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# The use of skill tests to predict status in junior Australian football

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**Abstract**
This study examined whether skill tests were predictive of status in junior Australian football. Players were recruited from the 2013 under 18 (U18) West Australian Football League competition and classified into two groups: elite (state U18 squad representative; $n$ = 25; 17.9 ± 0.5 years) and subelite (nonstate U18 squad representative; $n$ = 25; 17.3 ± 0.6 years). Both groups completed the Australian football kicking (AFK) and Australian football handballing (AFHB) tests, assessing kicking accuracy/ball speed and handballing accuracy on dominant and nondominant sides. A multivariate analysis of variance (MANOVA) modelled the main effect of "status", whilst logistic regression models were built for the predictive analysis using the same test parameters. Between-group differences were noted across all parameters, with the combination of kicking accuracy and ball speed on the dominant and nondominant sides being the best predictor of status for the AFK test (wi = 0.25, AUC = 89.4%) and the combination of accuracy on the dominant and nondominant sides being the best predictor of status for the AFHB test (wi = 0.80, AUC = 88.4%). The AFK and AFHB tests are predictive of status, suggesting that their use is warranted as a means of talent identification in junior Australian football.

**Keywords:** *talent identification, predictive modelling, team sports, technical ability*

## Introduction

Identifying junior athletes who possess the potential for success in multidimensional team sports may appear challenging due to the complexity of the games' skill requirements. For example, according to Launder's model of a skilful player, elite team sport athletes possess a unique blend of physical, technical and tactical mastery (Launder, 2001). Thus, the challenge for talent identification scouts is to select juniors who possess a balance of both skill and physiology (Farrow, Pyne, & Gabbett, 2008). Current talent identification practices within elite sporting organisations such as the Australian Football League (AFL) are often the combination of subjective (e.g. talent scouts viewing players in match play) and objective (e.g. a draft combine; a battery of tests spread over 4 days which are designed to measure Australian football-specific attributes) examinations (Burgess, Naughton, & Hopkins, 2012). However, subjectively assessing skill proficiency within junior playing competitions may be unreliable due to the potential perceptual differences of what coaches or talent scouts believe constitute technical skill, whilst the tests used within the draft combine are often delimited to physical variables and hence neglect to reliably examine the remaining components of the sport (e.g. technical proficiency). Additionally, judging prospective playing ability on physical variables could be misleading, as although they have been used to identify initial talent in multidimensional sports (Keogh, 1999; McGee & Burkett, 2003; Pyne, Gardner, Sheehan, & Hopkins, 2005; Sierer, Battaglini, Mihalik, Shields, & Tomasini, 2008), physical variables do not fully encapsulate playing ability (Woods, Raynor, Bruce, McDonald, & Collier, 2014). Consequently, technical skill testing may further highlight the combination of traits that best characterises the potential for success in sports such as Australian football.

The difficulty encountered when designing a test of technical skill specific to Australian football is that the technical requirements of the game are multidimensional. For example, a senior AFL player will often dispose the ball by foot, using either foot (i.e. kick), over short (~25 m), medium (~35 m) or long (~45 m) distances (Appleby & Dawson, 2002), whilst often handballing from either hand for distances less than 15 m (the shortest legal kick distance) during a

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game. Additionally, players are required to execute these disposals to dynamic or stationary targets, all whilst being temporally and spatially constrained. Thus, skill tests specific to Australian football should be valid and reliable measures of the technical skills commonly executed under match conditions.

Despite the scarcity of research examining sports-specific skill in junior Australian football, it is hypothesised that elite players will be more technically proficient than their subelite counterparts. For example, recent research has shown that a winning AFL team has a higher disposal efficiency (the number of disposals successfully executed to a teammate) when compared to a team that loses (Sullivan et al., 2014), suggesting that it may be advantageous for AFL recruiters to identify technically proficient juniors. The aim of this study was to identify whether technical skills (specifically kicking accuracy and ball speed and handballing accuracy) were predictive of status (elite/subelite) in junior (under 18) Australian football.

## Methodology

From a total sample of 86 under 18 (U18) West AFL players with a mean age of 17.6 ± 0.6 years, two groups, namely elite ($n$ = 25; 17.9 ± 0.5 years) and subelite ($n$ = 25; 17.3 ± 0.6 years), were selected. The elite sample consisted of 25 participants who had been selected in the 2013 State U18 Academy playing squad (elite developmental talent pathway), whilst the subelite sample consisted of 25 participants randomly chosen using the random number generation package in Excel (Microsoft, Redmond, USA) from the remaining cohort of 61 U18 West AFL players not selected in the Academy playing squad. At the time of recruitment, all participants were injury-free and participating in regular Australian football games and/or training sessions. The relevant Human Research Ethics Committee provided ethical approval with all participants and parents/guardians (if participants were under 18 years of age) providing informed consent prior to testing.

Participants completed kicking and handballing tests, referred to herewith as the Australian football kicking (AFK) test and Australian football handballing (AFHB) test. The AFK test was completed on an outdoor football field, with the ambient temperature and wind speed recorded prior to testing to ensure similarities between testing sessions. A wind speed and temperature variations of less than 5 km · hr$^{-1}$ and 5°C, respectively, were deemed as being within the acceptable limits, with testing conditions being within these climatic zones. Due to the methodological design of the AFHB test, testing was completed in a biomechanics laboratory. A standardised warm-up was completed by all participants, which consisted of light jogging and dynamic stretches, whilst a practice trial of both tests on the dominant and nondominant sides was completed in an attempt to minimise trial error. Testing took place at the end of the 2013 season to ensure participants were at peak technical proficiency. The elite and subelite participants were tested on separate occasions; thus, no more than 25 participants were tested at a time. For both tests, 10 s was allocated between each disposal (kick or handball). A Stalker Radar gun (Applied Concepts Inc., New York, USA) was used to measure the peak ball speed during the AFK test. Ball speed was not assessed in the AFHB test, as an expert panel of coaches ($n$ = 3 state-level coaches with a minimum of 10-year experience) deemed this variable as an unimportant assessment point for the handball in Australian football, specifically noting that speed was not a teaching point when coaching the handball.

### *The AFK test*

Before commencing the test, participants were required to nominate their dominant and nondominant leg, with dominance being defined as their preferred kicking leg. One kick was completed at each distance (short, 20 m; medium, 30 m; long, 40 m) with the first three being on their dominant leg. This influenced the side that they disposed the ball to; for example if their dominant leg was their left leg, they would kick to the targets on the right of their body. To begin the test, the participant was given possession of a football (AFL match standard) and stood on the start cone facing away from the targets. When cued by a whistle blown by the scorer, the participant ran to the turn cone, made a 180° degree turn (self-directed) and disposed the ball from behind the release line to a specified target player; positioned within a target circle (Figure 1). The target player was randomly assigned before each disposal by the scorer; however, each target was only called once per side. The designated target player was required to call for the ball whilst remaining within the perimeter of the circle as the participant manoeuvred around the turning cone, but the remaining targets were stationary. Once the three disposals on their dominant side (one at each distance) were completed, the participant was then instructed to use their nondominant leg to dispose the ball to the target players on the opposite side. Participants were cued to “kick the ball to the target player as quickly and as accurately as possible” but if the ball was not disposed within 3 s of the trial commencing, they received a score of 0. For additional descriptive information beyond this paragraph, refer Figure 1. To assess participant’s kicking accuracy, two criterion variables were used; these being the participant’s total score on their

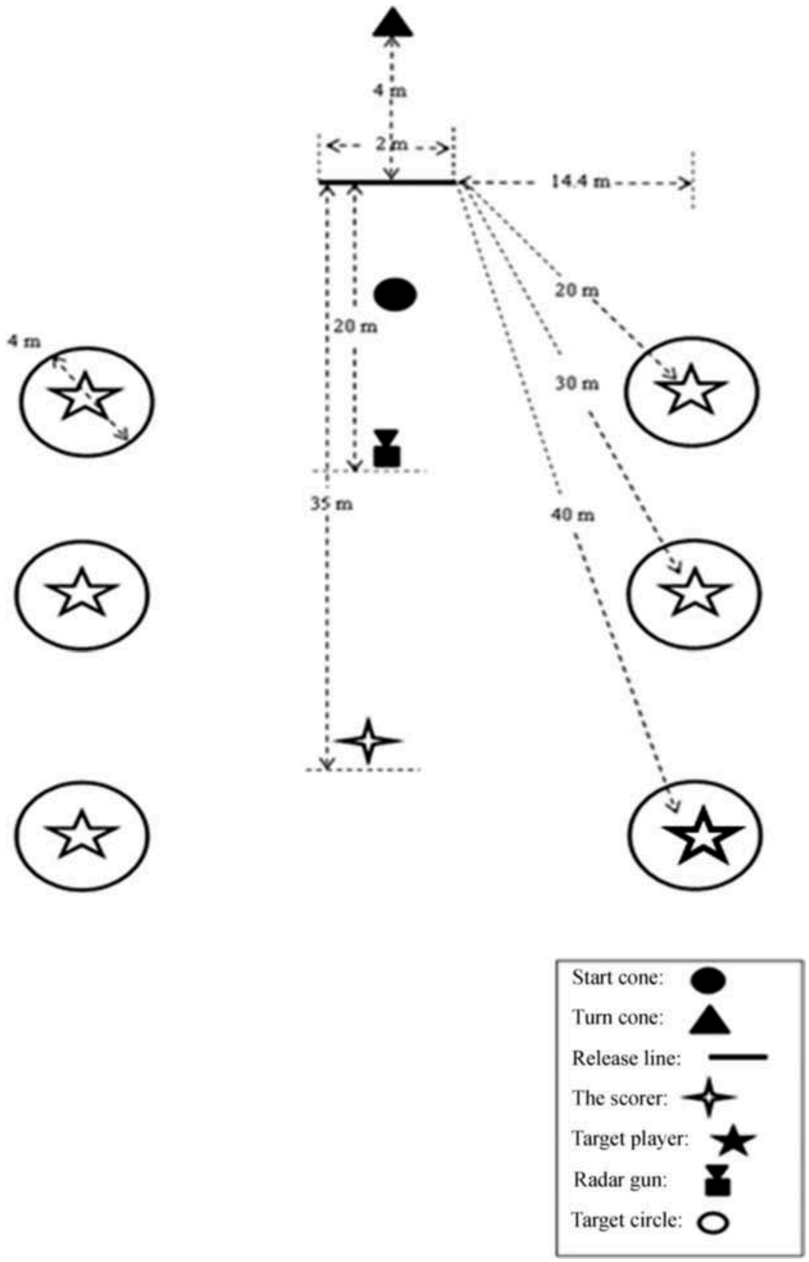


Figure 1. The Australian football kicking test as adapted from the AFL skills kicking test.



dominant leg and their total score on their nondominant leg. Additionally, two criterion variables were used to assess a participant's ball speed; these being their average peak ball speed on each side. Accuracy was assessed through the use of the following scoring criteria:

- **3 points**: The ball reached the target player on the full and they did not have to leave the target circle to receive possession.
- **2 points**: The ball reached the target player on the full; however, they were required to place one foot outside of the target circle to receive possession.
- **1 point**: The ball reached the target player on the full, but they had to place both feet outside of the target circle to receive possession.
- **0 points**: The target player did not receive possession of the ball on the full.

*Psychometric properties of the AFK test*

To ensure one kick at each distance was a true representation of a participants' kicking accuracy; eight elite participants (deemed as being elite kickers by the expert panel of coaches) were required to have three kicks to each distance, with the targets being randomly allocated by the scorer to minimise any

Table I. The test–retest reliability ICC and inter-rater reliability kappa-statistic.

| Distance | ICC | κ |
|---|---|---|
| Short dominant | 0.82 | 0.84 |
| Short nondominant | 0.97 | 0.87 |
| Medium dominant | 0.95 | 0.78 |
| Medium nondominant | 0.84 | 0.80 |
| Long dominant | 0.95 | 0.80 |
| Long nondominant | 0.90 | 0.73 |
| Average | 0.91 | 0.80 |

learning effect. This was undertaken separately from their main trial. The same test protocols were followed, with two-way mixed intraclass correlation coefficients (ICC) indicating strong correlations at each distance for both the dominant and nondominant sides (Table I). To ensure the inter-rater reliability of the scoring criteria, two independent scorers assessed the same 10 trials, with the kappa-statistic (κ) being used to assess the level of agreement between the scores given at each distance. The level of agreement for the kappa-statistic is as follows: < 0 less than chance agreement, 0.01–0.20 slight agreement, 0.21–0.40 fair agreement, 0.41–0.60 moderate agreement, 0.61–0.80 substantial agreement and 0.81–0.99 almost perfect agreement (Landis & Koch, 1977). The strength of agreement at each distance can be seen in Table I.

### *The AFHB test*

Following a similar protocol to the AFK test, participants were required to nominate their dominant and nondominant hand prior to commencing the test, with hand dominance being defined as a participant's preferred hand for handballing. Following this, the participant was informed that the first nine handballs were to be on their dominant side. To begin the test, the participant was given possession of an AFL match standard football and stood at the first cone facing the target, which was divided into nine small squares; each randomly numbered, ranging from one to nine. The grid was arranged as a 3 × 3 grid, with each square consisting of a 50 cm width and height for a total grid measurement of 150 cm × 150 cm. Despite being a fundamental skill within the game, there is scarce notational research specifying handballing characteristics; thus, the same expert panel of coaches as used within the AFK test construction indicated that these measurements reflected similar target sizes to those a player would commonly aim at when handballing in match play. Additionally, participants were required to handball 8 m in an effort to hit the targets, with this distance being deemed as the most similar to those undertaken in match play by the same expert panel of coaches.

When ready, the participant was required to handball once to each target, with the order being randomly chosen by a caller. Once the nine handballs on the dominant side had been completed, the participant was then required to use their nondominant side. The participants were given 1 point if they successfully handballed the ball anywhere within the perimeter of the target number chosen; however, "line-balls" (handballs which hit the perimeter of the target, not within the target) were classified as a "miss" and thus scored 0. The participants were cued to "handball as quickly and as accurately as possible", but if the handball was not completed within 3 s of the target being called, they were given a miss for that target. To ensure the accuracy of the scores given, each trial was recorded through the use of a digital video camera (Sony, HDR-XR260VE) for later analysis. To assess a participant's handballing accuracy, two criterion variables were used; these being the participant's total score (maximum of nine) on each of their dominant and nondominant sides.

### *Statistical analysis*

Mean and standard deviation were calculated for all skill test variables (kicking accuracy and ball speed on both dominant and nondominant sides and handballing accuracy on both dominant and nondominant sides), whilst a multivariate analysis of variance (MANOVA) was used to test the main effect of "status" (two levels: elite and subelite) on the skill test variables. The effect size of status on the skill test variables was calculated using Cohen's *d*-statistic, as described in Cohen (1988). All between-group comparisons were done using the SPSS software (Version 19. SPSS Inc., USA). The type-I error rate was set at $P < 0.05$.

Logistic regression models were built to predict status for both tests, using the skill test variables as the explanatory variables, with status coded as a binary variable (1 = elite and 0 = subelite). All modelling and visualisation were done using the statistical computing software R (Version 2.15.1, Developmental Core Team, Auckland, New Zealand). Due to the smaller sample size, separate logistic regression models were built for each skill test; thus, the test variables that significantly differed according to status were used as the predictor variables and were included in the full models for both skill tests. Following this, the most parsimonious model was found for each test by reducing the full model using the "dredge" function in the *Mumin* package (Burnham & Anderson, 2002). This function returns the best model using Akaike's information criterion weights (wi). To ensure the strength of the best model, a null model was built and used as a comparator.

Additionally, the *pROC* package (Robin et al., 2011) was used to run a sensitivity analysis on the strongest combination model and for separate models containing only single-term predictors, to assess the ability of the predictive model to discriminate between elite and subelite participants. Bootstrapped receiver operating curves were produced for each model, and the area under the curve (AUC) was calculated, with an AUC of 1 (100%) representing perfect discriminant power. The point on the curve at which the sum of the elite and subelite scores is maximised could be considered the value (e.g. the sum of the predictor values for a participant) at which a "cut-off" might be acceptable for selecting participants (Woods et al., 2014). Here, the receiver operating curve was used to produce such cut-off indicators by using the total score for each player (arbitrary units) and for the individual predictors included in the final model.

## Results

According to the Pillai's trace ($V$), the MANOVA revealed a significant effect of status on the technical variables ($V$ = 0.623, $F$(7, 42.000) = 9.930, $P$ = 0.000) with the follow-up univariate analysis revealing a significant effect of ball speed and kicking accuracy for the AFK test and handballing accuracy for the AFHB test (Table II). Consequently, the full logistic regression models were built using the four predictor variables (dominant accuracy, nondominant accuracy, dominant ball speed and nondominant ball speed) for the AFK test and the two predictor variables (dominant and nondominant accuracy) for the AFHB test.

Table II. Between-group effects (mean ± *s*).

| Measurement | Elite | Subelite | Effect size |
|---|---|---|---|
| **AFK test** | | | |
| DomAcc (AU)[a] | 7.6 ± 1.3 | 5.5 ± 2.2 | 1.03 |
| NonDomAcc (AU)[a] | 5.4 ± 1.6 | 3.3 ± 2.7 | 0.86 |
| DomBS (km · hr$^{-1}$)[a] | 62.1 ± 4.0 | 57.3 ± 4.2 | 1.01 |
| NonDomBS (km · hr$^{-1}$)[a] | 58.4 ± 4.9 | 52.7 ± 4.6 | 1.03 |
| **AFHB test** | | | |
| DomAcc (AU)[a] | 6.0 ± 1.2 | 3.7 ± 1.7 | 1.20 |
| NonDomAcc (AU)[a] | 5.4 ± 1.2 | 3.6 ± 0.9 | 1.00 |

*Notes*: [a]Indicative of significant between-group differences (< 0.05). DomAcc denotes dominant accuracy, NonDomAcc denotes nondominant accuracy, DomBS denotes dominant ball speed, NonDomBS denotes nondominant ball speed, and AU denotes arbitrary units.

### *The AFK predictive model*

For the full model, a combination of dominant accuracy, dominant ball speed, nondominant accuracy and nondominant ball speed produced the best outcome (wi = 0.25, AUC = 89.4%), as shown in Table III and Figure 2. The receiver operating curve was maximised when the combined score of the AFK test variables equalled 127.3. Of the 25 elite participants, 21 (84%) had a combined score ≥ 127.3, whilst only 6 (24%) subelite participants had a combined score ≥ 127.3. Thus, the full model successfully detected 84% (21) of the true positives (elite participants) and 76% (19) of the true negatives (subelite participants).

The best single-term predictor of status for the AFK test was dominant leg accuracy (AUC = 79.8%), with

Table III. Model summary table showing the ranking of each model based on Akaike's weights (wi).

| Predictors | LL | df | AIC | delta | wi |
|---|---|---|---|---|---|
| **AFK test** | | | | | |
| ~DomAcc + DomBS + NonDomAcc + NonDomBS | −16.83 | 5.00 | 45.02 | 0.00 | 0.25 |
| ~DomAcc + DomBS + NonDomAcc | −18.09 | 4.00 | 45.06 | 0.04 | 0.25 |
| ~DomAcc + NonDomBS | −19.78 | 3.00 | 46.08 | 1.06 | 0.15 |
| ~DomAcc + NonDomAcc + NonDomBS | −18.77 | 4.00 | 46.43 | 1.41 | 0.12 |
| ~DomAcc + DomBS + NonDomBS | −19.10 | 4.00 | 47.10 | 2.08 | 0.09 |
| ~DomBS + NonDomAcc | −20.40 | 3.00 | 47.33 | 2.31 | 0.08 |
| ~DomBS + NonDomAcc + NonDomBS | −19.95 | 4.00 | 48.78 | 3.76 | 0.04 |
| Null (~1) | −34.66 | 1.00 | 71.40 | 26.38 | <0.001 |
| **AFHB test** | | | | | |
| ~DomAcc + NonDomAcc | −21.26 | 3.00 | 49.05 | 0.00 | 0.80 |
| ~DomAcc | −23.82 | 2.00 | 51.89 | 2.84 | 0.19 |
| ~NonDomAcc | −27.13 | 2.00 | 58.52 | 9.48 | 0.03 |
| Null (~1) | −34.66 | 1.00 | 71.40 | 22.35 | <0.001 |

*Notes*: LL denotes the log likelihood, df denotes degrees of freedom, AIC denotes the Akaike's information criterion, DomAcc denotes dominant accuracy, NonDomAcc denotes nondominant accuracy, DomBS denotes dominant ball speed, NonDomBS denotes nondominant ball speed, and AU denotes arbitrary units.

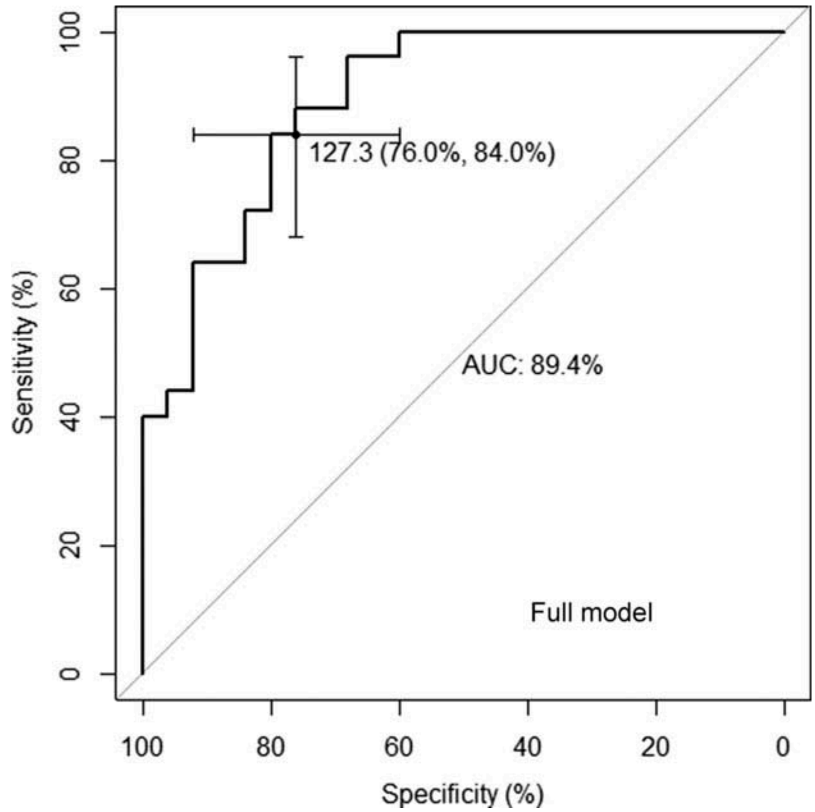


Figure 2. Bootstrapped receiver operating curve for the full logistic regression model for the Australian football kicking test.

a score of 6.5 being the value maximising the receiver operating curve (Figure 3a). This was followed by nondominant and dominant leg ball speed (AUC = 79.5% and AUC = 78.7%, respectively), with speeds of 50.7 km · hr$^{-1}$. (14.08 m · s$^{-1}$) and 61.0 km · hr$^{-1}$ (16.94 m · s$^{-1}$), respectively, maximising the receiver operating curve (Figure 3c and d). Finally, accuracy on the nondominant leg was the weakest single-term predictor of status (AUC = 74.5%), with a score of 3.5 maximising the receiver operating curve (Figure 3b). Of the six subelite participants who had a combined score ≥ 127.3, one exceeded the cut-off value for each kicking variable, whilst the remaining five participants exceeded the cut-off on only one kicking variable.

### *The AFHB predictive model*

The full model which included the combination of a participant's dominant and non-dominant handballing accuracy was the model that best predicted the status (wi = 0.80, AUC = 88.4%), as shown in Table III and Figure 4. The receiver operating curve was maximised when a combined score (i.e. sum of dominant and nondominant accuracy scores) equalled 8.5 (Figure 4a). Of the 25 elite participants, 23 (92%) had a combined score ≥ 8.5, whilst only 6 (24%) subelite participants had a combined score ≥ 8.5. Thus, the model successfully detected 92% of the true positives (elite participants) and 76% of the true negatives (subelite participants). Handballing accuracy on the dominant side was the best single-term predictor of status (AUC = 85%), with a score of 5.5 maximising the receiver operating curve (Figure 4b), whilst the handballing accuracy on the nondominant side had an AUC of 78.2% and a maximised receiver operating curve score of 3.5 (Figure 4c). Of the six subelite players who had a combined score ≥ 8.5, three exceeded the cut-off value for each handballing variable, whilst the remaining three exceeded the cut-off on only one handballing variable.

## Discussion

Whilst predictive modelling has previously been used to identify potential talent within elite sport (Keogh, 1999; McGee & Burkett, 2003; McLaughlin, Howley, Bassett, Thompson, & Fitzhugh, 2010; Mikulić & Ružić, 2008; Sierer et al., 2008; Woods et al., 2014), this is the first study to the authors' knowledge that has developed a predictive model that successfully predicts selection within an elite junior Australian football team based upon technical skill tests. Results showed significant differences between elite and subelite participants in measures of kicking accuracy and ball speed on both dominant

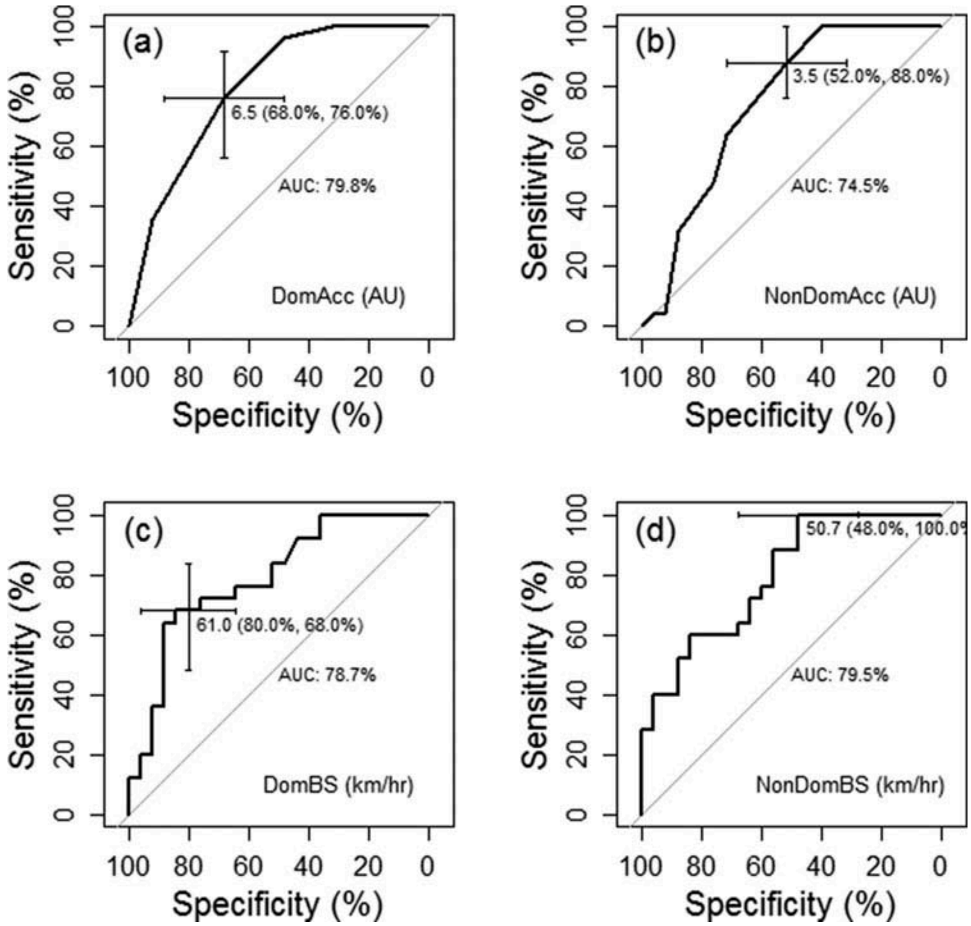


Figure 3. Bootstrapped receiver operating curve for the four predictor variables included as single-term models: (a) the dominant leg kicking accuracy, (b) nondominant leg kicking accuracy, (c) dominant leg ball speed, and (d) nondominant leg ball speed, for the Australian football kicking test.

and nondominant sides. In addition, handballing accuracy on both dominant and nondominant sides was significant between elite and subelite participants. The combination of all technical variables was however the greatest predictor of status for both tests, with both full models detecting greater than 80% of the elite participants and 76% of the subelite participants, respectively. Thus, consistent with the perceptions about technical ability, the vast majority of participants selected in the elite junior Australian football team appear to have a greater technical proficiency when compared to their subelite counterparts. However, although being outside the scope of this research (due to the restricted sample size), it would be interesting for future analyses to tailor predictive models specific to positional groups, thus uncovering junior players who may be better technically equipped to play specific field positions (i.e. a defender kicking the ball from defence).

Despite the originality of this research, the technical differences noted between the two levels of expertise were to be expected based upon the findings of others (Ali, Foskett, & Gant, 2008; Russell, Benton, & Kingsley, 2010). Specifically, Russell et al. (2010)and Ali et al. (2008) reported differences between elite and subelite soccer players in measures of accuracy and speed for passing and goal shooting tests specific to soccer. Thus, despite the different sports, the results suggest that elite players possess a greater technical proficiency when compared to their subelite peers. Being technically superior may be highly advantageous, as it may allow a player to execute more intricate tactical strategies implemented by a coach, potentially leading to greater team success. Consequently, these players may be looked upon more favourably by elite team selectors.

For both tests, the variables that significantly differed according to status were included as predictor variables within the full logistic regression models, and according to the AUC presented in both Figures 2 and 4a, it was the combination of each variable that best predicted the status. Thus, a score of greater than 127.3 and 8.5 for the AFK and AFHB tests, respectively, may be seen as acceptable cut-off values for identifying potential elite U18 players within the West AFL. Of particular interest

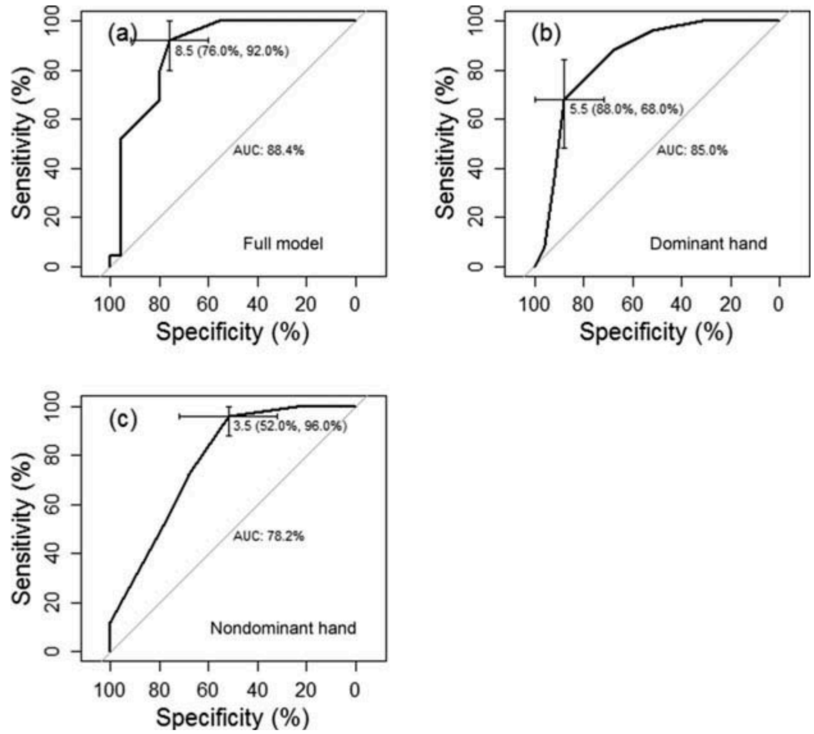


Figure 4. Bootstrapped receiver operating curve for (a) the full logistic regression model and the two predictor variables included as single-term models, (b) dominant handballing accuracy, and (c) nondominant handballing accuracy for the Australian football handballing test.



were the low discriminating scores for the accuracy variables from the nondominant side for both tests (Figures 3b and 4c). This may suggest that both groups lack proficiency when kicking and handballing on their nondominant side. From this finding, it could be inferred that the elite participants were better able to supplement this inefficiency on their nondominant side with a superior performance on their dominant side. Additionally, although being speculated, due to the multidimensional nature of Australian football, the elite participants may have possessed other desirable attributes (e.g. see Keogh, 1999; Lorains, Ball, & MacMahon, 2013; Woods et al., 2014) that outweighed a technical inefficiency. Nonetheless, accuracy on the nondominant side for both tests may not be a good single-term predictor of future success.

When the results of the current research are analysed with those of Keogh (1999) and Woods et al. (2014), it strengthens the notion that talent identification within multidimensional sports should incorporate assessments of a player's both physical and technical abilities. Specifically, the results of this study complement those detailed by Woods et al. (2014) who used physical variables to predict selection within an elite junior Australian football team. Interestingly, the author stated that physical assessments alone may not encapsulate playing ability within Australian football; thus, the current research may provide a deeper insight into the skill differences between junior Australian football players, as well as further highlighting the characteristics of elite junior players. Based on these combined findings, the most rigorous approach for identifying junior players appears to be a very specific set of physical and technical variables.

## Conclusion

Significant differences were evident between the elite and subelite participants in all measures of technical ability. It was however the combination of kicking accuracy and ball speed (of both dominant and nondominant sides) and handballing accuracy (of both dominant and nondominant sides) that were the greatest predictors of status for both tests, whilst dominant limb accuracy was the greatest single-term predictor of status for both tests. Nonetheless, there are some implications that should be acknowledged for future research, namely the construction of the AFK test. Although one kick at each distance was shown to be reflective of a participant's kicking ability, it may be worthwhile incorporating two kicks at each distance to accommodate a potential poor kick, thus limiting bias against a participant who may happen to make one poor attempt. Further, although being outside the scope of the current research, future examination of the relative age of both participant groups may provide additional insight to help explain the acquisition of greater technical skill and thus likelihood of obtaining higher selection as discussed by Pyne, Gardner, Sheehan, and Hopkins (2006) and Coutts, Kempton, and Vaeyens (2014). Finally, confirmation of test results like those reported within the current research may be further strengthened with complementary subjective player rating scales made by expert coaches or talent scouts, whilst additional physical and tactical variables may provide a holistically comprehensive approach when identifying junior players who possess the potential for success in the game.

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