Hamstring Strain Injury Risk Factors in Australian Football Change over the Course of the Season

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ABSTRACT

SIM, A., R. G. TIMMINS, J. D. RUDDY, H. SHEN, K. LIAO, N. MANIAR, J. T. HICKEY, M. D. WILLIAMS, and D. A. OPAR. Hamstring Strain Injury Risk Factors in Australian Football Change over the Course of the Season. *Med. Sci. Sports Exerc.*, Vol. 56, No. 2, pp. 297–306, 2024. **Background/aim:** This study aimed to determine which factors were most predictive of hamstring strain injury (HSI) during different stages of the competition in professional Australian Football. **Methods:** Across two competitive seasons, eccentric knee flexor strength and biceps femoris long head architecture of 311 Australian Football players (455 player seasons) were assessed at the start and end of preseason and in the middle of the competitive season. Details of any prospective HSI were collated by medical staff of participating teams. Multiple logistic regression models were built to identify important risk factors for HSI at the different time points across the season. **Results:** There were 16, 33, and 21 new HSIs reported in preseason, early in-season, and late in-season, respectively, across two competitive seasons. Multivariate logistic regression and recursive feature selection revealed that risk factors were different for preseason, early in-season, and late in-season HSIs. A combination of previous HSI, age, height, and muscle thickness were most associated with preseason injuries (median area under the curve [AUC], 0.83). Pennation angle and fascicle length had the strongest association with early in-season injuries (median AUC, 0.86). None of the input variables were associated with late in-season injuries (median AUC, 0.46). The identification of early in-season HSI and late in-season HSI was not improved by the magnitude of change of data across preseason (median AUC, 0.67). **Conclusions:** Risk factors associated with prospective HSI were different across the season in Australian Rules Football, with nonmodifiable factors (previous HSI, age, and height) mostly associated with preseason injuries. Early in-season HSI were associated with modifiable factors, notably biceps femoris long head architectural measures. The prediction of in-season HSI was not improved by assessing the magnitude of change in data across preseason. **Key Words:** HAMSTRING, INJURY, AUSTRALIAN FOOTBALL SEASON

APPLIED SCIENCES

Hamstring strain injuries (HSI) are a common injury across many sports (1), including Australian Football (2), and significant work has been conducted to identify factors associated with an increased risk of future injury (3). These risk factors are often categorized as either modifiable or nonmodifiable. Older age and a history of HSI are the two most commonly reported nonmodifiable risk factors (3). Modifiable risk factors, which can be addressed through intervention, are extensive, but biceps femoris long head (BFlh) fascicle length (4) and eccentric hamstring strength (5) are current prominent variables.

Most prospective cohort studies assess risk factors at a single time point, typically the beginning of a season (e.g., in the preseason) (6). This approach has limitations, as any changes in the measured variables leading up to injury, which could be up to 9 months after the preseason assessment, are not accounted for. Few have explored if more frequent assessments of risk factors improve the association with and/or prediction of future HSI risk. It was recently reported that more frequent assessments of eccentric knee flexor strength and BFlh architecture did not improve the ability to predict new HSI in Australian Football (7). However, that study did not consider the possibility that risk factors may vary depending on the time of season, nor did it examine if changes in possible risk factors across time (e.g., an increase in eccentric strength

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Submitted for publication March 2023.
Accepted for publication August 2023.
Supplemental digital content is available for this article. Direct URL citations appear in the printed text and are provided in the HTML and PDF versions of this article on the journal's Web site (www.acsm-msse.org).

0195-9131/24/5602-0297/0
MEDICINE & SCIENCE IN SPORTS & EXERCISE®

DOI: 10.1249/MSS.0000000000003297

from the start to the end of preseason) at an individual level altered the ability to predict HSI.

Therefore, the primary aim of this study was to determine which factors were most predictive of the risk of HSI during preseason, early in-season, and late in-season in professional Australian Football. The secondary aim was to determine if the magnitude of change in possible risk factors across preseason was predictive of future in-season HSI.

METHODS

The methods used in this study pertaining to the study design, participants, and data collection have been described previously (7) but are included in detail here for the ease of the reader.

Study Design and Participants

This study was approved by the ACU Human Research Ethics Committee (approval no. 2017-208H) and was conducted across two Australian Football League seasons (November 2017 to August 2018 and November 2018 to August 2019, including preseason but not including finals). Each player from six teams competing in the Australian Football League provided written informed consent before their participation.

At the start of preseason, team medical staff were responsible for providing details of individual players' history of HSI in the past 12 months and if they had ever sustained an anterior cruciate ligament (ACL) injury. Eccentric knee flexor strength and BFlh architecture were assessed at the start of preseason (November/December), end of preseason (February/March), and middle of the competitive season (May/June), respectively. Because of scheduling constraints, the actual dates for assessments were not identical across the six different teams involved in this study. A standardized injury report form was completed by the medical staff if any player sustained an HSI during the study period.

Eccentric Knee Flexor Strength

The assessment of eccentric knee flexor strength was performed during the execution of the Nordic hamstring exercise similar to previous studies using an instrument device (NordBord, VALD, Queensland, Australia) (8). Players knelt on a cushioned board with their ankles secured immediately superior to the lateral malleolus by individual ankle hooks attached to uniaxial load cells. All players completing this assessment were familiar with the Nordic hamstring exercise. Participants were told to slowly lean forward forcefully contracting their knee flexors to control their descent. All players maintained their trunk and hips in a neutral position while holding their hands across the chest throughout the exercise. Players performed a single set of 1–3 maximal repetitions as determined by each team's practices after a self-selected warm-up. The highest peak force produced by each leg throughout the test was recorded as eccentric knee flexor strength. Relative eccentric knee flexor strength was obtained by scaling its value relative to the mass of the player ($N \cdot kg^{-1}$) (7).

BFlh Architecture

The assessment of BFlh architecture has been reported previously (9–12). The measurements of muscle thickness, pennation angle, and fascicle length of the BFlh were obtained from ultrasound images taken along the longitudinal axis of the muscle belly using a two-dimensional, B-mode ultrasound (frequency, 12 MHz; depth, 8 cm; field of view, 14 × 47 mm) (GE Healthcare Vivid-i, Wauwatosa, WI). Along the line of BFlh, the halfway point between the ischial tuberosity and the knee joint fold was determined as the scanning site. The architecture assessments were conducted on players lying on a massage plinth after at least 5 min of inactivity. The assessor (R.G.T.) adjusted the orientation of the probe accordingly. The reliability of the assessor has been previously established with an intraclass correlation >0.90 reported for BFlh fascicle length.

Offline analysis was undertaken after the images were collected (MicroDicom, Version 0.7.8, Bulgaria). Muscle thickness was determined by the distance between the superficial and the intermediate aponeuroses of the BFlh. Pennation angle was determined by the angle between the intermediate aponeurosis and a fascicle of interest. The angles of superficial and intermediate aponeurosis were defined as the angle between the line marked as the aponeurosis and an intersecting horizontal reference line across the capture image (13). Because part of the fascicle is not visible in the ultrasound probe's field of view, the following equation from Blazevich and colleagues was used for estimation (13):

$$FL = \sin(AA + 90^\circ) \times MT / \sin(180^\circ - (AA + 180^\circ - PA))$$

where FL is fascicle length, AA is aponeurosis angle, MT is muscle thickness, and PA is pennation angle. Fascicle length was reported in absolute terms (cm) and relative to muscle thickness from a single image. The same assessor (R.G.T.) collected and analyzed all scans. The assessor has evidenced reliability in determining measures of BFlh muscle architecture at rest with ICC >0.95 and %TE <5.0% across the measurement of all architectural variables.

Prospective HSI Reporting

An HSI was defined as posterior thigh pain that prevented a player from performing subsequent exercise and was confirmed by physical examination by the team physiotherapist or doctor (14,15). The team medical staff filled out a standard injury report form for each HSI, which requested details about the injured limb, the injured muscle, the activity type performed when the injury occurred, and the number of days required for the player to return to full participation in training and competition.

Statistical Analysis

Statistical analyses were performed using the Python 3.9.2 programming language (Python Software Foundation, https://www.python.org/) and the following packages: scikit-learn, statsmodel, panda, numpy, matplotlib, and seaborn.

General Modeling Approach

The general modeling approach applied to this study can be found in Figure 1A.

Data preprocessing. For all analyses, an observation was removed if it consisted of at least one missing value. Additionally, players who sustained an HSI in previous time points within a season were censored from building models to predict HSI that occurred in later timepoints. For example, a player who sustained an HSI in preseason was excluded from training models to predict HSI that occurred in early in-season and later in-season. Likewise, players who sustained an HSI in early in-season were excluded from training models to predict HSI occurring in late in-season.

Correlation analysis was conducted on input predictor variables to identify redundant predictors. A Pearson's correlation coefficient threshold of >0.8 was applied, and if the pairwise correlation between two predictors exceeded the threshold of 0.8, the predictor with the higher mean pairwise correlation across all other predictor variables was removed.

After this, the remaining input predictor variables were normalized (16) into the range of 0 and 1, using the following equation:

$$x_{\text{norm}} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

where x is the value to scale, $\min(x)$ is the smallest value of the predictor, and $\max(x)$ is the largest value of the predictor.

Predictor selection. The aims of the predictor selection process in the current study were to eliminate redundant predictors and to identify which subset of risk factors achieved the highest predictive performance across the different time points. A wrapper feature selection method, specifically recursive feature elimination, was used to search through different subsets of risk factors associated with HSI (17). Recursive feature elimination, which is robust to overfitting (18), was conducted in this study by fitting a logistic regression with all input predictor variables and recursively eliminating predictors that were less important based on the coefficients. Once the predictor with the lowest coefficient was removed, the model was fitted with the remaining predictors to repeat the process. This process was repeated until there was only one remaining predictor, after which the importance of individual predictors was ranked. Preliminary analyses using this dataset showed that models built using recursive feature elimination outperformed models built using all predictors. Recursive feature elimination, however, does not identify the optimal number of predictors.

Finding the optimal number of predictors. Stratified k-fold cross-validation was used to determine the optimal number of predictors. In this study, $k = 5$ was applied to divide data into five stratified folds. For each split, one fold of the data was used as testing data and the remaining folds ($k - 1$) were used as training data. The number of selected predictors resulting in the highest area under the curve (AUC) averaged across five folds was chosen as the optimal number of predictors.

Performance evaluation. Once the optimal number of risk factors was determined, the final step was to evaluate the performance of logistic regression with selected risk factors. It is a common practice to allocate 20%–30% of data for testing and 70%–80% of data for training (6). Any split within this threshold has been shown to have an accurate estimation of the model's performance (19). A 20%/80% train-test split was used in this study. Stratified cross-validation was used to preserve the percentage of injured and uninjured athletes for all iterations. Because the given dataset was relatively small (<455 observations), 1000 iterations of evaluation were performed. The metric used to evaluate predictive performance was AUC (20). AUC measures the ability of the models to correctly predict prospectively injured and uninjured players. An AUC of 0.5 indicates prediction no better than random chance, whereas an AUC of 1.0 indicates perfect prediction.

Analysis 1

The aim of analysis 1 was to determine which risk factors best predicted HSI at different time points throughout the season.

The general modeling approach was applied to analysis 1. The subset of data used for analysis 1 has been illustrated in Figure 1B, where d_1 are data assessed at the start of preseason, d_2 are data assessed at the end of preseason, and d_3 are data assessed in the middle of in-season. i_1 is the window after d_1

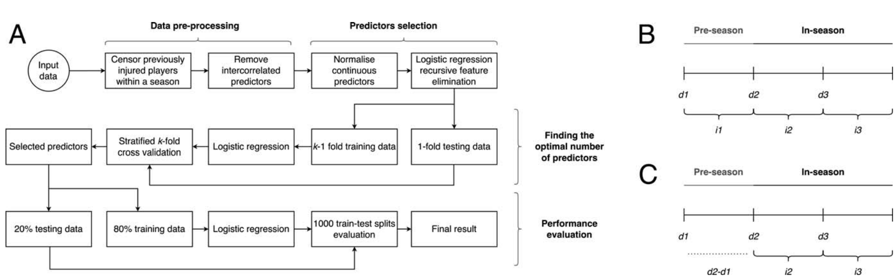

FIGURE 1—A. Adopted workflow process to identify important risk factors and build optimal models for performance evaluation. B. The modeling approach for analysis 1. *d* represents data assessment at different time points, where d_1 are data assessed at the start of preseason, d_2 are data assessed at the end of preseason, and d_3 are data assessed in the middle of in-season. *i* represents HSI that occurred within individual assessment time frames, where i_1 are prospective HSI that occurred in preseason, i_2 are prospective HSI that occurred in early in-season, and i_3 are prospective HSI that occurred in late in-season. C. The modeling approach for the analysis 2. *d* represents data assessment in different time points, where d_1 are data assessed at the start of preseason, d_2 are data assessed at the end of preseason, and $d_2 - d_1$ are magnitude of change of data in preseason. *i* represents HSI that occurred within individual assessment time frames, where i_2 are prospective HSI that occurred in early in-season, i_3 are prospective HSI that occurred in late in-season, and $i_2 + i_3$ are prospective HSI that occurred throughout in-season.

TABLE 1. Types of predictor variables and target variables included in individual models for analysis 1 and analysis 2.

	Input Predictor Variables					Target Variables		
	Nonmodifiable Risk Factors	Modifiable Risk Factors				HSI		
Model	d_1	d_1	d_2	d_3	$d_2 - d_1$	i_1	i_2	i_3
Analysis 1								
$d_1 - >i_1$	✓	✓				✓		
$d_2 - >i_2$	✓		✓				✓	
$d_3 - >i_3$	✓			✓				✓
Analysis 2								
HSI occurred in early in-season (i_2)								
d_1	✓	✓					✓	
d_2	✓		✓				✓	
d_1 and d_2	✓	✓	✓				✓	
$d_2 - d_1$	✓				✓		✓	
d_1 and d_2 and ($d_2 - d_1$)	✓	✓	✓		✓		✓	
HSI occurred in late in-season (i_3)								
d_1	✓	✓						✓
d_2	✓		✓					✓
d_1 and d_2	✓	✓	✓					✓
$d_2 - d_1$	✓				✓			✓
d_1 and d_2 and ($d_2 - d_1$)	✓	✓	✓		✓			✓

Nonmodifiable risk factors: height, weight, age, previous HSI, and previous ACL injury;
modifiable risk factors: muscle thickness (cm), pennation angle (°), fascicle length (cm), relative fascicle length (fascicle length divided by muscle thickness), eccentric knee flexor strength (N), relative eccentric flexor strength (N·kg^{-1}), and between-limb imbalance (%).
d_1, data assessed at the start of preseason; d_2, data assessed at the end of preseason; d_3, data assessed in the middle of in-season; d_1 and d_2, data assessed at start and end of preseason; $d_2 - d_1$, magnitude of change in data between start and end of preseason.
i_1, HSI occurred in preseason; i_2, HSI occurred in early in-season; i_3, HSI occurred in late in-season.

during which prospective HSI could have occurred throughout preseason, i_2 is the window after d_2 during which prospective HSI could have occurred early in-season, and i_3 is the window after d_3 during which prospective HSI could have occurred during late in-season.

Analysis 1 used all nonmodifiable risk factors assessed at the start of preseason and modifiable risk factors assessed at multiple time points (d_1 or start of preseason, d_2 or end of preseason, and d_3 or middle of in-season) as predictor variables. Prospective HSI that occurred between individual assessment time frames (i_1 or between the start and end of preseason, i_2 or between the end of preseason and the middle of in-season, and i_3 or between the middle of in-season and the end of the in-season before the commencement of finals) were the target of the prediction models. (Refer to Table 1 for types of input predictor variables and target variables included in each of the individual models.)

Analysis 2

Analysis 2 aimed to determine whether the magnitude of change in data between the start and the end of preseason, as well as more frequent assessment during preseason, improved the ability to predict in-season HSI, beyond the data collected at the start and end of preseason alone.

The general modeling approach was applied to analysis 2. The subset of data used for analysis 2 has been illustrated in Figure 1C, where d_1 are data assessed at the start of preseason, d_2 are data assessed at the end of preseason, $d_2 - d_1$ is the magnitude of change in the risk factors across preseason. i_2 is the window during which prospective HSI could have occurred early in-season, and i_3 is the window during which prospective HSI could have occurred during late in-season.

Analysis 2 used all nonmodifiable risk factors assessed at the start of preseason and modifiable risk factors assessed at the start and end of preseason as predictor variables. Prospective HSI that occurred during the in-season periods (i_2 and i_3) were the target of the prediction models. Additionally, the magnitude of change in modifiable risk factors was determined as the absolute difference between values captured at the end of preseason and values captured at the start of preseason. (Refer to Table 1 for types of input predictor variables and target variables included in individual modeling approaches.)

RESULTS

Three-hundred and eleven male Australian Football players, with a total number of 455 player seasons (23.7 ± 3.8 yr, 188.1 ± 7.6 cm, 86.5 ± 8.8 kg) across the 2018 and 2019 seasons, were evaluated on at least one occasion. Of these player seasons, 381 (83.7%) did not sustain an HSI and 74 (16.3%) did.

After the removal of missing values for analysis 1, the total number of injured and uninjured player seasons during i_1 was 14 and 339 respectively ($d_1 - >i_1$; Table 2). For i_2, the total number of injured and uninjured player seasons with complete datasets assessed at d_2 was 24 and 259, respectively ($d_2 - >i_2$; Table 2). For i_3, the total number of injured and uninjured player seasons (with complete datasets assessed at d_3) was 11 and 225, respectively ($d_3 - >i_3$; Table 2).

For analysis 2, the total number of injured and uninjured player seasons with complete datasets during early in-season (i.e., i_2) was 23 and 219, respectively (i_2; Table 3). For late in-season (i.e., i_3), the total number of injured and uninjured player seasons with complete datasets was 9 and 210, respectively.

Analysis 1

The performance of the individual models in analysis 1 can be found in Figure 2. Data that were assessed at the end of preseason and used to predict HSI that occurred early in-season

TABLE 2. The results of analysis 1

Model	Risk Factors[a]	Frequency HSI	Non-HSI	Total	AUC IQR	Standard Deviation	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
$d_1 - >i_1$	Previous HSI, height, age, muscle thickness	14	339	353	0.16	0.12	0.40	0.73	0.83	0.89	0.99
$d_2 - >i_2$	Pennation angle, fascicle length	24	259	283	0.16	0.11	0.37	0.77	0.86	0.93	1.00
$d_3 - >i_3$	Previous ACL, height, age, pennation angle, fascicle length, relative eccentric knee flexor force, eccentric knee flexor force imbalance	11	225	236	0.25	0.17	0.02	0.33	0.46	0.58	0.91

Performance is measured as AUC.
The performance of models built with selected predictors assessed and evaluated at start of preseason and HSI that occurred in preseason ($d_1 - >i_1$), end of preseason and HSI that occurred in early in-season ($d_2 - >i_2$), and middle of in-season and HSI that occurred in late in-season ($d_3 - >i_3$). The descriptive summary is the outcome of 1000 iterations of train-test splits.
[a] Risk factors were selected by recursive feature elimination and fivefold cross-validation.

displayed the best predictive performance (median AUC = 0.86, interquartile range [IQR] = 16; Table 2) ($d_2 - >i_2$; Fig. 2). The prediction of preseason HSI using data assessed at the start of preseason ($d_1 - >i_1$; Fig. 2) resulted in a median AUC of 0.83 and an IQR of 0.16. By contrast, data assessed at the middle of the in-season period and used to predict HSI that occurred late in-season ($d_3 - >i_3$; Fig. 2) resulted in the poorest predictive performance (median AUC = 0.46, IQR = 0.25; Table 2).

Preseason HSI. Players with a history of HSI are more likely to sustain an HSI in preseason (Fig. 3A–C, $P < 0.01$). Shorter players displayed a higher risk of sustaining HSI in preseason (Fig. 3A). Results also showed that older athletes were associated with an increased risk of HSI in preseason (Fig. 3B, $P < 0.05$; Supplemental Table 1, Supplemental Digital Content, The P-value of individual risk factors determined by multivariate logistic regression models in analysis 1, http://links.lww.com/MSS/C912), and players who had thicker BFlh muscles were also more susceptible to HSI in preseason (Fig. 3C).

Early in-season HSI. Players with a greater BFlh pennation angle and shorter fascicle length were at significantly increased risk of sustaining HSI during the early in-season period (Fig. 3D and E; $P < 0.05$; Supplemental Table 1, Supplemental Digital Content, http://links.lww.com/MSS/C912).

Late in-season HSI. Although height, age, history of ACL injury, BFlh pennation angle, fascicle length, relative eccentric knee flexor strength, and relative eccentric knee flexor force imbalance were selected as predictive predictors (Fig. 3F–K), the overall predictive performance of AUC was below 0.5 (median AUC = 0.46, IQR = 0.25; Table 2).

Analysis 2

The performance of the individual models in analysis 2 can be found in Figure 4A and B. The predictions of neither early in-season HSI (median AUC = 0.67, IQR = 0.15; Table 3) nor late in-season HSI (median AUC = 0.67, IQR = 0.26; Table 4) were improved by assessing the magnitude of change in data across preseason. For HSI occurring early in-season, the model with the best predictive performance used BFlh fascicle length and pennation angle, which were assessed at the end of preseason. The resulting median AUC was 0.84 and the IQR was 0.16 (Table 3). Predicting late in-season injuries using the absolute change in BFlh pennation angle and fascicle length across preseason, as well as history of ACL, displayed the best predictive performance (median AUC = 0.67, IQR = 0.26; Table 4). However, the predictive performance was not significantly improved when compared with relative BFlh fascicle length and fascicle length, which were assessed at the start of preseason only (median AUC = 0.65, IQR = 0.25; Table 4).

DISCUSSION

This study aimed to assess whether the factors associated with HSI in professional Australian Football changed across the season. The current study found that the subset of risk factors that best predicted the occurrence of HSI was different between the preseason and the in-season periods. This study also aimed to assess whether the magnitude of change in HSI risk factors across the preseason period improved the prediction

TABLE 3. The performance of models built with selected predictors assessed at start of preseason (d_1), end of preseason (d_2), start and end of preseason (d_1, d_2), the magnitude of change of data in preseason ($d_2 - d_1$), data assessed at the start and end of preseason and the magnitude of change of data in preseason (d_1, d_2, [$d_2 - d_1$]) as predictor variables, and HSI occurred in early in-season (i_2) as target variable

Models	Risk Factors[a]	Frequency HSI	Non-HSI	Total	AUC IQR	Standard Deviation	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
d_1	Fascicle length (d_1), relative fascicle length (d_1)	23	219	242	0.15	0.11	0.29	0.60	0.68	0.75	0.96
d_2	Pennation angle (d_2), fascicle length (d_2)	23	219	242	0.16	0.11	0.44	0.75	0.84	0.91	1.00
d_1 and d_2	Pennation angle (d_2), fascicle length (d_2)	23	219	242	0.16	0.11	0.44	0.75	0.84	0.91	1.00
$d_2 - d_1$	Previous HSI, pennation angle (c_1), fascicle length (c_1), eccentric knee flexor force imbalance (c_1)	23	219	242	0.15	0.11	0.25	0.59	0.67	0.74	0.98
d_1 and d_2 and ($d_2 - d_1$)	Pennation angle (d_2), fascicle length (d_2)	23	219	242	0.16	0.11	0.44	0.75	0.84	0.91	1.00

Performance is measured as AUC.
[a] Risk factors were selected by recursive feature elimination and fivefold cross-validation.
d_1 and d_2, models built with nonmodifiable risk factors assessed at the start of preseason and modifiable risk factors assessed at the start and end of preseason; $d_2 - d_1$, models built with nonmodifiable risk factors assessed at the start of preseason and magnitude of change of modifiable risk factors between start and end of preseason; c_1, magnitude of change of specific risk factor between start and end of preseason.

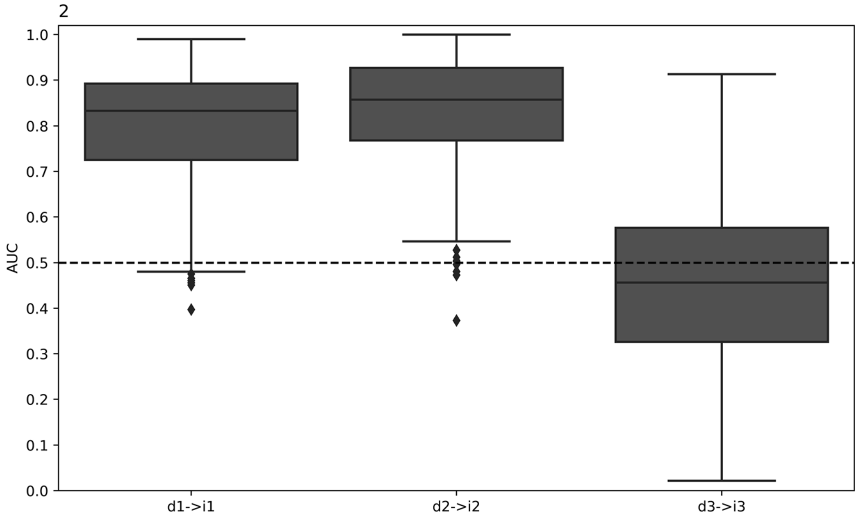

FIGURE 2—The results of analysis 1. The performance of models built with selected predictors assessed and evaluated at the start of preseason and HSI that occurred in preseason ($d_1 - >i_1$), end of preseason and HSI that occurred in early in-season ($d_2 - >i_2$), in the middle of preseason, and HSI that occurred in late in-season ($d_3 - >i_3$).

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of HSI sustained in-season beyond using measures taken at the start or end of preseason alone. The magnitude of change in eccentric knee flexor strength and BFlh muscle architecture variables across the preseason period generally displayed poorer predictive performance than the absolute measures themselves (particularly those taken at the end of preseason).

Did more frequent assessment of risk factors improve the prediction of future HSI?. The best performing model in the current study was built using BFlh fascicle length and pennation angle assessed at the end of preseason and aimed to predict only HSI that occurred during the first half of the in-season period. This model predicted prospective HSI with a median AUC of 0.86. A previous study attempted to predict HSI in elite Australian Footballers using age, previous HSI, and eccentric knee flexor strength data, collected across two AFL seasons (6). When predicting HSI that occurred within the same season, the median AUC values for the 2013 and 2015 AFL seasons were 0.58 and 0.57, respectively (6). In this previous study, when data from the 2013 AFL season were used to predict HSI that occurred during the 2015 AFL season, the median AUC was 0.52 (6). It was suggested that more frequent measures of the risk factors examined may have improved predictive performance. However, another study reported that more frequent measurements of modifiable risk factors did not improve the ability to identify athletes at an increased risk of HSI beyond data collected at a single timepoint (7). In support of these previous findings (7), we observed that more frequent measurements did not improve the ability to predict the occurrence of HSI. However, the assessment of different risk factors at different timepoints did improve predictive performance. In addition, we used recursive feature elimination to optimize predictive performance and improve the interpretability of built models. Results from preliminary analyses suggest that the selected predictors are likely to deliver better predictive performance than using all predictors. The findings of our study suggest that a subset of risk factors, as opposed to all risk factors, used in previous studies may have been more effective in predicting prospective HSI.

Does the magnitude of change in risk factor data across preseason improve the ability to predict HSI throughout the season beyond the absolute values?. In addition to suggesting that more frequent measures of the risk factors examined may improve predictive performance (6), previous work has also noted that assessing risk factors at the start of preseason alone assumes that these factors will remain constant throughout the season (or up to the point of HSI). It is suggested that changes in HSI risk factors may influence the risk of injury to a greater extent than the absolute values of those risk factors measured at a single timepoint (6,21). AUC values of 0.7 and above are regarded as having significant effects in sport science domains (22). In the current study, models built with the magnitude of change in risk factors across preseason were less optimal when attempting to predict HSI during early in-season, or i_2 (median AUC of 0.66), as well as HSI during late in-season, or i_3 (median AUC of 0.63). Conversely, models built using the absolute values measured at the end of preseason, or d_2, performed better when predicting HSI during early in-season, or i_2 (median AUC of 0.83). However, the performance of all models attempting to predict late in-season HSI, or i_3, was the poorest.

The current results suggest that risk factor data assessed at the end of preseason provide the strongest performance when predicting in-season HSI. Despite the magnitude of change in modifiable risk factor data performing poorly from a prediction standpoint, it is important to acknowledge that significant adaptations in eccentric knee flexor strength and BFlh muscle architecture can be elicited in as little as 2 wk (23). For example, an increase of BFlh fascicle length and a reduction in BFlh pennation angle have been observed after just 14 d of an eccentric strength training intervention (23). Given this, it is likely that athletes saw significant adaptations across the

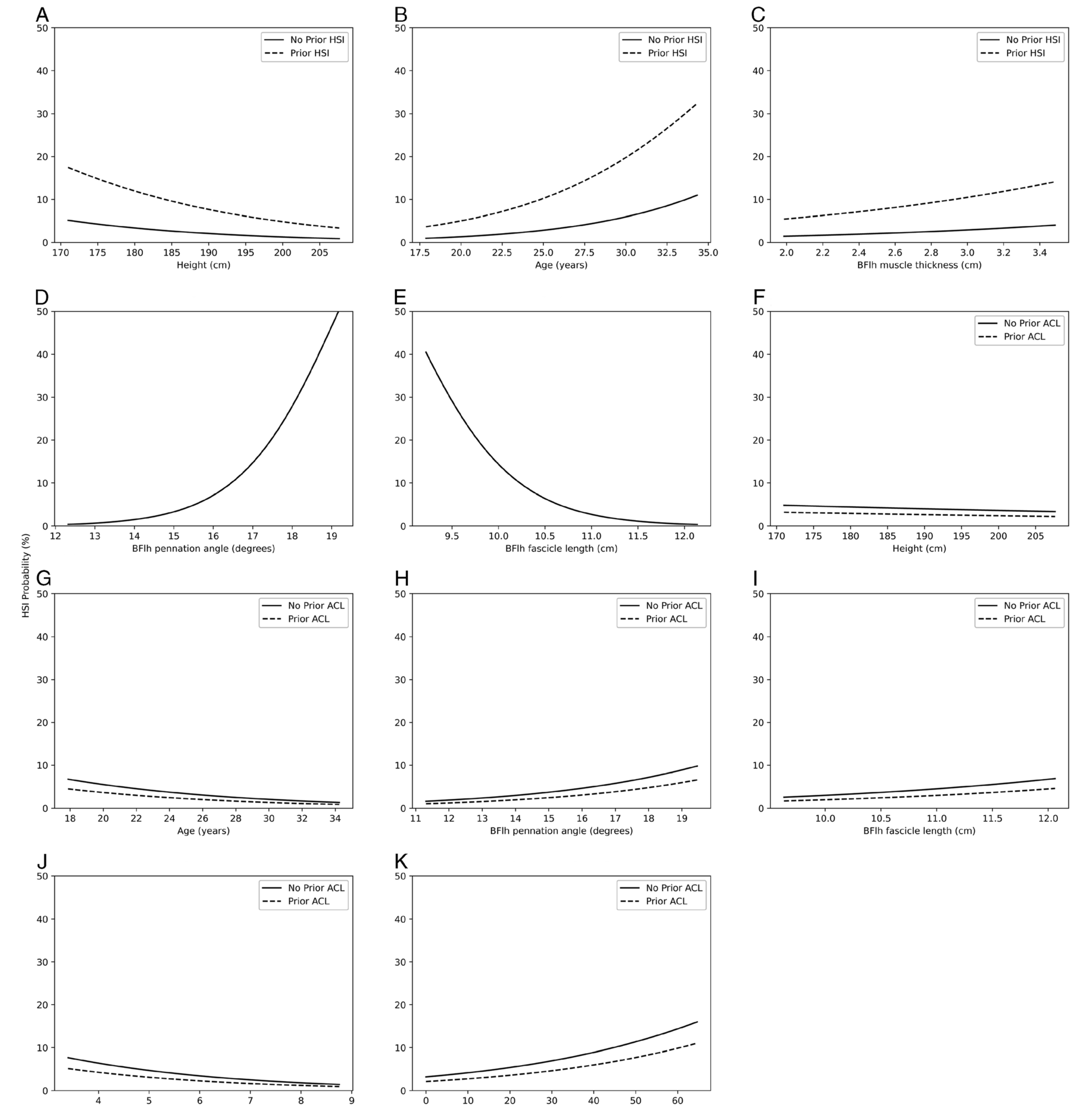

FIGURE 3—A. The effect of change in height on HSI probability in preseason with other factors set as mean constants (age = 23.54 yr, muscle thickness = 2.64 cm). B. The effect of change in age on HSI probability in preseason with other factors set as mean constants (height = 188.07 cm, muscle thickness = 2.64 cm). C. The effect of change in muscle thickness on HSI probability in preseason with other factors set as mean constants (height = 188.07 cm, age = 23.54 yr). D. The effect of change in pennation angle on HSI probability in early in-season with fascicle length set as mean constant (fascicle length = 10.72 cm). E. The effect of change in fascicle length on HSI probability in early in-season with pennation angle set as mean constant (pennation angle = 15.37°). F. The effect of change in height on HSI probability in late in-season with other factors set as mean constants (age = 23.13 yr, pennation angle = 15.39°, fascicle length = 10.74 cm, relative eccentric knee flexor force = 5.45 N·kg^{-1}, eccentric knee flexor force imbalance = 9.33%). G. The effect of change in age on HSI probability in late in-season with other factors set as mean constants (height = 188.05 cm, pennation angle = 15.39°, fascicle length = 10.74 cm, relative eccentric knee flexor force = 5.45 N·kg^{-1}, eccentric knee flexor force imbalance = 9.33%). H. The effect of change in pennation angle on HSI probability in late in-season with other factors set as mean constants (height = 188.05 cm, age = 23.13 yr, fascicle length = 10.74 cm, relative eccentric knee flexor force = 5.45 N·kg^{-1}, eccentric knee flexor force imbalance = 9.33%). I. The effect of change in fascicle length on HSI probability in late in-season with other factors set as mean constants (height = 188.05 cm, age = 23.13 yr, pennation angle = 15.39°, relative eccentric knee flexor force = 5.45 N·kg^{-1}, eccentric knee flexor force imbalance = 9.33%). J. The effect of change in relative eccentric knee flexor force on HSI probability in late in-season with other factors set as mean constants (height = 188.05 cm, age = 23.13 yr, pennation angle = 15.39°, fascicle length = 10.74 cm, eccentric knee flexor force imbalance = 9.33%). K. The effect of change in eccentric knee flexor force imbalance on HSI probability in late in-season with other factors set as mean constants (height = 188.05 cm, age = 23.13 yr, pennation angle = 15.39°, fascicle length = 10.74 cm, relative eccentric knee flexor force = 5.45 N·kg^{-1}).

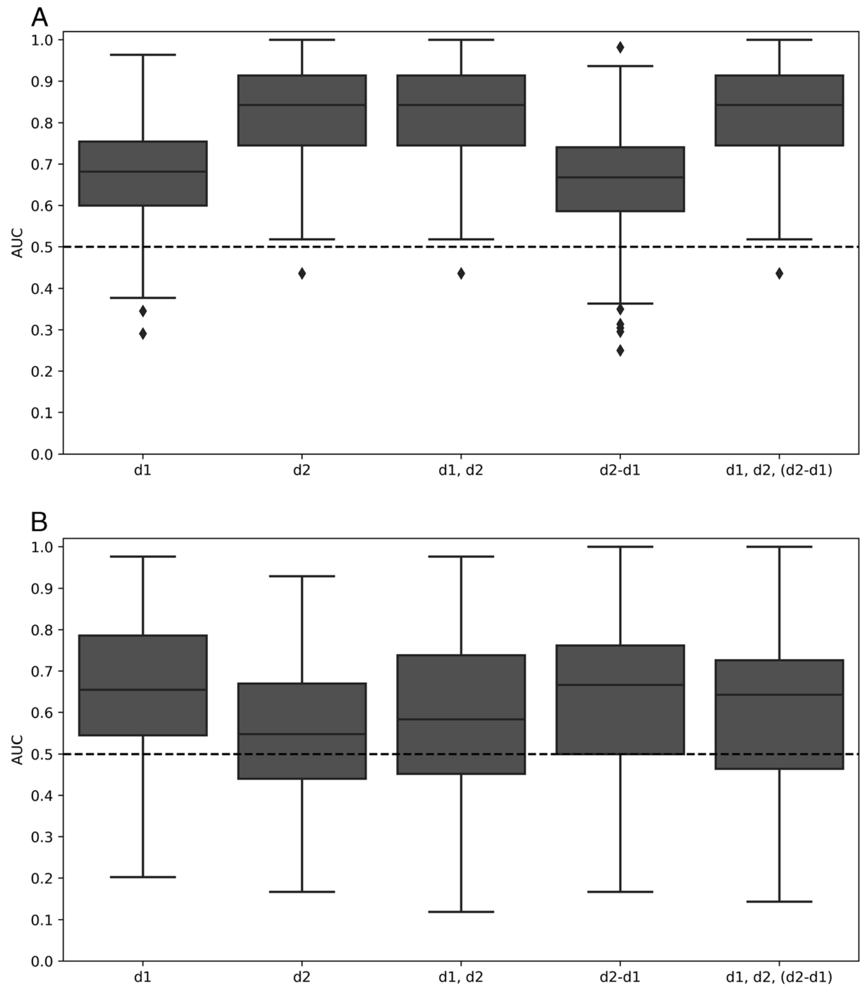

FIGURE 4—A. The performance of models built with selected predictors assessed at start of preseason (d_1), end of preseason (d_2), start and end of preseason (d_1, d_2), the magnitude of change of data in preseason ($d_2 - d_1$), data assessed at the start and end of preseason and the magnitude of change of data in preseason (d_1, d_2, [$d_2 - d_1$]) as predictor variables, and HSI that occurred in early in-season (i_2) as target variable. B. The performance of models built with selected predictors assessed at start of preseason (d_1), end of preseason (d_2), start and end of preseason (d_1, d_2), the magnitude of change of data in preseason ($d_2 - d_1$), data assessed at the start and end of preseason and the magnitude of change of data in preseason (d_1, d_2, [$d_2 - d_1$]) as predictor variables, and HSI that occurred in late in-season (i_3) as target variable.

preseason period and that modifiable risk factor data assessed at the end of preseason provided a better indication of athletes' physical status during the in-season period compared with data collected at the start of preseason. In contrast to this, data collected at the midpoint of the in-season period displayed the worst predictive performance when used to predict injuries that occurred during the second half of the in-season period. This suggests that despite these data being more etiologically

TABLE 4. The performance of models built with selected predictors assessed at start of preseason (d_1), end of preseason (d_2), start and end of preseason (d_1, d_2), the magnitude of change of data in preseason ($d_2 - d_1$), data assessed at the start and end of preseason and the magnitude of change of data in preseason (d_1, d_2, ($d_2 - d_1$)) as predictor variables, and HSI occurred in late in-season (i_3) as target variable

		Frequency			AUC						
Models	Risk Factors[a]	HSI	Non-HSI	Total	IQR	Standard Deviation	Minimum	Lower Quartile	Median	Upper Quartile	Maximum
d_1	Fascicle length (d_1), relative fascicle length (d_1)	9	210	219	0.25	0.16	0.20	0.54	0.65	0.79	0.98
d_2	Eccentric knee flexor force imbalance (d_2)	9	210	219	0.23	0.16	0.17	0.44	0.55	0.67	0.93
d_1 and d_2	Previous ACL, pennation angle (d_1), fascicle length (d_1)	9	210	219	0.29	0.18	0.12	0.45	0.58	0.74	0.98
$d_2 - d_1$	Previous ACL, pennation angle (c_1), fascicle length (c_1)	9	210	219	0.26	0.19	0.17	0.50	0.67	0.76	1.00
d_1 and d_2 and ($d_2 - d_1$)	Fascicle length (c_1)	9	210	219	0.27	0.20	0.14	0.46	0.64	0.73	1.00

Performance is measured as AUC.
d_1 and d_2, models built with nonmodifiable risk factors assessed at the start of preseason and modifiable risk factors assessed at the start and end of preseason; $d_2 - d_1$, models built with nonmodifiable risk factors assessed at the start of preseason and magnitude of change of modifiable risk factors between start and end of preseason; c_1, magnitude of change of specific risk factor between start and end of preseason.
[a] Risk factors were selected by recursive feature elimination and fivefold cross-validation.

relevant, there may exist other factors that influence the risk of HSI occurring during the latter half of the season to a greater extent than those examined in this study.

In which phase of the season was the predictive performance for HSI best?. The best performing model aimed to predict HSI during the first half of the in-season period and was built using data collected at the end of preseason (median AUC of 0.86; Table 2). By contrast, the poorest performing model was built using data collected at the midpoint of the in-season period and aimed to predict HSI in the second half of the in-season period (median AUC of 0.46; Table 2). It has previously been reported that an increase in BFlh fascicle length during early in-season can be observed across all players (9). However, it was observed that players with a history of HSI saw greater decreases in BFlh fascicle length during the latter part of the in-season period when compared with players without a history (9). This may, to an extent, explain why BFlh fascicle length assessed at the end of preseason did not present strong association with late in-season HSI, when compared with early in-season HSI (9).

Absolute risk factor data assessed at the end of preseason may provide practitioners with the most insight regarding HSI risk, and that additional assessments of the studied variables throughout the in-season period may not add further value. The relatively poor performance of the models built to predict late in-season HSI suggests that there may be additional factors that influence the risk of injury to a greater extent in the latter stages of the season.

Limitations. Because BFlh fascicles were longer than the ultrasound field of view (14 $\times$ 4.7 mm), extrapolation methods were used to calculate BFlh fascicles (24). Although the extrapolation method was proven to be highly reliable in an earlier study (ICC > 0.97) when validated against cadaveric data (13), the drawback is that it may overestimate BFlh fascicle length (25). Because of the lack of a standardized classification system (26), not all HSI reported in this study offer details pertaining to the muscle that was injured. Further subgroup analysis may be conducted if more injury data of the injured muscle were recorded. Because player exposure data were not presented in this study, reported HSI incidence did not consider the amount of time spent training and competing. In addition, the use of athlete tracking technologies to account for high-speed running and strength training exposure may offer more insights regarding HSI risk. Warm-up procedures were not standardized for strength assessments. Future studies should consider standardizing warm-up practices to limit the effect it may have on the strength outcomes. The data used in the current study were collected across multiple clubs at differing time points as part of their routine practices. Accordingly, it was not possible to standardize the warm-up and testing protocols for the assessment of eccentric knee flexor strength. The effect that a standardized warm-up protocol across all participating teams could have had on the peak eccentric knee flexor force values observed is unknown. Additionally, whether identifying peak eccentric knee flexor force from one versus three repetitions of the NHE would have affected the current results is also unknown. It is possible that there is a learning/feedback effect that may influence the results observed after three repetitions compared with one repetition; however, participants in this study were all very familiar with the assessment of eccentric knee flexor force during the NHE, which likely reduced the possibility of this. The use of logistic regression in this study assumes linearity between target variable and risk factors. Complex nonlinear models may be used with proper hyperparameter tuning practice. Although previous studies showed the use of nonlinear models outperformed logistic regression in injury prediction (22,27), these studies were conducted on a larger dataset. Earlier work showed no improvements in predictive performance when complex modeling approach was used (6). The absence of a standardized fine-tuning process on small and imbalanced dataset may be the cause, which result in overfitting. Despite this study recording a high number of prospective HSI in comparison with previous research (28), the relatively low injury rates and the class imbalance problem that this presents remain a limitation of this study and as well as most prospective sports injury studies in general. It is unclear whether predictive performance would be improved if class imbalance was addressed. Furthermore, the presence of missing data results in reduced numbers of player seasons used for the analysis in this study. Although AUC is used in many studies (6,7,29), other metrics should be considered thoroughly when evaluating the generalization of binary classifiers. In addition, future studies should use interpretability methods in machine learning to help experts better understand the decisions of trained models beyond predictive performance. Finally, previous work suggests that HSI risk factors are not transferable to different sporting populations (30) so applications of the current findings to other sports (e.g., soccer, rugby) should be done with caution.

CONCLUSIONS

This study has demonstrated that the risk factors most associated with prospective HSI change throughout an Australian Football season. Nonmodifiable risk factors (history of HSI, age, and height) demonstrated a strong association with preseason HSI, whereas early in-season HSI were better explained by modifiable risk factors. Conversely, late in-season injuries did not present any strong associations with either modifiable or nonmodifiable risk factors examined in this study. The magnitude of change in modifiable risk factors across preseason did not improve the prediction of in-season HSI. The results of this study suggest that assessing the same risk factors at multiple time points throughout the season may not be the best approach when identifying athletes at an increased risk of HSI. Instead, assessing different risk factors at specific time points may provide practitioners with more insight; however, the practical relevance of this is questionable. Future research is warranted to investigate the effectiveness of assessing risk factors at varying time points to improve HSI risk mitigation efforts.

No external funding sources were required for this study. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of this study do not constitute endorsement by the American College of Sports Medicine.

Conflict of interest: Human-Centred Intelligent Learning and Software Technologies Research Lab (HilstLab), Peter Faber Business School, Australian Catholic University, Sydney, Australia.

Sports Performance, Recovery, Injury and New Technologies (SPRINT) Research Centre, Australian Catholic University, Fitzroy, Victoria, Australia, and School of Behavioural and Health Sciences, Australian Catholic University, Fitzroy, Victoria, Australia.

Assoc. Prof. David Opar is listed as a coinventor on a patent, filed by the Queensland University of Technology (QUT), for a field-testing device of eccentric hamstring strength, which is now known commercially as the NordBord. The association between NordBord measures and future HSI is directly examined in this manuscript. Assoc. Prof. Opar has received revenue distributions from QUT based on revenue that QUT has generated through the commercialization of his intellectual property.

Assoc. Prof. Opar is a minority shareholder in Vald Performance Pty Ltd., the company responsible for commercialization of the NordBord, among other devices. He has received research funding from Vald Performance, for work unrelated to the current manuscript. Assoc. Prof. Opar was previously the Chair of the Vald Performance Research Committee, a role that was unpaid.

Assoc. Prof. Opar has family members who are minor shareholders and/or employees of Vald Performance.

Dr. Joshua Ruddy is a former employee of Vald Performance Pty Ltd., the company responsible for commercializing the field-testing device of eccentric hamstring strength used in the current study. Dr. Ruddy's primary contribution to this manuscript occurred after his employment at Vald Performance.

Dr. Morgan Williams is a member of the Vald Research Committee. Dr. Morgan Williams has been provided donations of equipment and funds for travel and subsidence by Vald Performance to conduct research unrelated to this project. Dr. Morgan Williams has received payment for reports for Vald Performance unrelated to this and any research study.

No other authors declared any conflicts.

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