Detecting injury risk factors with algorithmic models in elite women's pathway cricket

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Abstract

This exploratory retrospective cohort analysis aimed to explore how algorithmic models may be able to identify important risk factors that may otherwise not have been apparent. Their association with injury was then assessed with more conventional data models. Participants were players registered on the England and Wales Cricket Board women's international development pathway (*n* = 17) from April 2018 to August 2019 aged between 14-23 years (mean 18.2 ± 1.9) at the start of the study period. Two supervised learning techniques (a decision tree and random forest with traditional and conditional algorithms) and generalised linear mixed effect models explored associations between risk factors and injury. The supervised learning models did not predict injury (decision tree and random forest area under the curve [AUC] of 0.66 and 0.72 for conditional algorithms) but did identify important risk factors. The best-fitting generalised linear mixed effect model for predicting injury (Akaike Information Criteria [AIC] = 843.94, conditional r-squared = 0.58) contained smoothed differential 7-day load ($P < 0.001$), average broad jump scores ($P < 0.001$) and 20 m speed ($P < 0.001$). Algorithmic models identified novel injury risk factors in this population, which can guide practice and future confirmatory studies can now investigate.

Practical implications

- Empirical evidence for the use of a load measure involving session rating of perceived exertion, which had a stronger association with injury than overs bowled.
- Guidance for sport practitioners on what physical tests may be most worthwhile for injury risk screening in this context.
- Demonstration of alternative application in using algorithmic models to identify injury risk factors as opposed to conventional use of such models to predict injuries.

Introduction

Injuries occur because of complex and non-linear interactions amongst multiple variables. However, even with the use of more sophisticated statistical approaches, it can be difficult to fully capture their dynamic and multiplex nature [1]. It has been proposed algorithmic modelling may provide a more accurate and informative alternative to conventional data model approaches [2]. Data model approaches include traditional regression models, whereby the values of the parameters in question are estimated from the data, and the model is then used for information and/or prediction [2]. Conversely, algorithmic models treat the data mechanism as unknown. This includes supervised learning techniques, which are a type of machine learning methodology that can account for the kind multifaceted interactions found between injury risk factors [3]. Commonly used supervised learning techniques are decision tree and random forest classifiers.

Initial studies attempting to predict sporting injuries with supervised learning techniques have had mixed success. A study in Australian football demonstrated similar predictive power to a random coin toss, with a poor area under the receiver operating characteristic curve median range of 0.52 to 0.58 [4]. A model developed in Spanish soccer demonstrated better predictive power (area under the receiver operating characteristic curve [AUC] = 0.84), although this study had a smaller sample and the authors acknowledged the complexity of the final model involving 10 different classifiers and 66 predictors [5]. Another model with reasonable predictive power (AUC score of 0.88) was developed in professional soccer, with only three variables contributing to the best performing classifier, out of 42 predictor variables included in the models [6]. Given their previous limited success in predicting injury, the value of such approaches might not necessarily be in the more conventional application of predicting injuries, but as a useful way to explore and extract the most important risk factors associated with injury [7]. It has been suggested conventional statistical approaches can be used to inform algorithmic models [1], but the reverse could also be true, with the best solution (for a given research question) sometimes being a combination of approaches [2].

The aim of the present study was to conduct an exploratory analysis to investigate how algorithmic models may be able to identify important risk factors for injury in an international women's cricket development pathway in England and Wales, which may not otherwise have been apparent. More conventional data models were then used to assess the association between these risk factors and injury.

Methods

Setting

This prospective cohort study encompassed 17 months (1st April 2018 – 31st August 2019 inclusive) of the ECB women's international development pathway. This pathway is to develop players who have the potential to compete at an international level but are not yet part of the senior professional international team. It is made up of the England Women's Academy and Senior Academy squads. At the time of data collection there was no fixed playing schedule, but competitive matches were irregularly scheduled each year.

Participants

Players registered on the England and Wales Cricket Board (ECB) women's international development pathway were included in the study (n = 17). Registered players were contracted to the pathway on a part-time basis and were aged between 14-23 years (mean 18.2 ± 1.9) at the start of the study period. Of the group, 29% (n = 5) were classified as pace bowlers (an approach to bowling where the ball is delivered at high speeds), 59% (n = 10) spin bowlers (a technique where the ball is delivered slower than a pace bowler, with the potential to change direction when it hits the ground) and 12% (n = 2) all-rounders (who are proficient at both bowling and batting), with all participants batting when required.

Procedures

This study meets the ethical standards of this journal [8], with approval initially obtained from the University of Bath Research Ethics Approval Committee for Health (REACH) [reference: EP 18/19 095]. All players provided informed written consent (assent and parental consent was also obtained for players under 18 years) for their data to be routinely collected and analysed by ECB and a University research partner.

Study outcomes

For this study, ECB medical staff working with the international pathway defined and recorded any injury that resulted in a player being either available with or without necessary modified activity (non-time loss) or completely unavailable (time-loss) for match selection during the year, regardless of whether a match was scheduled. Medical illnesses were also recorded but not included, as such complaints were deemed independent to injury risk factors. The availability status of each player was collected every contact day (e.g. match, camp, tour or training day) using an Excel spreadsheet. Categorisation included new and recurrent complaints, with each complaint requiring the squad physiotherapist to record body region and diagnosis based on the Orchard Sports Injury Classification System Version 10 [9].

A range of physical profiling measures (descriptions provided in supplementary Table 1) were collected by ECB Science & Medicine staff each year in January, June and October. Daily load data was collected throughout the year using a standardised data collection form completed by the player, strength & conditioning coach, and/or physiotherapist. Load data included a measure of the number of balls bowled (with six balls equating to one 'over') for both matches and training, and a total load calculated by the duration (in minutes) of each training session with a session rating of perceived exertion (sRPE) from 0 to 10 (0 being 'rest' and 10 being 'my hardest ever effort') [10]. Training sessions for this total load included strength & conditioning (speed, strength, robustness, endurance, mobility) and skill (batting, bowling and throwing/fielding) sessions.

Several load monitoring measures were assessed for this study. A differential load measure (both linear and polynomial) originally proposed by Lazarus et al [11] and shown to be a potential viable alternative to the often used 'acute:chronic workload ratio' (ACWR) in male fast bowlers [12], was calculated. The ACWR has previously been used in cricket injury research to explore the association between injury risk and load [13], but there is poor evidence to support ACWR as a risk factor for injury [14-15], and a number of methodological concerns with this metric have been raised [16]. Differential load represents the smoothed rate of change in load from one week to the next, with a 7 day time constant used, as this was the best performing differential load time window when a variety (time constants of 7, 14, 21 and

28 days) were tested previously [12]. A 7-day exponentially-weighted moving average (EWMA) of just bowling overs was also calculated (for comparison against the total load measure), along with a measure of the number of consecutive days bowled.

Statistical analyses

Descriptive statistics

Injury data was summarised in Microsoft Excel with descriptive statistics based on means and standard deviations.

Supervised learning techniques

All estimations were made using R (version 3.6.0, R Foundation for Statistical Computing, Vienna, Austria). Outliers over 3 standard deviations (SD) higher on load measures and any physical profiling factors that had over 30% missing data (deemed as a substantial cut-off due to the model omitting all accompanying data for any missing values, which would greatly reduce the overall number of data points in the model) were removed. Two different supervised learning techniques were conducted using the *Rattle* package [17]: a decision tree and random forest. The package includes ten-fold cross validation, which was used for model parameter optimisation on randomly selected training data (comprising 70% of the total). The model was validated using the remaining testing (30%) data. Model performance was measured by the probability a positive case will be ranked higher than a negative case, visualised as a receiver operator characteristic (ROC) curve, with the degree of separability represented by a value known as area under the curve (AUC). The higher the AUC (between 0 and 1) the better predictive power of the model, with 0.5 indicating prediction is no better than random chance [4] and 1 representing perfect prediction [18].

All continuous data was standardised before building the predictive models by converting to within-individual z scores for the load measures and within-team z-scores for the physical profiling factors. Standardisation is common practice when using machine learning techniques as models can be sensitive to different ranges and magnitudes of predictor variables [19]. Players were assigned a numerical code for identification purposes, which was labelled as such in the models, so it was not included as an input variable.

As traditional algorithms used in decision trees and random forest can also favour correlated predictor variables, both techniques were also run with conditional algorithms that have been suggested to provide a fairer means of comparison to help identify truly relevant predictor variables [20]. The AUC of both traditional and conditional algorithms was reported to evaluate model performance. The aim of the study, however, was not to evaluate the predictive power of each model, but instead identify which risk factors consistently made meaningful contributions across the different models.

Generalised liner mixed effect models

The important injury risk factors identified by the supervised learning techniques, were included in multivariate analyses to identify the overall best-fitting model, as determined by the GLMERSelect stepwise selection procedure [21]. Polynomial and interaction terms were evaluated in this process. Separate generalised linear mixed-effect models (GLMM) were used to model the association between the risk factors and injury risk, undertaken using the *lmer* package [22]. Fixed effects in the model were the intercept and load/profiling measure, with the square of the measure included to estimate the mean quadratic, where appropriate. A random effect was included for the interaction of player identity and the respective load measure. The different models were evaluated and compared using conditional r-squared and the Akaike Information Criterion (AIC) provided by the *performance* package [23].

Results

Descriptive statistics

A total of 6,027 player days were included in the study (mean 355 ± 153 days/player). There were 50 injuries recorded for 16 (94%) players, with 1 (6%) remaining injury free. The 50 injuries consisted of 26 (52%) injuries to the upper extremity and 24 (48%) to the lower extremity.

Supervised learning techniques

Decision tree

A traditional algorithm decision tree with a minimum of 20 splits and 7 variables allowed in any leaf, with a maximum depth of 30, including 1,064 observations from 47 input variables, found 2 rules for predicting injury:

1. A player with a broad jump average z-score < -0.71, with a smoothed differential 7-day load z score < -0.71.
2. A player with a with a broad jump average z-score < -0.71, with a smoothed differential 7-day load z score >= -0.71 and a smoothed differential 7-day load z score >= 2.20

A conditional algorithm decision tree also found 2 (but different) rules for predicting injury:

1. A broad jump average z-score <= -0.81
2. A broad jump average z-score > -0.81 and left arm rotator cuff external rotation strength z score > -0.95.

The decision tree had poor overall probability of predicting injury with the training data (56% for each rule). When evaluating the model performance on the testing data set (30% of the data randomly split) the conditional algorithm (AUC of 0.66) performed slightly better (but still poorly) than the traditional algorithm (AUC of 0.57).

Random Forest

The best performing random forest model had 100 trees with 8 variables tried at each split and included 1,064 observations (null values were excluded) from 47 input variables. When evaluating model performance on the testing data set, the conditional algorithm (AUC of 0.72) performed marginally better (but still poorly) than the traditional algorithm (0.65), mostly in correctly classifying instances of no injury, which was the majority of the dataset.

The five variables that scored highest for importance from the traditional and conditional algorithm random forests are shown in Table 1 and Figure 1, respectively. Smoothed differential 7-day load and broad jump average were also found to be important variables in both random forest types, with right shoulder total range of motion and right shoulder rotator cuff internal rotation strength also featuring in the traditional and conditional random forests, respectively.

Table 1: Five variables that scored highest for importance from the traditional algorithm random forest

Factor	No injury	Injury	MeanDecreaseGini	MeanDecreaseAccuracy
Differential 7-day (poly)	8.52	7.61	7.08	9.90
Broad jump average	1.85	3.27	1.59	2.89
Right shoulder total ROM	2.18	2.24	0.39	2.58
Left leg single leg hop	1.55	2.45	0.20	2.06
20 m speed	1.69	2.53	0.68	1.88

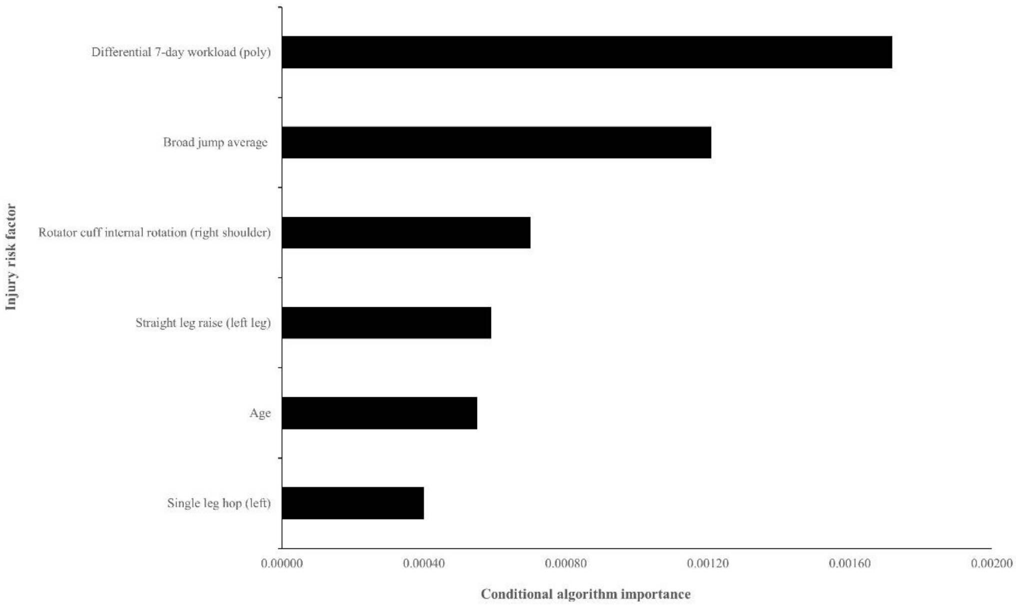

Figure 1: Five variables that scored highest for importance from the conditional algorithm random forest

Generalised linear mixed effect models

A model (AIC = 843.94, conditional r-squared = 0.58) containing polynomial smoothed differential 7-day load ($P < 0.001$), average broad jump scores ($P < 0.001$) and 20 m speed ($P < 0.001$) provided the best overall model fit.

A change in within-athlete smoothed differential 7-day load above or below 2 SDs from the mean was associated with increased injury risk, with a smaller effect for lower average broad jump scores and slower 20 m speed (fig 2).

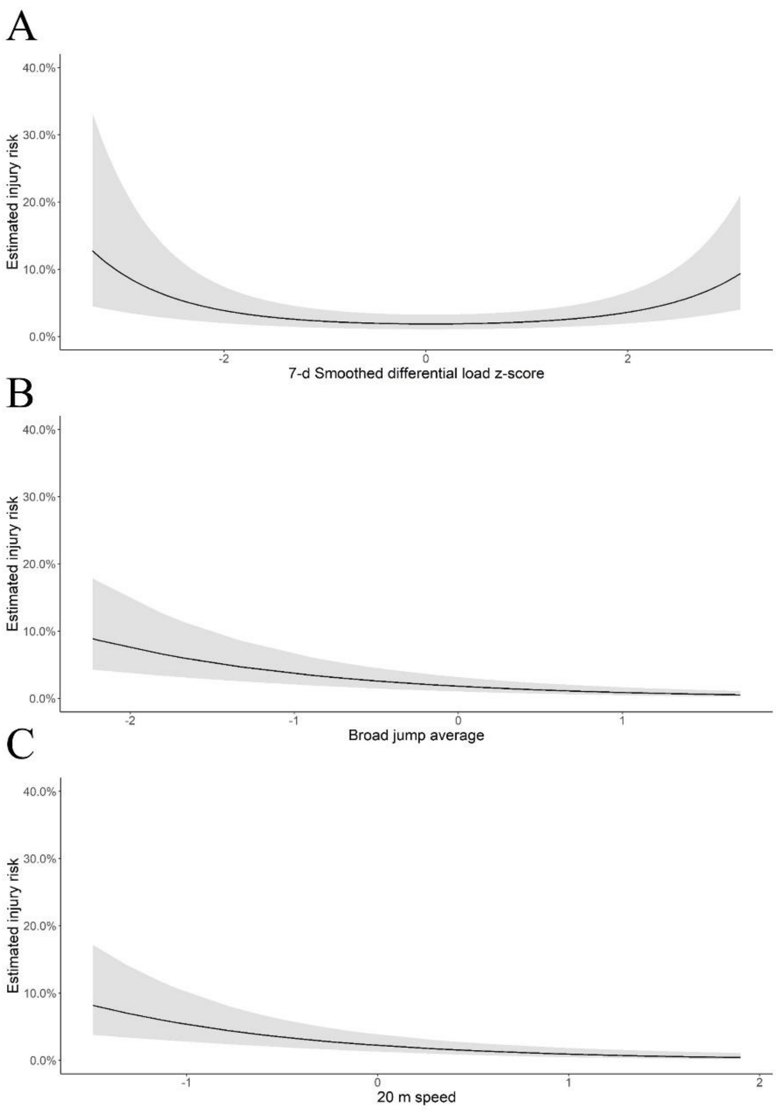

Figure 2: Associations between injury risk and predictor variables: A) smoothed differential load; B) broad jump performance and C) 20 m speed

Discussion

This is the first study to explore the application of algorithmic models to identify key risk factors in cricket that may otherwise not have been apparent, then assess their association (using data models) with injury risk. The application of these techniques did find novel risk factors. The best performing predictive model included 7-day differential load, average broad jump score and 20 m speed that explained 58% of variance in injury.

The smoothed 7-day differential load had a polynomial relationship with injury risk, with an increased injury risk associated with a 2 to 4 standard deviation increase above or below a player's mean. This finding lends support to previous research that highlighted the need to pay special attention to bowlers returning from a period of unloading [12]. These findings also demonstrated that the sRPE load measure had a stronger association with injury (through its greater contribution to the models) than the number of overs bowled. The sRPE load measure is likely to better capture the 'total load' undertaken by players (i.e., beyond bowling workloads), which may explain its greater sensitivity to injury risk [13]. Data from this measure may be enriched further by combining it with Global Positioning System (GPS) data, which has been effectively used in cricket to highlight the differing physical demands between playing position [24] and match formats [25].

The importance of broad jump performance and 20 m speed as injury risk factors emerged from the findings of this study, albeit with smaller effects on injury risk than differential load. This insight may help practitioners prioritise risk factors in this this setting. The importance placed on lower extremity factors perhaps reflects the consistently high incidence of thigh injuries in cricket injury surveillance research [26-28]. The broad jump test assesses lower limb explosive power [29] and may be a useful practical measure for practitioners in this context. In a sample of collegiate women soccer players, 10 and 30 m speed were shown to be (one of multiple factors) negatively correlated with lower body strength [30]. Well-developed lower body strength, along with repeated-sprint ability and speed, have been shown to be associated with better tolerance to higher workloads and reduced risk of injury in a sample of amateur hurling athletes [31]. As these previous studies include collegiate and amateur samples, it would be worthwhile for future research to ascertain whether similar associations are found with elite players where there would be arguably less variation in lower body strength as there might be with amateur samples. The associations found in this study were arrived at through a statistical process and provides a framework on how such techniques can be applied in other samples to identify novel risk factors pertinent to a given context.

The aim of the study was to explore which factors may be consistently associated with injury risk and not to use machine learning to necessarily predict injuries, but to assess the predictive performance of the models. Similar to previous research, the supervised learning models in this study were unable to predict injuries with an AUC range of 0.57 – 0.65 for the traditional algorithm, compared to a median AUC range of 0.52 – 0.58 found in previous research that aimed to predict hamstring strain injuries in Australian football [4]. It is worth noting for both supervised learning techniques used in this study, the conditional algorithm performed marginally better (but still poorly) than the traditional algorithm (AUC range of 0.66 – 0.72) and may be more appropriate for use in this context with a larger data set. Also, in line with previous research, of all the factors included in the models, only a limited number contributed to the best performing models [6]. The exact nature of the potential association between broad jump scores, 20 m speed and injury warrants exploration in future research. Further validation on the importance of these factors is also needed, with low model sensitivity and specificity, reflected by the poor AUC range. While researchers continue to explore how these supervised learning techniques can be best utilised in sports injury, such predictive models alone, do not currently have practical value for injury management practitioners.

The extent to which the findings of the current study can be generalised to other cricket playing populations is a limitation of the current study. Given the nature of data collection and the algorithmic models used, these findings may only be relevant to the sample of the study and other contexts that share similar characteristics. Being part of the international development pathway, the average player age for this sample can be younger than a sample of more senior players. This may affect the predictor variables selected by the models and injury types that could be specific to this context. Other limitations that need to be considered are the inclusion of both time loss and non-time loss injuries. Including just time loss injuries may improve the accuracy of the models to identify the factors that are most pertinent in the development of more severe injuries. However, there is a lack of knowledge about the extent to which non-time loss injuries may interact or potentially contribute to the development of a subsequent time loss injury and only including those injuries that resulted in time loss may not fully capture the true burden of injuries [32]. Consequently, all injuries were included in this analysis, with the aim of providing as much data as possible for the algorithmic models. Furthermore, even though data was collected over a reasonable time period, there is still only a small number of players and injuries included in the sample with complete data for every measure not available for every player. This context is needed when considering the results and some degree of caution is recommended when interpreting the outcomes with the potential for model overfitting. A considerable limitation when using supervised learning techniques with injury risk is the amount of data required for these methodologies to make meaningful inferences [33].

Conclusion

Overall, this study aimed to explore how algorithmic models might help identify important injury risk factors that may not otherwise have been apparent, with their association with injury then assessed with more conventional data models. The methodology provides a framework for these techniques to be applied to explore uncovering novel injury risk factors in other settings, with the findings having potential to inform and guide practice, by identifying the most pertinent factors and associations. In this sample of elite female cricketers, both high and low values of differential load were found to be associated with injury risk. Average broad jump scores and 20 m speed also contributed to the predictive models and so future research should aim to validate the importance of these factors and better understand their exact association with injury risk.

Conflict of Interest

The authors declare no conflict of interest.

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Supplementary table

Supplementary Table 1: Physical profiling measure descriptions

Physical Profiling Measure	Description
Height	Subjects measured in centimetres (cm) with shoes removed, using the stretch stature method. Stature is the maximum distance from the floor to the vertex (highest point on the skull when head is held in Frankfort plane) of the head.
Weight	Subjects weighed in kilograms (kg) with any excess clothing removed. Weight recorded to nearest 0.1 kg.
Body Mass	Assessments conduced in accordance with the International Society for the Advancement of Kinanthropometry (ISAK) protocols.
Sum of 8 skinfolds	A skinfold calliper is used to assess skinfold thickness in millimetres. Measurements taken for biceps, triceps, sub-scapular, iliac crest, supra-spinal, abdominal, front thigh and medial calf.
Total shoulder range of motion	Subject in crook lying with no pillow under their head. Shoulder is abducted to 90 degrees with deltoid insertion at edge of the plinth. Elbow flexed to 90 degrees and forearm in mid prone. The tester passively rotates the shoulder into internal and external rotation until a firm end point is reached or the scapula or head of humerus begins to move. Angle of internal and external rotation is recorded. If the subject reports any pain the test is stopped at the onset of pain.
Combined elevation	Subject is in prone with their forehead on the floor, arms outstretched overhead with the hands clasped together and the elbow straight and thumbs pointing skywards. The subject is instructed to lift their arms as high as possible off the floor in a smooth movement whilst keeping elbows straight and forehead on the floor. The tester records the point the ulna styloid reaches to the nearest 0.5cm. Test is repeated two times and the best score recorded.
Dorsiflexion lunge test	Subjects are instructed to lunge forward until their knee touches the wall. The heel is required to remain in contact with the floor at all times. The foot is moved away from the wall to the point where the knee can only make slight contact with the wall, while the heel remains in contact with the floor. This puts the ankle joint in maximal dorsiflexion. The leg not being tested can rest on the floor and participants are allowed to hold the wall for support. The maximum distance from the wall to the tip of the big toe is recorded in centimetres (cm).
Straight leg raise test	The subject is supine without a pillow under their head. The subject's leg is lifted by the posterior ankle while keeping the knee fully extended. The tester continues to lift the subject's leg by flexing at the hip until the subject complains of pain or tightness in the back or back of their leg. Hip flexion (in degrees) is recorded.
Total hip range of motion	Internal and external rotation assessed. For internal rotation the subject is instructed to allow their hips to fall into this position keeping their knees together. When the subject reaches end of range the tester records the angle of hip internal rotation by placing an inclinometer on the lateral aspect of the tibia just distal to the lateral malleoli. For external rotation, the tester passively moves the hip into external rotation. The tester stops the motion when a firm end feel is reached or the pelvis begins to rotate. The range in degrees is recorded. If the subject reports pain the range of hip flexion at onset of pain is recorded.

Grip strength	Quantified by measuring the amount of static force that the hand can squeeze around a dynamometer.
Total thoracic spine rotation	Sitting over the edge of a box. Hold a stick with arms crossed. Rotate to right and then left. Measure degrees of movement in both directions.
Rotator cuff Strength	Subject is seated in 90 degrees of glenohumeral joint abduction, 90 degrees of elbow flexion, and neutral supination/pronation forearm position. Their feet are off the floor and they grip the bed with their opposite hand. The subject is instructed to keep their body position and shoulder position still and a handheld dynamometer is used by the tester to measure both internal and external rotation braking force. This is expressed as a % of the subject's body weight.
Single leg hop & hold	Subject stands on one leg behind a marked line. Subject then hops forwards as far as possible whilst 'sticking' the landing and holding the landing position for 3 seconds. Subject performs up to 3 hops on each leg, but is also allowed sub-maximal warm up jumps. Distance is marked and measured from the line to the front of the landing foot. Quality of movement is assessed from both front-on and side-on.
Broad jump	Subject stands on two legs with heels on a marked line. The subject then jumps forwards as far as possible whilst 'sticking' the landing and holding the landing position for 3 seconds. Subject performs up to 3 hops, but is also allowed sub-maximal warm up jumps. Distance is marked and measured from the line to the heel of the foot (shortest distance). The quality of the movement and distance is assessed from both front-on and side-on.
Sumo Deadlift - 5 rep maximum	Subject stands with feet wider than shoulder-width apart, and their toes point out at a 45 degree angle. The subject then bends at the hips to lower and grab the bar with either an overhand or mixed grip. Ensuring back is flat in this bottom position the subject then drives through their heels and extends their knees and hips to lift the bar to mid-thigh height. The subject pulls their shoulders back at the top of the move then carefully lowers the bar back to the ground. The weight that can be lifted for a maximum of 5 repetitions is recorded in kilograms.
Hip thrust - 5 rep maximum	Subject sits with their shoulders and shoulder blades against a bench. A barbell is rolled over the legs until it's directly over their hips. The subject puts their elbows on the bench and hands on the bar to steady it. Ensure the subject's body is aligned and spine is neutral. The subject then braces their core, drives through their heels and squeeze their glutes to lift their hips (and barbell). The subject comes down smoothly with core still braced. The maximum weight that can be lifted for 5 repetitions is recorded in kgs.
Triple hop test	The subject jumps as far as possible on a single leg three consecutive times, without losing balance and landing firmly. The distance is measured from the start line to the heel of the landing leg.
10m, 20m, 30, 40m speed	Subjects complete a standardised warm up. Measure a 20m or 40m lane placing timing gates at 0m, 10m, 20m, 30m and/or 40m. The first gate is set at a height of 0.5m, the rest are set at a height of 1m. Mark the start line at 0.5m before first timing gate with tape. Subjects begin each trial from stationary start with the toe of their front foot on the start line. Subject must be visibly static with no countermovement or sway. Subjects are allowed 3 trials with a minimum of 3 minutes between trials. Time recorded to nearest 0.01 second.

Run Two	Subjects complete a standardised warm up. The test is set up at a standard wicket with a timing gate at one end. If a wicket is not available, a distance of 17.68m is marked out. An additional timing gate 5m from the turn will allow greater analysis of this test as this will specifically measure speed in and out of the turn. A static camera is set back 6-8m to capture this footage. This can act as a cricket specific 5-0-5 test within the main test. A start line is marked with tape 0.5m before the first timing gate. Subjects begin each trail from stationary start with the toe of their front foot onto the start line and the bat held in front of them with 2 hands. Subjects must be visibly static, with no countermovement or sway. Subjects spring to the far batting crease, ground their bat behind the crease, turn and sprint back through the timing gates. Subjects must ground their bat through the finish line. Subjects must avoid breaking the beam of the gates with their bat. Subjects are allowed 2 trials either side of their turn with a minimum of 3 minutes between trials. Times are recorded to the nearest 0.01 second.
505 agility test	Subject accelerates maximally to a 15m line, turn on their right leg and sprint back 5m through the finish line as quickly as possible. During the turn, the participant must not touch their hand down on the floor. The subject repeats this again, but this time performs a left leg turn and continues to alternate. The subject must touch the 'turn-around line' on each effort, failing to place their foot on, or across the line, results in a failed attempt. Each subject completes a minimum of three efforts, each separated by a 2-3 minute rest. The sprint is timed with a stopwatch in seconds. The average of the three efforts is recorded. Times are recorded to the nearest 0.01 second.
Yo-Yo	Cones are used to mark out 3 lines, with 2 lines 5m apart and 1 20m from the other. Subjects starts behind the middle line and begins running when signalled by the beep. They turn at the top cone and run back to the starting point when signalled by the beep. There is an active recovery period of 10 seconds between every 40m shuttle, during which the subject must walk or jog around the bottom cone and return to the starting point. A warning is given when the subject does not complete a successful shuttle in the allocated time and the subject is removed from the test after 2 consecutive warnings. A warning is also given if the subject fails to intersect the 20m line with their foot when turning i.e. do not allow subjects to turn short of the line. False starts are prohibited as they give subjects extra time to complete the shuttle. False starts should be punished with a warning. The last completed shuttle is used as the performance score.