 | 52 | 52 | 52 | 3 | 4 | 5 | 20.2 | 20.2 | 20.2 | 33 | 43 | 56 | 0.9 | 0.9 | 0.9 | 13 | 17 | 22 | 1.4 | 1.4 | 1.4 |
| RB | 24 | 31 | 40 | 77 | 77 | 77 | 4 | 6 | 7 | 22.4 | 22.4 | 22.4 | 32 | 42 | 55 | 1.3 | 1.3 | 1.3 | 13 | 18 | 23 | 1.8 | 1.8 | 1.8 |
| TE | 31 | 40 | 52 | 73 | 73 | 73 | 4 | 5 | 7 | 19.7 | 19.7 | 19.7 | 44 | 58 | 75 | 1.1 | 1.1 | 1.1 | 14 | 18 | 23 | 1.7 | 1.7 | 1.7 |
| WR | 33 | 43 | 56 | 81 | 81 | 81 | 5 | 6 | 8 | 19.7 | 19.7 | 19.7 | 60 | 78 | 101 | 1.3 | 1.3 | 1.3 | 20 | 26 | 34 | 2.0 | 2.0 | 2.0 |

Note: NFL = National Football League, CB = Cornerback, S = Safety, LB = Linebacker, DL = Defensive Line, OL = Offensive Line, QB = Quarterback, RB = Running Back, TE = Tight End, WR = Wide Receiver, The number of efforts is derived from Sanchez et al.¹⁸ calculated as Mean + SD, Month 2 is calculated as month 3/1.3, month 1 is calculated as month 2/1.3. The distance per effort is calculated as Table 1 distance/# of efforts, respectively.

OPERATIONALIZING THE REVERSE ACWR

The Reverse ACWR Model provides a systematic approach to determine pre-season training progressions to achieve position-specific movement capacity. By using scientifically derived workloads, practitioners may limit the risk of workload progression-related injuries, while providing sufficient stimulus to prepare the athlete for competition. With this approach, practitioners can use publicly available player tracking data to determine target monthly workloads to enhance athletic performance, readiness, and roster availability. The Reverse ACWR Model provides practitioners with a general framework, which may serve as the basis of the periodization process. Thus, practitioners may calculate a target cumulative amount of accelerations, decelerations, and high-speed yards to achieve within a training session, and how to progress external workload volume in preparation for the upcoming season. Importantly, the presented external workload targets are representative of the entire training sessions, whereby practitioners must also carefully calculate the training volumes of dynamic warm-ups to ensure appropriate training volume prescription. However, the challenge of this model is determining how to incorporate this knowledge into the design of daily exercise prescriptions. The following section provides a brief example of how the Reverse ACWR Model can be incorporated into training programs, using the data from Table 2.

Practitioners often choose to train specific movements on different days of the week. In line with this structure, the following example will emphasize high velocity, acceleration, and deceleration (change of direction) on days 1, 2, and 3 of weekly training, respectively. For this example, sport-specific training will be performed on day 4. Examples of sport-specific training include 7 on 7 for skilled positions, sled pushes, and technical development for the bigs (i.e., linemen). The following section provides an example program for the safety position. Grouping position groups may be a feasible and simpler option for programs looking to adopt this model with limited resources or coaching staff. To achieve this, practitioners may average player tracking data and group similar positions into training groups.

High-Velocity Training - Day 1

Based on the calculations presented in Table 2, in-game movement demands (+1 SD of mean)

of the safeties included 8 high-velocity efforts for an average of 21 m. Application of the Reverse ACWR Model suggests that to prepare athletes for these demands, the high-velocity training days during months 1, 2, and 3 should include 5, 6, and 8 high-velocity efforts, respectively. Since the target distance is 20 m, flying 20's could be prescribed. Thus, a sample high-velocity training day in the first month may include a dynamic warm-up, potentiation (such as resisted sled sprints), and 5x flying 20s.

Acceleration Training - Day 2

Position-specific data suggests that the safety position in the NFL is exposed to 57 acceleration efforts above 3.5 m/s^{-2} with an average distance of 1.4 meters. For context, a maximum acceleration effort would be higher than 3.5 m/s^{-2} in this population. Within the scope of gameplay, these acceleration efforts are coupled with deceleration efforts. However, within the context of this example, acceleration efforts and deceleration efforts will be considered separate entities. Application of the Reverse ACWR Model suggests that to prepare athletes for these demands, the acceleration training day during months 1, 2, and 3 should include 34, 44, and 57 acceleration efforts, respectively. To achieve this in the first month, the acceleration training day may include a dynamic warm-up, agility ladder training with a 1.4-m acceleration after the ladder movement²⁰, and multidirectional accelerations from both passive and active starts. The combination of the post-ladder acceleration and multidirectional accelerations should equal the target efforts for the month.

Deceleration Training - Day 3

Positional movement demands of the safeties during NFL games require 37 deceleration efforts below 3.5 m/s^{-2} with an average distance of 1.8 m. Application of the Reverse ACWR Model suggests that to prepare athletes for these demands, the deceleration training day during months 1, 2, and 3 should include 22, 28, and 37 deceleration efforts, respectively. Practitioners may achieve these movement demands in training by using change of direction drills, such as the pro-agility shuttle (5 m-10 and m-5 m in opposite directions). Since there are two change of direction efforts in the pro-agility shuttle, there are two deceleration efforts. Thus, performing the pro-agility shuttle in each direction would count as four deceleration efforts. Using this approach, practitioners may systematically prescribe deceleration-based training with drills

that allow for ~1.8-m decelerations.

Sport-Specific Training - Day 4

The average play count for an NFL Safety is 69, with an average total movement distance of 69 m per play. Due to the dynamic intermittent nature of American football, players will not be in a state of constant maximal effort for 69 m. After each play, players will engage in a low-intensity effort to return to a similar position on the field, jog to the huddle, or their starting position. Safeties participate in sport-specific training such as 7 on 7, which replicates these low-intensity distance demands while players jog back to their starting positions after each play. Application of the Reverse ACWR Model suggests that to prepare athletes for in-game demands, the sport-specific training day during months 1, 2, and 3 should include 41, 53, and 69 plays, respectively.

The limitations of the Reverse ACWR Model are important to recognize. First and foremost, injury etiology is multifactorial and this approach will not ensure injury prevention. Specifically, this model is designed to assist in mitigating the risk of workload progression-related injuries (e.g. soft tissue). Also, the Reverse ACWR Model is designed to provide practitioners with a systematic framework for developing movement volume capacities and does not ensure that performance metrics (e.g. maximum velocity) will improve. Several types of ACWR exist, which indicates the necessity for careful examination of how the ACWR was calculated, before reverse engineering training volumes and progressions. Specific to American Football, which is a collision-based intermittent dynamic sport, more work is needed to understand the appropriate progression and preparatory training stimuli to decrease collision-based injuries (e.g. acromioclavicular joint). This method assumes that practitioners have access to relevant position-specific movement demand data collected through one or many competitive seasons. When these resources are not available, practitioners must be very specific in the selected data for target training volumes, ensuring that the level of play, training age, sex, and other key determinants are as close as possible to the training demographic. Lastly, GPS data by nature is predominantly linear, requiring practitioners to make assumptions that decelerations likely also include change of direction. Thus, in the present model, we use deceleration efforts as a proxy to assist in the change of direction program design and prescription, as well as linear deceleration.

CONCLUSION

The availability of in-game player tracking data is a game changer for the design of sport and position-specific training programs. Combining this data with the Reverse ACWR Model provides a foundational framework for the periodization process, that allows practitioners to systematically quantify workload progressions to develop the capacity to perform in-game demands. Here, the authors present an example utilizing NFL data, however, this model can be applied to any sport and team that has the capability of measuring in-game movement demands. The Reverse ACWR Model allows for the calculation of appropriate training volumes, which otherwise can be difficult to determine. By providing practitioners with volume-based guidelines designed to improve movement capacity and minimize workload progression-related injuries, the Reverse ACWR Model can be used as a tool for practitioners to utilize during the planning component of the periodization process.

CONFLICTS OF INTEREST

The author records no conflicts of interest.

FUNDING DETAILS

No funding was received for this project.

ETHICAL APPROVAL

Ethics for this study were approved in line with the University of Hawaii's Review Board.

DATES OF REFERENCE

Submission - 26/07/2024

Acceptance - 18/09/2024

Publication - 10/01/2025

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APPENDIX

Appendix 1. Functional Definitions of External Workload Metrics¹⁹

| External Workload Metric | Functional Definition |
|--------------------------------------|--|
| Total Distance | Meters traveled during a game while the player is on-field |
| Maximum Velocity | Peak velocity achieved for a player while on-field |
| Positional Maximum Velocity | Maximum velocity per position used to calculate high-velocity thresholds. Calculated as the 75th percentile of all maximum velocities from player–games. |
| High-Velocity Efforts | Count of times a player reaches a velocity above 85% of his positional maximum velocity and sustains that velocity for at least |
| 0.5 s | |
| High-Velocity Distance | Total distance traveled by a player at velocities above 85% of his positional maximum velocity |
| Acceleration (Deceleration) Effort | Count of times a player accelerates above 3.5 ms^{-2} (decelerates below -3.5 ms^{-2}) and sustains that acceleration for 0.3 s |
| Acceleration (Deceleration) Distance | Total distance traveled by a player while accelerating above 3.5 ms^{-2} (decelerating below -3.5 ms^{-2}) |