Prediction of Hamstring Injuries in Australian Football Using Biceps Femoris Architectural Risk Factors Derived From Soccer

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Background: Hamstring strain injuries are the most common injuries in team sports. Biceps femoris long head architecture is associated with the risk of hamstring injury in soccer. To assess the overall predictive ability of architectural variables, risk factors need to be applied to and validated across different cohorts.

Purpose: To assess the generalizability of previously established risk factors for a hamstring strain injury (HSI), including demographics, injury history, and biceps femoris long head (BFlh) architecture to predict HSIs in a cohort of elite Australian football players.

Study Design: Cohort study; Level of evidence, 3.

Methods: Demographic, injury history, and BFlh architectural data were collected from elite soccer (n = 152) and Australian football (n = 169) players at the beginning of the preseason for their respective competitions. Any prospectively occurring HSIs were reported to the research team. Optimal cut points for continuous variables used to determine an association with the HSI risk were established from previously published data in soccer and subsequently applied to the Australian football cohort to derive the relative risk (RR) for these variables. Logistic regression models were built using data from the soccer cohort and utilized to estimate the probability of an injury in the Australian football cohort. The area under the curve (AUC) and Brier score were the primary outcome measures to assess the performance of the logistic regression models.

Results: A total of 27 and 30 prospective HSIs occurred in the soccer and Australian football cohorts, respectively. When using cut points derived from the soccer cohort and applying these to the Australian football cohort, only older athletes (aged $\geq$25.4 years; RR, 2.7 [95% CI, 1.4-5.2]) and those with a prior HSI (RR, 2.5 [95% CI, 1.3-4.8]) were at an increased risk of HSIs. Using the same approach, height, weight, fascicle length, muscle thickness, pennation angle, and relative fascicle length were not significantly associated with an increased risk of HSIs in Australian football players. The logistic regression model constructed using age and prior HSIs performed the best (AUC = 0.67; Brier score = 0.14), with the worst performing model being the one that was constructed using pennation angle (AUC = 0.53; Brier score = 0.18).

Conclusion: Applying cut points derived from previously published data in soccer to a dataset from Australian football identified older age and prior HSIs, but none of the modifiable HSI risk factors, to be associated with an injury. The transference of HSI risk factor data between soccer and Australian football appears limited and suggests that cohort-specific cut points must be established.

Keywords: risk; injury prediction; hamstring injury; muscle injury; fascicle length

Hamstring strain injuries (HSIs) are the most common injuries in team sports such as soccer[5,6,10] and Australian football,[15] lead to reduced performance after return to play,[27] and pose a significant financial burden for athletes and their sporting organizations.[11] As such, identifying factors that increase the risk of an HSI has been the focus of ongoing research. Indeed, 2 of the most consistently identified risk factors are older age and a prior HSI, both of which are nonmodifiable.[8] Recent work has focused on identifying modifiable factors that could be targeted via an intervention to potentially mitigate the risk of future HSIs. Among this work, a study conducted in elite soccer players reported that athletes with biceps femoris long head (BFlh) fascicles shorter than 10.56 cm were approximately 4 times more likely to sustain a prospective HSI than their counterparts with "longer" fascicles.[24] However,

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this cut point was determined retrospectively from the data to which it was ultimately applied. While such an approach is commonly used to establish associations between factors and the risk of an injury, its use to identify the risk of injuries at an individual level requires further validation.

To determine the predictive ability of injury risk factors, Bahr[1] proposed a 3-step process. First, a risk factor and its associated cut point must be established in a specific cohort. Subsequently, the generalizability of risk factors and their cut points must be validated in separate cohorts (whose data were not used to determine the cut point). The final step is to conduct randomized controlled trials to test the effectiveness of a combination of risk factor screening (based on data generated from the first 2 steps) and interventions targeted at those deemed "at risk." It should be noted that the framework outlined by Bahr[1] specifically relates to the application of dichotomized risk factor data (cut points used to assign high- and low-risk groups), and while this is an appropriate series of steps to determine the utility and generalizability of risk factors, it does not directly assess the predictive performance of continuous variables. Bahr[1] further stated that the eventual goal of injury prediction is the successful development of a screening tool. As an extension of the Bahr[1] framework, techniques such as logistic regression, which establish univariate and multivariate models to estimate the probability of future (hamstring strain) injuries, can be used to assess the performance of factors associated with future HSIs to predict injury occurrence at the individual level. While logistic regression is a commonly employed statistical approach, there is a dearth of work in sports injury research that has developed logistic regression models in one cohort and then applied these models to a separate cohort in a different sport. The addition of a separate cohort is necessary for the theoretical screening tool that is proposed by Bahr,[1] who further suggested that such tools need to be validated in all cohorts that could use the tool. Such an approach would allow for a more thorough understanding of the generalizability of factors that may be associated with future HSIs across cohorts.[23]

Despite architectural characteristics of the BFlh being associated with the risk of future HSIs in elite soccer players, no research has investigated the generalizability of these risk factor cut points when applied to a separate cohort, nor has the predictive ability of these data in another cohort of athletes from a different sport been determined. Accordingly, this study aimed to assess the ability of BFlh architecture, in conjunction with age and prior injury (which are previously established cut points determined in elite soccer players), to identify the risk of HSIs in elite Australian football players at both a group level and an individual level. We hypothesized that previously established cut points for HSI risk factors derived from BFlh architectural, age, and prior HSI data in soccer players would be associated with an HSI in Australian football players.

METHODS

Study Design

Data for this prospective cohort study were collected during the 2014-2015 A-League season and the 2018 Australian Football League (AFL) season. The A-League and the AFL are the premier competitions in Australia for soccer and Australian football, respectively. For both cohorts, demographic (age, height, weight), injury history, and BFlh architectural data were collected at the beginning of the preseason periods (soccer cohort: June 2014; Australian football cohort: November 2017). Any prospectively occurring HSIs throughout the preseason and in-season periods (excluding finals) of both leagues (soccer cohort: June 2014–May 2015; Australian football cohort: November 2017–August 2018) were reported to the research team; these included injuries incurred in training or in match play. Data collected during the 2014-2015 A-League season have been previously published.[24] Ethical approval for the collection of both datasets was granted by the Australian Catholic University Human Research Ethics Committee (No. 2014-26V [soccer dataset] and No. 2017-208H [Australian football dataset]).

Participants

A total of 321 athletes (152 soccer players from 9 teams; 169 Australian football players from 4 teams) provided informed consent to participate before data collection. The age (years), height (cm), and weight (kg) of each athlete were provided at the beginning of the preseason period for both cohorts. Additionally, team medical staff completed a retrospective injury questionnaire that reported, in a binary manner (yes/no), each athlete's history of hamstring injuries in the past 12 months as well as the history of anterior cruciate ligament injuries at any stage throughout the athlete's career.

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TABLE 1
Variables Used to Determine the RR and to Build Univariable and Multivariable Logistic Regression Models[a]

RR	Univariable Logistic Regression Model	Multivariable Logistic Regression Model
Age	Age	Age and prior HSI
Prior HSI	Prior HSI	Age, prior HSI, and fascicle length
Height	Fascicle length	Age, prior HSI, and pennation angle
Weight	Pennation angle	Age, prior HSI, and relative fascicle length
Fascicle length	Relative fascicle length	All variables[b]
Muscle thickness		
Pennation angle		
Relative fascicle length		

[a]All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. No interaction terms were included in any of the models. HSI, hamstring strain injury; RR, relative risk.

[b]All variables (age, prior HSI, height, weight, fascicle length, muscle thickness, pennation angle, and relative fascicle length) were included in a stepwise regression model. The final model was built using the subset of variables that minimized the model's Akaike information criterion.

BFlh Architectural Assessment

The collection of BFlh architectural characteristics of both cohorts was undertaken as previously reported.[12,16-18,24] Muscle thickness, pennation angle, and fascicle length of the BFlh were determined from images taken along the longitudinal axis of the muscle belly utilizing 2-dimensional B-mode ultrasound (frequency: 12 MHz; depth: 8 cm; field of view: 14 × 47 mm) (Vivid i; GE Healthcare). The scanning site was determined as the halfway point between the ischial tuberosity and the knee joint fold along the BFlh. All architectural assessments were performed with participants in a relaxed, prone position with the hips in neutral and knees fully extended. To gather ultrasound images, the linear array ultrasound probe, with a layer of conductive gel, was placed on the skin over the scanning site, aligned longitudinally and perpendicular to the posterior thigh with the hips in normal unrestrained rotation. Care was taken to ensure that minimal pressure was placed on the skin by the probe and the operator. Finally, the orientation of the probe was manipulated slightly by the operator to optimize fascicle identification. Ultrasound image analysis was undertaken offline (MicroDicom version 0.7.8). For each image, 6 points were identified as described by Kellis et al.[13] Muscle thickness was defined as the distance between the superficial and intermediate aponeuroses of the BFlh. The fascicle of interest, which was the clearest and could be seen across the entire field of view, was outlined and marked on the image. The angle between this fascicle and the intermediate aponeurosis was defined as the pennation angle. The angle of the superficial and intermediate aponeuroses was determined as the angle between the line marked as the aponeurosis and an intersecting horizontal reference line input across the captured image. Fascicle length was determined as the length of the outlined fascicle between the aponeuroses. As the entire fascicle was not visible in the probe's field of view, it was estimated via the following validated equation[25]:

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

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 (the quotient of the fascicle length and muscle thickness). All BFlh architectural assessments and analyses were conducted by the same operator (R.G.T.) with published reliability (intraclass correlation coefficient range = 0.95-0.99; typical error range = 2.1%-3.4%).[25] The extrapolation technique and equation have been validated against cadaveric tissues.[13]

Prospective HSI Data

A prospective HSI was defined as acute pain in the posterior thigh that resulted in the cessation of activity. Each injury was confirmed by a clinical examination conducted by the medical officials (ie, physical therapist, doctor) of each club. Club medical officials subsequently provided the research team with a medical report detailing the injured limb, the location and mechanism of the injury, and the number of days taken to return to full match availability.

Statistical Analysis

Differences between the 2 cohorts were assessed using an independent t test. After this, using the soccer cohort's dataset, receiver operating characteristic curves were utilized to determine optimal cut points for continuous variables. These cut points were established as the value that maximized the difference between sensitivity and 1 – specificity, as described in the original work.[24] All cut points derived from the soccer cohort were then applied to the Australian football cohort to determine relative risks (RRs), the associated 95% CIs, and sensitivity and specificity. As a prior HSI is a dichotomous variable, the cut point used to determine the RR of future HSIs in the Australian football cohort was determined by comparing those with and without a history of HSIs. All variables included in the RR analyses can be found in Table 1. A RR was deemed

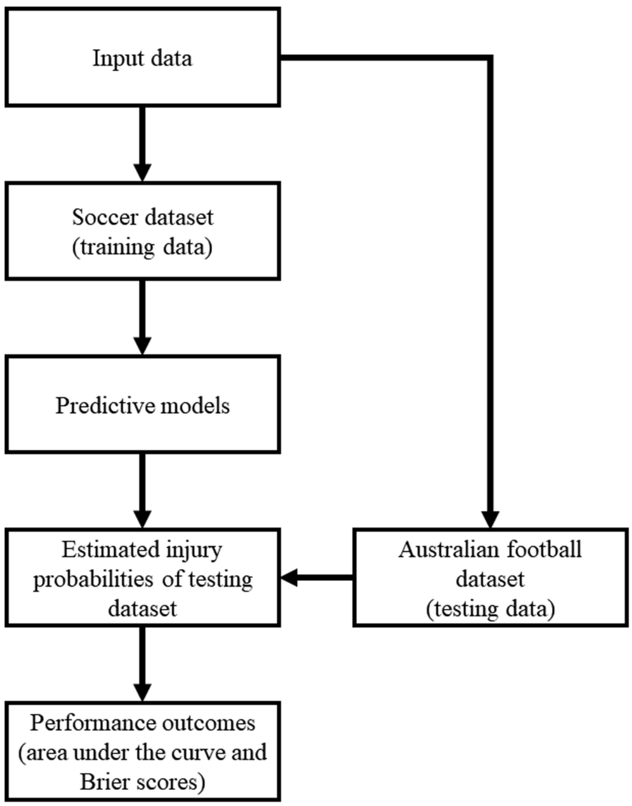

Figure 1. The logistic regression modeling approach implemented in this study.

to be significant when the 95% CI did not cross 1.0. After the determination of RR, univariable and multivariable logistic regression models were built using the soccer dataset and then subsequently applied to the Australian football dataset to assess the generalizability and predictive performance of these models. The variables included in these models and the process by which they were built can be found in Table 1 and Figure 1, respectively.

To assess the performance of each logistic regression model to predict future HSIs in the Australian football cohort, the area under the curve (AUC) and the Brier score were determined. The AUC, determined from a receiver operating characteristic curve, measures the ability of a model to distinguish between prospectively injured and uninjured observations. An AUC of 1.0 indicates that the predicted injury probabilities for the prospectively injured athletes are all greater than the predicted injury probabilities for the uninjured athletes. An AUC of 0.5 indicates a classification of no better than random chance. The AUC could also be considered as analogous to a percentage where an AUC of 0.5 equates to a successful prediction 50% of the time and an AUC of 1.0 equates to a successful prediction 100% of the time. The Brier score, graded on a scale from 0 to 1, is a measure of the precision of probabilistic predictions, with a Brier score closer to 0 indicating better precision. Calibration plots for all logistic regression models were constructed to provide a visual representation of how well a model can estimate the probability of an event (ie, prospective HSI) across the spectrum of predicted probabilities.

All statistical analyses were performed using the R statistical programming language[19] and the following packages: caTools, dplyr, ggplot2, DescTools, scoring, OptimalCutpoints, and ggpubr.

RESULTS

Participant Characteristics

Complete prospective follow-up data were obtained for all participants. A total of 152 soccer players (age, 24.7 ± 5.0 years; height, 179 ± 6 cm; weight, 75.6 ± 6.6 kg) and 169 Australian football players (age, 23.6 ± 3.5 years; height, 188 ± 8 cm; weight, 86.4 ± 8.7 kg) were included in the analyses. All descriptive data and differences between the 2 cohorts can be observed in Appendix Table A1 (available in the online version of this article). Of the athletes who were included in this study, 27 soccer players and 30 Australian football players sustained a prospective HSI during their respective seasons. For both cohorts, more HSIs were sustained in matches (soccer: n = 20; Australian football: n = 17) compared with during training (soccer: n = 6; Australian football: n = 13), although not all injuries had this information available (soccer: n = 1; Australian football: n = 0). For soccer players, the number of HSIs sustained per position was the following: midfielder, 11; forward, 9; and defender, 7. For Australian football players, the number of HSIs was the following: midfielder, 6; forward, 11; back, 11; and ruck, 2. Descriptive statistics for both the prospectively injured and uninjured athletes of both cohorts can be found in Table 2.

RR, Sensitivity, and Specificity

The RR of Australian football players sustaining a prospective HSI, as well as sensitivity and specificity values, based on the cut points derived from the soccer cohort can be found in Figure 2. Older athletes (aged ≥25.4 years; RR, 2.7 [95% CI, 1.4-5.2]) and those with a prior HSI (RR, 2.5 [95% CI, 1.3-4.8]) were at an increased risk of HSIs. Height, weight, fascicle length, muscle thickness, pennation angle, and relative fascicle length were not associated with an increased risk of HSIs in Australian football players when using cut points derived from the soccer cohort (Figure 2). All RR, sensitivity, and specificity data can be found in Appendix Table A2.

Logistic Regression Models

The AUC and Brier score of each logistic regression model that was built using the soccer dataset and subsequently applied to the Australian football dataset can be found in Table 3 (model coefficients are provided in Appendix Table A3, and variable importance for each individual model is provided in Appendix Figure A1). The model constructed using age and prior HSIs performed best (AUC = 0.67; Brier score = 0.14), with the worst performing model being a univariable model containing pennation angle (AUC =

TABLE 2
Athlete Characteristics[a]

	Australian Football			Soccer		
	Injured (n = 30)	Uninjured (n = 139)	*P* Value	Injured (n = 27)	Uninjured (n = 125)	*P* Value
Age, y	24.9 ± 3.5	23.3 ± 3.5	.029	27.0 ± 3.8	24.2 ± 5.1	.002
Prior HSI, n	10	18	<.001	9	21	.063
Height, cm	186 ± 7	188 ± 8	.850	180 ± 7	179 ± 6	.395
Weight, kg	84.8 ± 8.5	86.8 ± 8.7	.253	76.4 ± 6.7	75.4 ± 6.6	.463
Fascicle length, cm	10.10 ± 0.89	10.20 ± 0.60	.581	10.30 ± 1.48	11.10 ± 1.49	.018
Muscle thickness, cm	2.60 ± 0.22	2.61 ± 0.26	.862	2.52 ± 0.31	2.51 ± 0.32	.918
Pennation angle, deg	15.6 ± 1.0	15.4 ± 1.2	.561	14.2 ± 1.4	13.2 ± 1.5	.002
Relative fascicle length[b]	3.88 ± 0.31	3.94 ± 0.26	.217	4.11 ± 0.45	4.44 ± 0.50	.001

[a]Data are presented as mean ± SD unless otherwise indicated. All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. HSI, hamstring strain injury.
[b]Relative fascicle length refers to fascicle length relative to muscle thickness.

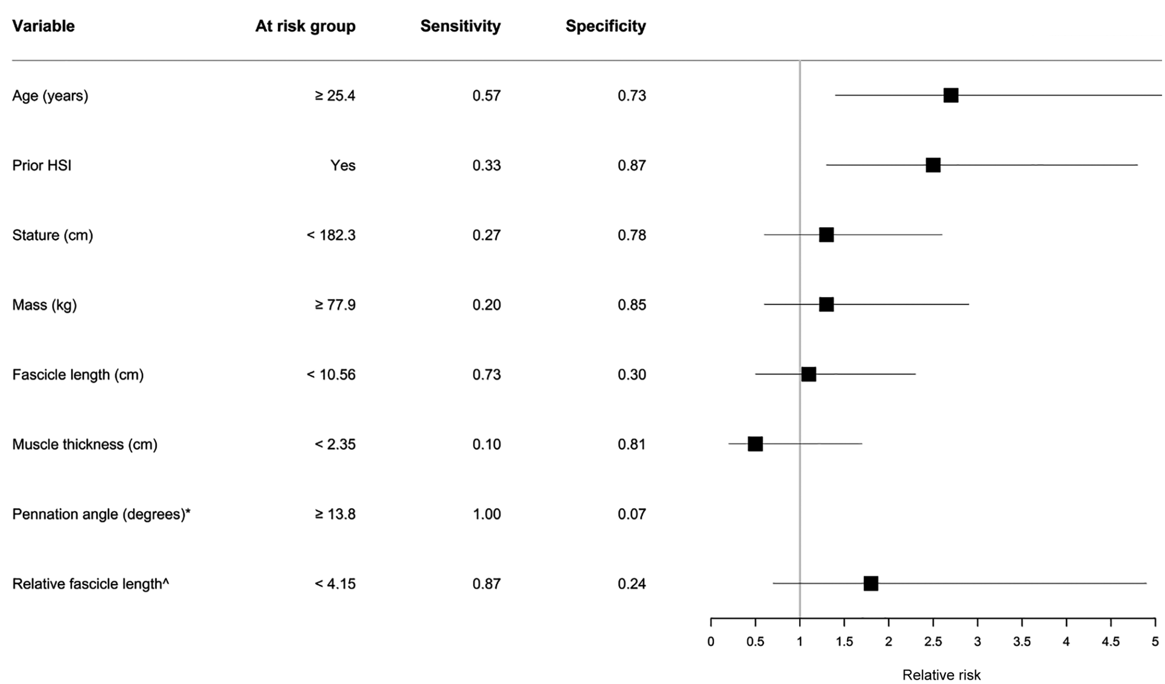

Figure 2. The relative risk (RR) of Australian football players sustaining a prospective hamstring strain injury (HSI), as well as sensitivity and specificity values, based on risk factor cut points derived from a previously collected dataset in soccer. If the 95% CI (represented by the black horizontal lines) crosses the gray vertical line (RR, 1.0), this indicates a nonsignificant RR. All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. *The RR and 95% CI for pennation angle could not be calculated because of a sensitivity value of 1.00, which indicates that there were no HSIs in the low-risk group. ^Relative fascicle length refers to fascicle length relative to muscle thickness.

0.53; Brier score = 0.18). The calibration of each univariable model and multivariable model is illustrated in Figures 3 and 4, respectively.

DISCUSSION

The key finding of this study was that previously reported risk factors derived from BFlh architectural variables in soccer players were not associated with a risk of future HSIs in Australian football players. However, the risk of future HSIs in Australian football players was associated with older age (≥25.4 years) and prior HSIs, with the age cut point generated from a previously collected dataset in soccer. This study is the first to apply statistical cut points derived from one sporting cohort to determine the risk of HSIs in another sporting cohort, which is recommended as a critical step in establishing the predictive ability of risk factor data.[1,20]

TABLE 3
AUC and Brier Score for Each Logistic Regression Model[a]

	AUC	Brier Score
Univariable		
Age	0.64	0.14
Prior HSI	0.60	0.14
Fascicle length	0.54	0.15
Pennation angle	0.53	0.18
Relative fascicle length	0.56	0.16
Multivariable		
Age and prior HSI	0.67	0.14
Age, prior HSI, and fascicle length	0.65	0.14
Age, prior HSI, and pennation angle	0.62	0.17
Age, prior HSI, and relative fascicle length	0.65	0.15
Stepwise regression[b]	0.65	0.15

[a]Models were built using data from the soccer cohort and utilized to estimate the probability of prospective HSIs in the Australian football cohort. Estimated injury probabilities were compared with the actual outcomes to determine the predictive performance of each model. All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. AUC, area under the curve; HSI, hamstring strain injury.

[b]All variables (age, prior HSI, height, weight, fascicle length, muscle thickness, pennation angle, and relative fascicle length) were included in a stepwise regression model. The final model was built using the subset of variables that minimized the model's Akaike information criterion. The final variables included were age, prior HSI, and relative fascicle length. Note that these are the same variables that were included in one of the a priori–determined models.

In contrast to the findings of the original investigation of the soccer cohort,[24] cut points derived from BFlh architectural variables in soccer players were not associated with the risk of HSIs when applied to an Australian football cohort. Previous research has reported that soccer players with BFlh fascicles shorter than 10.56 cm were at a 4-fold increased risk of HSIs compared with their counterparts with longer fascicles.[24] In the current study, however, BFlh fascicle length was not associated with the risk of HSIs, with Australian football players possessing fascicles shorter than 10.56 cm having a similar level or risk (RR, 1.1) compared with athletes with longer BFlh fascicles. This suggests that while BFlh architecture may play an important role in identifying elite soccer players' risk of future HSIs, injury risk cut points derived from this cohort are not generalizable to Australian football players. There are a number of potential reasons as to why data from soccer may not readily transfer to Australian football, not least because of differences in anthropometric and architectural characteristics between cohorts (Appendix Table A1). While it might be expected that risk factor cut point data from one sport, subsequently applied to another, are unlikely to have transference, in reality, practitioners from various sports rely on literature not specific to their sport to guide their HSI prevention and/or risk mitigation strategies. The present work provides evidence that an assumption of transference between sports cannot be guaranteed for modifiable risk factor cut points and highlights the importance of replication work across different cohorts for variables found to be associated with future HSIs. However, age and a prior HSI were associated with an increased risk of HSIs in the soccer cohort,[24] and when these same cut points were applied to Australian football players, an association was still present. These findings add to the existing body of evidence reporting age and prior HSIs as strong, albeit nonmodifiable, risk factors for a future HSI.[9]

When identifying the risk of HSIs at an individual level (via logistic regression) the model built using age and prior HSI was superior to all other models. In prior research, models built using the BFlh tended to outperform other models[24]; however, in the current study, including BFlh architectural variables in the models typically reduced their predictive performance. The results of the logistic regression models are in line with the RR (association) data suggesting that age and prior HSIs offered the best predictive ability within the Australian football cohort. Despite this, the model built using age and prior HSIs only had an AUC of 0.67. This value suggests that if we were to randomly select a prospectively injured athlete and an uninjured athlete, the likelihood that the best performing model would have allocated the prospectively injured athlete with a higher predicted injury probability (compared with the uninjured athlete) is only equal to 67%. While there is no consensus on how to subjectively describe and/or interpret AUC data, an AUC of >0.75 indicates that model performance was closer to perfect prediction than random chance. Given that all AUC values of the logistic regression models reported in the current work were $\leq$0.67, this suggests that their ability to correctly classify the prospectively injured and uninjured athletes was closer to random chance than it was to perfect predictive performance; as illustrated by the multivariable calibration curves (Figure 4), the models tended to overestimate the probability of future HSIs. This is likely a function of the models being built using data from the soccer cohort in which BFlh architecture influenced the risk of HSIs and highlights the fragility of the transference of logistic regression models between different sports.

Prior research has attempted to investigate the ability of other variables to identify the risk of HSIs in elite Australian football players. For example, an association between high-speed running distances and the risk of HSIs at a group level in elite Australian football players has been reported previously.[22] At an individual level, one study[4] has investigated the ability of internal and external training load data to predict lower limb noncontact injuries in elite Australian football players. In this previous study, data from 2 seasons were used to predict injury occurrence in a third season. The best performing model was able to classify the athletes who sustained a prospective hamstring injury and the uninjured athletes with an AUC of 0.72. While this study utilized an independent training and testing dataset (as per the current methods), it is important to note that the cohorts were not entirely independent. Whether the ability of internal and external training loads to predict the occurrence of HSIs is generalizable across cohorts from different sports remains to be

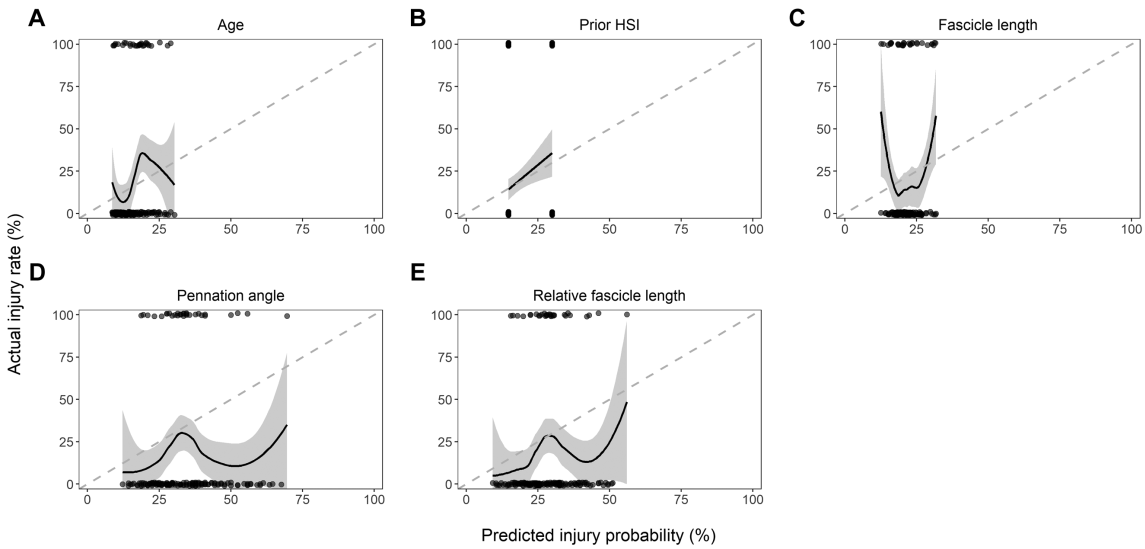

Figure 3. Calibration plots for all univariable logistic regression models with actual and predicted rates of a hamstring strain injury (HSI). Calibration is a measure of how well a model can estimate the probability of an event. For example, if we were to take every observation with a predicted injury probability of 25%, a perfectly calibrated model would suggest that the actual rate of injuries for these observations was equal to 25%. The 45° diagonal line represents perfect calibration, and the gray shaded areas indicate the 95% CI. All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. Relative fascicle length refers to fascicle length relative to muscle thickness. Points at 100 on the y-axis represent predicted injury probabilities of subsequently injured athletes (with predicted probabilities shown on the x-axis), while points at 0 on the y-axis represent predicted injury probabilities of athletes who avoided subsequent injuries. Excluding plot B (prior HSI), all points are separated by height for visual clarity: (A) age, (B) prior HSI, (C) pennation angle, (D) fascicle length, and (E) relative fascicle length.

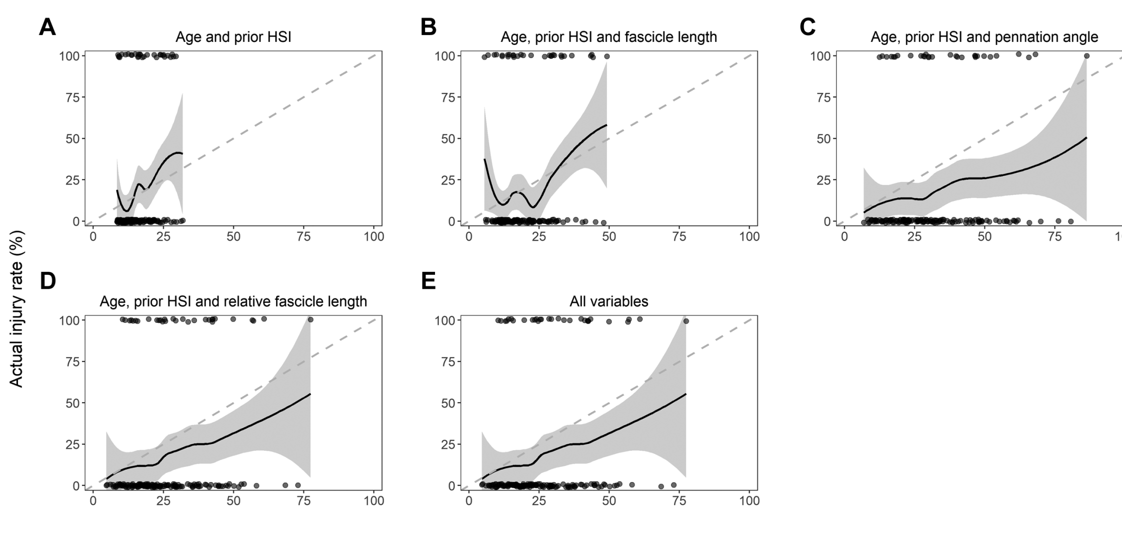

Figure 4. Calibration plots for all multivariable logistic regression models with actual and predicted rates of a hamstring strain injury (HSI). Calibration is a measure of how well a model can estimate the probability of an event. For example, if we were to take every observation with a predicted injury probability of 25%, a perfectly calibrated model would suggest that the actual rate of injuries for these observations was equal to 25%. The 45° diagonal line represents perfect calibration, and the gray shaded areas indicate the 95% CI. All architectural variables (fascicle length, muscle thickness, pennation angle, and relative fascicle length) were derived from the biceps femoris long head. Relative fascicle length refers to fascicle length relative to muscle thickness. Points at 100 on the y-axis represent predicted injury probabilities of subsequently injured athletes (with predicted probabilities shown on the x-axis), while points at 0 on the y-axis represent predicted injury probabilities of athletes who avoided subsequent injuries. (A) Age and prior HSI; (B) age, prior HSI, and fascicle length; (C) age, prior HSI, and pennation angle; (D) age, prior HSI, and relative fascicle length; and (E) stepwise regression including all variables as inputs (final model included age, prior HSI, and relative fascicle length).

seen. These results do, however, suggest that the addition of internal and external training load data may contribute to the improvement of multivariable HSI prediction models in Australian football players.

Another study with a similar design to the current investigation has reported on the predictive performance of HSI risk factors in elite Australian football players.[23] Low levels of eccentric knee flexor strength, in addition to older age and a history of HSIs, have previously been associated with an increased risk of HSIs in a cohort of elite Australian football players.[14] A follow-up to the original investigation used these data to build predictive models and identify the risk of injuries in another cohort of elite Australian football players 2 years later.[23] Despite age, prior HSIs, and eccentric knee flexor strength being strongly associated with the risk of HSIs in the original dataset,[14] the predictive models built using these variables were only able to classify the prospectively injured and uninjured athletes in the follow-up cohort with a mean AUC of 0.52.[23] In comparison, the worst performing multivariable model in the current study was that which was built using age, prior HSIs, and pennation angle (AUC = 0.62). The current findings suggest that the architectural variables included in this study, while not displaying a significant association with the risk of HSIs, may facilitate better predictive performance than eccentric knee flexor strength. However, as mentioned previously, prior research used independent training and testing datasets from the same sport.[4,23] Accordingly, the results may be difficult to compare to the current study, which is the first to use testing and training datasets from 2 different sporting cohorts.

Recent recommendations[3] have suggested using the Brier score as a predictive performance metric, which has been rarely, if ever, reported in the sports injury literature. While the Brier score did not offer a different interpretation of the current results in comparison to the AUC, it is important for researchers and practitioners alike to understand how to interpret the Brier score as a means to facilitate comparisons between future studies. Graded on a scale from 0 to 1, the Brier score is a measure of the precision of probabilistic predictions, with a lower Brier score indicating better precision. When building predictive models, it is important to assess not only the ability of a model to distinguish between the prospectively injured and uninjured athletes (for which the AUC is a metric well suited to do so) but also how precise the predicted injury probabilities are. The Brier score reflects the ability of a model to correctly predict the actual rate of injuries observed. In the current study, the multivariable model with the lowest Brier score was built using age and prior HSIs (Brier score = 0.14). The addition of fascicle length to this model did not negatively affect the Brier score, although it did reduce the AUC from 0.67 to 0.65. The addition of all other architectural variables, however, negatively impacted the Brier score (Table 3). The calibration curves illustrated in Figures 3 and 4 provide a visual representation of each model's ability to correctly predict the actual observed injury rates. The use of calibration curves, while requiring a subjective interpretation, can provide a more granular understanding of model errors when considered in conjunction with AUC and Brier score data. These curves suggest that the addition of the architectural variables to the multivariable models tends to result in an overestimation of injury rates (Figure 4), and this would have been indeterminate based on the objective measures of model performance only.

From a practical perspective, the results of this study suggest that practitioners must proceed cautiously when interpreting and translating the findings of an investigation in one sporting cohort to another sporting cohort as it relates to HSI risk factors. It may be tempting, based on the seminal work,[24] to conclude that 10.56 cm is an appropriate cut point for classifying athletes as having either short or long BFlh fascicles. However, this cut point was determined retrospectively from the data to which it was applied and, as a result, is closely fit to the original soccer cohort. While this cut point displays some level of predictive ability in the soccer cohort,[24] it was not appropriate for identifying Australian football players at an increased risk of HSIs. The best performing model in the current study achieved an AUC of 0.67. This indicates that if we were to randomly observe a prospectively injured athlete and an uninjured athlete, the likelihood that the model will have allocated the prospectively injured athlete with a higher predicted injury probability is equal to 67%. These results suggest a poor ability to correctly identify the risk of HSIs at an individual level, even using previously reported risk factors. Accordingly, practitioners should be cautious when using risk factor data from a different sport to make inferences regarding their athletes' risk of future HSIs.

There are limitations in this study that must be acknowledged. First, the measure of BFlh fascicle length is an estimation made from the validated equation reported in the Methods section.[2,13] This estimation is necessary because of the small transducer field of view utilized in this study. The methodology and equation employed for this estimation have been compared against cadaveric hamstring samples, have been reported as valid and reliable,[13,25] and have been associated with the risk of injuries.[24] However, the utilization of other methods for determining BFlh architecture[7] may have provided different results. This notwithstanding, the validity of the current work is strengthened, as the method of BFlh architectural assessment and analysis was consistent across both cohorts. Second, the data used to build the predictive models in this study was collected at the beginning of preseason training for each study period. It is unknown whether more frequent measures of the architectural variables included in this study would have impacted predictive performance. Additionally, although a prior HSI was significantly associated with the risk of injuries in this study, previous research has suggested that more granular measures of the effect of prior injuries (such as measures of session availability) may provide more insight.[21] Third, BFlh architectural data were used to predict all HSIs. While the exclusive prediction of BFlh injuries may have resulted in different findings, it would have also negatively affected statistical power. Finally, the current study does not report running exposure data from either cohort. Previous literature has shown that Australian football players cover significantly longer distances during high-velocity running and sprinting as well as exert significantly more sprint efforts compared to soccer players.[26] Differences in running exposure between the 2 cohorts may have influenced our findings; however, we were unable to account for this.

In conclusion, modifiable HSI risk factors and their cut points previously established in a cohort of elite soccer players were not able to identify the risk of HSIs in a cohort of elite Australian football players at both a group level and an individual level. Currently, the ability of predictive models to correctly identify athletes at an increased risk of HSIs is suboptimal. While the efficacy of the current methods to identify the risk and predict the occurrence of HSIs may warrant further investigation, practitioners should proceed with caution when interpreting and implementing the findings of previous research that is not specific to their cohort of interest.

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