Journal of Science and Medicine in Sport xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Journal of Science and Medicine in Sport

journal homepage: www.elsevier.com/locate/jsams

Original research

Multisensory assessment and machine learning for athlete classification in talent identification

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ARTICLE INFO

Article history:
Received 2 August 2025
Received in revised form 16 February 2026
Accepted 19 March 2026
Available online xxxx

Keywords:
Talent identification (TID)
Sensorimotor assessment
Autonomic function
Machine learning (ML)
Athlete classification
Olympic diving

ABSTRACT

Background: Talent identification in elite sport is challenged by maturation confounding and limited objective assessment tools. This preliminary study examined whether visual-vestibular-somatosensory and autonomic (VVS-A) measures distinguished podium-level from entry-level divers using machine learning.
Objectives: (1) Identify VVS-A features distinguishing podium-level divers from a Come and Try group using traditional statistical comparisons; (2) evaluate machine-learning models' ability to classify podium-level athletes; and (3) examine the distribution of classification probabilities using lift-curve analysis.
Design: Cross-sectional exploratory study with machine-learning classification.
Methods: Sixty participants from an Olympic diving talent identification programme underwent VVS-A assessment. Somatosensory function was evaluated via ankle proprioception using the AMEDA device. Visual, vestibular, and autonomic functions were assessed using the Prism-Neuro Eye system. Group differences were examined using independent-sample Student's *t*-tests. Supervised ML models were trained on selected VVS-A measures and evaluated using cross-validation and a held-out test set.
Results: Podium-level athletes demonstrated superior ankle proprioception (Left: $p < 0.001$, $d = 1.57$; Right: $p < 0.001$, $d = 1.83$) and visual-vestibular smooth pursuit ($p = 0.001$, $r = 0.51$). No group differences were observed for voluntary saccades or autonomic metrics. A calibrated Ridge Logistic Regression model classified podium-level athletes with high accuracy within this sample (94.4%; AUC = 0.889).
Conclusions: Selected VVS-A measures were associated with differences in current performance level in Olympic diving. However, the cross-sectional design, age differences between groups, and limited sample size preclude conclusions regarding predictive validity, necessitating longitudinal sport-specific validation before informing applied practice within talent identification contexts.

Practical implications

- *Sensorimotor measures differed between groups*: Podium-level athletes demonstrated superior ankle proprioception (AMEDA Left: $p < 0.001$, $d = 1.57$; Right: $p < 0.001$, $d = 1.83$) and visual-vestibular smooth pursuit performance ($p = 0.001$, $r = 0.51$) compared with a Come and Try group.
- *Machine learning differentiated groups within this sample*: A calibrated Ridge Logistic Regression model differentiated podium-level athletes from the Come and Try group with 94.4% accuracy on the held-out test set (AUC = 0.889), with somatosensory ankle proprioception and visual-vestibular smooth pursuit contributing most strongly to model output.
- *Classification probabilities concentrated podium-level athletes within ranked outputs*: Lift curve analysis demonstrated that higher-ranked model probabilities contained a greater proportion of podium-level athletes within this sample.
- *Implications for practice*: VVS-A profiling warrants further scientific investigation and longitudinal validation before implementation. The key applied question is how VVS-A assessment might be integrated alongside coaching evaluation within developmentally sensitive talent identification frameworks, rather than whether it should replace or correct coaching judgement. If validated, VVS-A measures may complement but should not be used independently of coach-led

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https://doi.org/10.1016/j.jsams.2026.03.011

assessment, anthropometric, physiological, technical, and psychosocial evaluation within multifaceted talent identification systems.

1. Introduction

Talent identification (TID) in sport typically relies on coach-led assessments integrating observations of anthropometric characteristics, physiological capacities, technical skill execution, and contextual performance behaviours.[1] Experienced coaches often apply integrative, developmental judgement that extends beyond discrete measurable attributes. In Olympic performance pathways, these approaches are often formalised within national talent identification programmes. Such approaches are susceptible to multiple selection biases, including the relative age effect, whereby chronologically older athletes within annual age cohorts are disproportionately selected and retained, and biological maturation biases, where advanced physical development is conflated with talent potential. These biases can operate independently or compound one another within talent pathways.[2–4] Recent work has proposed corrective adjustments accounting for relative, biological, and training age; however, these approaches are not yet consistently embedded within applied talent identification systems.[4] Misidentification within talent identification systems, including false negatives (overlooking athletes with potential) and false positives (selecting athletes who do not progress), incurs significant opportunity costs, impacting medal tallies and straining finite resources such as coaching and facilities.[5] Australia's historical data underscore these stakes, with an estimated AUD$37 million per gold medal (1980–1996), likely higher given $489 million invested for 2024 Paris and Brisbane 2032 Olympics.[5,6] Predicting senior success is complicated by non-linear adolescent growth, where chronological age and biological maturation diverge.[7] Debates over early specialisation versus sampling highlight uncertainty in optimal talent pathways.[7,8] Existing TID approaches may overlook latent potential, leading to selection inefficiencies and suboptimal resource allocation.[9]

Sensorimotor integration, encompassing somatosensory, visual, and vestibular functions, is crucial for elite sport performance,[10] yet it remains largely absent from talent identification protocols that primarily emphasise anthropometric characteristics, physiological capacities, and technical skill execution.[11]The sensorimotor system organises functional joint stability during dynamic movements through a complex interplay of afferent, efferent, and central neural processes, with proprioception serving as a cornerstone for both conscious sensations (joint position sense, kinesthesia) and unconscious neuromuscular control.[12,13]

Proprioception, driven by mechanoreceptors in muscles, tendons, ligaments, and joint capsules, provides essential feedback on muscle length, tension, and joint position. This feedback enhances athletes' spatial awareness and enables precise movement execution.[12] Muscle spindles, in particular, play a vital role by triggering rapid reflexive responses that strengthen dynamic joint stability, critical for countering sudden displacements in sporting activities.[13] In Olympic diving, for instance, superior ankle proprioception underpins key tasks such as jumping, landing, and balancing, ensuring stability and precision through seamless sensorimotor integration.[11,14]

The visual and vestibular systems complement proprioception by integrating visual and vestibular inputs to maintain balance, postural control (i.e., upright stance stability via corrective torque), and gaze stability.[15] Located in the inner ear, the vestibular system uses semicircular canals to detect angular acceleration and otolith organs for linear acceleration, coordinating eye movements and posture.[16] These sensory inputs support eye movements, such as the vestibulo-ocular reflex (VOR) for gaze stabilisation, saccades, and smooth pursuit for tracking moving targets.[17,18] In sports requiring dynamic sensory integration like diving, athletes rely on visual-vestibular mechanisms, integrating visual cues and vestibular signals to gauge self-motion during aerial rotations.[16] Autonomic function, mediated by parasympathetic and sympathetic responses, regulates reflex timing (e.g., pupillary light reflex) under stress, enhancing performance precision.[19] The pupillary light reflex provides a direct measure of autonomic integration, with parasympathetic pathways driving rapid pupil constriction and sympathetic responses facilitating dilation and recovery, enabling adaptation to high-performance stressors such as those encountered in Olympic diving.[19] Reliable assessment of these autonomic metrics in healthy individuals further supports their potential for evaluating neural efficiency in balance and postural control during athletic demands.[19,20]

Sport-specific sensorimotor adaptations, such as enhanced VOR suppression in elite gymnasts and optimised vestibular function in football players, may improve postural control and visual tracking during complex movements.[18,21] Postural control depends on dynamic integration of sensorimotor inputs (somatosensory, visual, and vestibular), regulated through sensory reweighting, where the CNS adjusts reliance on these inputs based on their reliability to maintain orientation and equilibrium.[22,23] When environmental factors such as glare, water turbidity, or wave-induced movement obscure visibility in diving, the CNS may compensate by increasing reliance on vestibular and proprioceptive cues, consistent with sensory reweighting, whereby unreliable sensory inputs are down-weighted in favour of more reliable alternatives.[23] This adaptive mechanism reduces dependence on perturbed sensory systems whilst increasing reliance on unperturbed ones.[23,25] According to sensory reweighting theory, Olympic diving likely relies on dynamic sensory integration to control mid-air body orientation.[15,23] Talent development is widely recognised as a non-linear, multifactorial process shaped by interactions amongst biological, psychological, and environmental factors.[26]

The role of sensorimotor capabilities in talent identification remains unclear, as current evidence cannot determine whether superior VVS-A performance reflects innate predisposition, sport-specific adaptation, or both. This distinction is critical: if primarily trainable, these measures function as performance monitoring tools rather than stable talent identification markers. Our cross-sectional design can identify group differences but cannot determine whether these capabilities predict future success.

Whilst these sensory capabilities are measurable, their role in talent identification and development remains underexplored. Machine learning can analyse multivariate datasets to identify patterns associated with differences in current performance levels.[27] This preliminary cross-sectional study employed selected sensorimotor and autonomic measures (VVS-A) with machine learning to examine whether these measures were associated with differences between current performance levels in Olympic diving.

We aimed to (1): identify sport-specific VVS-A features distinguishing podium-level divers from a 'Come and Try' group using traditional statistical comparisons (2); assess and compare the accuracy of multiple machine learning models in classifying podium-level divers using these features; and (3) explore the distribution of classification probabilities to examine whether higher-density concentrations of podium-level athletes emerged within ranked model outputs.

This study is grounded in a post-positivist epistemological stance informed by a critical realist ontology. We assume that sensorimotor and autonomic capacities reflect real underlying physiological processes that exist independently of measurement but can only be accessed indirectly through fallible indicators. Accordingly, our analyses estimate probabilistic associations with current performance level rather than deterministic markers of talent. Inferences are therefore bounded by sampling constraints, measurement error, and the developmental, maturational, and contextual factors shaping athlete progression.

2. Methods

2.1. Participants

This study assessed VVS-A features in 60 athletes for TID purposes: 20 Olympic-level divers ('Podium' group) and 40 entry-level participants ('Come and Try' group) from a talent identification session. The Australian Institute of Sport's National Performance Pathway categorises athletes across five stages—Emerging, Developing, Podium Potential, Podium Ready, and Podium—based on sport-specific performance and future potential. For this study, Podium, Podium Ready, and Podium Potential tiers were combined into the 'Podium' group to prioritise medal-potential athletes. The Podium group ($n = 20$; 5 males, 15 females; aged 17–34 years) completed their VVS-A assessment at Sydney Olympic Park aquatic centre prior to a scheduled training session.

The Come and Try group was recruited via open invitation at the New South Wales Institute of Sport. Of 62 entry-level aspiring divers (38 females, 24 males; aged 9–16 years) who attended the session in a gymnasium (dry land), participants completed a questionnaire detailing their sporting background and weekly activity levels (see Supplementary Material 1). Athletes were randomly divided into groups and rotated sequentially through seven testing stations: warmup, stretching, strength, acrobatics, trampolining, dry board, and VVS-A assessment (Station 7). Due to time constraints, only 40 participants who happened to reach Station 7 completed VVS-A testing, forming the final Come and Try analysis group. These participants were not pre-selected but represented those who completed the station rotation sequence within the available time. VVS-A results were excluded from coach evaluations to ensure that traditional selection methods (Stations 1–6) remained independent of experimental measures. Detailed station procedures are provided in Supplementary Material 2.

2.2. Procedure – somatosensory assessment

Somatosensory performance was evaluated using the Active Movement Extent Discrimination Assessment (AMEDA) protocol (Prism Neuro Pty Ltd., Canberra, Australia), a validated tool for quantifying ankle inversion sensorimotor acuity with high reliability (ICC = 0.96[28,29]). See Supplementary Material 3 for details and example image.

Participants underwent a familiarisation session, performing five inversion depths (10°–14°), each assigned numeric scores (1–5), sequentially three times per ankle prior to the assessment phase. In the assessment phase, athletes completed 50 randomised trials per ankle (left first, then right) without feedback, comprising 10 trials per inversion depth. Participants stood on the device with the test foot on the inverting section and the non-test foot on a stable platform, assigning scores based on perceived movement magnitude whilst maintaining forward gaze without verbal feedback or visual cues.

Discrimination ability was quantified using area under the curve (AUC) for each adjacent angle pair (1 vs. 2, 2 vs. 3, 3 vs. 4, 4 vs. 5), with values averaged and converted to percentages (100% = perfect joint position sense; 50% = chance performance).[20] Movement precision was ensured via custom system (error < 0.02°), with responses recorded manually via tablet.

2.3. Visual-vestibular assessment and autonomic function

These functions were evaluated using Prism Neuro Eye software (Prism Neuro Pty Ltd., Canberra, Australia) with moderate to good test-retest reliability (ICC = 0.53–0.89[20]). Following headset-based calibration to map gaze positions across the visual field, four 60-second tests were administered sequentially: linear smooth pursuit (horizontal tracking), circular smooth pursuit (curvilinear tracking), voluntary saccades (rapid gaze shifts), and pupillary light reflex for autonomic responses under varying luminance.[20,30]

Key parameters assessed included smooth pursuit visual tracking error (deviation from ideal trajectories), time-to-target and time-on-target for voluntary saccades, and pupillary dynamics—comprising latency, peak constriction velocity, and average dilation velocity—to evaluate comprehensive VVS integration and autonomic function.

2.4. Data analysis aim 1

Normality and variance homogeneity of continuous variables were assessed using Shapiro–Wilk and Levene's tests to guide parametric and non-parametric analyses. Comparisons between Podium and Come and Try groups were conducted using independent samples Student's *t*-tests for normally distributed data, and Mann–Whitney *U* tests for non-normally distributed data. Effect sizes were calculated using Cohen's *d* for parametric comparisons and r for non-parametric comparisons, with statistical significance set at $p < 0.05$ (two-tailed). All analyses were conducted in Jamovi (v2.3.28.0). AMEDA performance was quantified as Area Under the Curve (AUC) from receiver operating characteristic (ROC) curve analysis, with higher AUC indicating better accuracy.[29]

2.5. Data analysis aims 2 and 3 – machine learning approach

A supervised learning framework was employed to develop prediction models for classifying Podium athletes based on sport-specific VVS-A features identified from group comparisons (See Supplementary Material 5 for data flow diagram). Seven VVS-A variables were included: bilateral AMEDA scores (AUC), autonomic response delay (msec), autonomic visual parasympathetic and sympathetic velocities (mm/s), visual-vestibular smooth pursuit performance (tracking error in AU), and voluntary saccades ratio (time-on-target/time-to-target).

Prior to model training, all features were standardised using z-score normalisation ($\mu = 0$, $\sigma^2 = 1$) to ensure equal contribution across different measurement scales. The complete dataset of 60 athletes (Come and Try n = 40, Podium n = 20) was randomly split into 70% training (n = 42) and 30% held-out test (n = 18) sets using stratified sampling to maintain proportional group representation (66.7% Come and Try, 33.3% Podium). The training set (14 Podium, 28 Come and Try) was used exclusively for model training and 10-fold cross-validation. The held-out test set (6 Podium, 12 Come and Try) was completely excluded from all model development procedures and reserved solely for final model evaluation to provide an unbiased estimate of generalisation performance to unseen data.

Six machine learning models were trained on the standardised features using 10-fold cross-validation: Logistic Regression (Ridge L2), Random Forest, Gradient Boosting, AdaBoost, CN2 Rule Induction, and k-Nearest Neighbours. The Ridge Logistic Regression model demonstrated superior performance and was selected for further analysis (AUC = 0.918).

2.5.1. Model optimisation and validation

To address potential overfitting concerns with the small dataset (n = 60), the Ridge Logistic Regression model's probabilities were calibrated using a Sigmoid Calibrated Learner on the training set. The decision threshold was optimised to maximise the F1 score (the harmonic mean of precision and recall, balancing sensitivity and specificity, where a higher score from 0 to 1 indicates better performance, with 1 being perfect).

The calibrated model was evaluated on the held-out test set (n = 18; 12 Come and Try, 6 Podium). Feature importance was assessed using permutation importance, measuring the drop in AUC when each feature's values were randomly shuffled ($p < 0.05$). An Explain (SHAP) Model analysis further validated interpretability on the held-out test set, ranking features by their impact on model predictions. These methods aimed to support decision-making by complementing subjective judgement with traditional statistical approaches and machine learning techniques. Lift curve analysis was subsequently performed on the held-out test set to examine the distribution of classification probabilities across ranked model outputs.

3. Results

3.1. Aim 1 – identification of sport-specific VVS-A features

Descriptive statistics for seven VVS-A variables across two groups (Come and Try, n = 40; Podium, n = 20) are presented in Table 1. Independent sample t-tests for normally distributed variables with equal variances (Levene's test, $p > 0.05$) showed significant differences for AMEDA Left ($t(58) = 5.75$, $p < 0.001$, Cohen's $d = 1.57$) and AMEDA Right ($t(58) = 6.67$, $p < 0.001$, Cohen's $d = 1.83$), with Podium

Table 1
Descriptive statistics for VVS-A variables by group.

	Olympic category	N	Mean	Median	SD	Minimum	Maximum	Shapiro–Wilk	
								W	p
AMEDA Left (AUC)	Come and Try	40	60.50	60.00	5.90	47.00	74.00	0.98	0.6197
	Podium	20	70.30	71.50	6.84	54.00	83.00	0.97	0.6616
AMEDA Right (AUC)	Come and Try	40	58.95	59.00	5.89	46.00	73.00	0.99	0.9240
	Podium	20	69.75	69.50	5.96	53.00	79.00	0.92	0.0924
Autonomic Response Delay (msec)	Come and Try	40	256.05	256.00	19.04	210.00	304.00	0.98	0.8132
	Podium	20	257.35	259.00	15.12	229.00	280.00	0.95	0.4382
Autonomic Visual Parasympathetic (mm/s)	Come and Try	40	3.31	3.40	0.86	1.56	5.49	0.97	0.5055
	Podium	20	3.69	3.62	0.63	2.60	5.46	0.94	0.2349
Autonomic Visual Sympathetic (mm/s)	Come and Try	40	0.61	0.64	0.14	0.32	1.01	0.97	0.3383
	Podium	20	0.63	0.64	0.14	0.38	0.93	0.99	0.9874
Visual-Vestibular Smooth Pursuit (AU)	Come and Try	40	20.08	17.14	11.25	8.75	52.17	0.83	<0.0001
	Podium	20	11.97	11.53	2.45	7.82	16.98	0.95	0.4030
Voluntary Saccades (Time on/Time to Target)	Come and Try	40	0.94	0.93	0.39	0.12	1.69	0.97	0.4669
	Podium	20	1.05	1.22	0.63	0.17	2.06	0.93	0.1488

athletes outperforming Come and Try participants. No significant differences emerged for Autonomic Response Delay ($t(58) = 0.27$, $p = 0.791$), Autonomic Visual Parasympathetic (peak constriction velocity; $t(58) = 1.76$, $p = 0.084$), or Autonomic Visual Sympathetic (average dilation velocity; $t(58) = 0.42$, $p = 0.676$). For variables with unequal variances (Levene's $p < 0.05$), Welch's t-test indicated no significant difference for Voluntary Saccades (Time on/Time to Target) ($t(26.71) = 0.76$, $p = 0.452$). For non-normally distributed variables (Shapiro–Wilk $p < 0.05$), Mann–Whitney *U* tests indicated a significant group difference for Visual-Vestibular Smooth Pursuit ($U = 195.50$, $p = 0.001$, rank biserial correlation $= 0.51$), with Podium athletes showing superior performance (lower visual tracking error). AMEDA Left, AMEDA Right, and Visual-Vestibular Smooth Pursuit were identified as key distinguishing features. Distributions for these variables are shown in Figs. 1–2.

3.2. Aim 2 – machine learning model performance

The Ridge Logistic Regression model achieved the highest cross-validation performance (AUC = 0.918), outperforming kNN (AUC = 0.880), Random Forest (AUC = 0.832), CN2 Rule Induction (AUC = 0.774), Gradient Boosting (AUC = 0.773), and AdaBoost (AUC = 0.607). The model demonstrated balanced performance with classification accuracy of 0.857, recall of 0.857, and specificity of 0.821.

The calibrated Logistic Regression model, using Sigmoid calibration, yielded an AUC of 0.889 on the held-out test set ($n = 18$), compared to 0.918 uncalibrated. It classified 100% (12/12) of Come and Try and 83.3% (5/6) of Podium athletes correctly, achieving a CA of 94.4%.

Permutation importance analysis (Fig. 3) identified AMEDA Right, AMEDA Left and visual-vestibular smooth pursuit as the most influential features, with AMEDA Right showing the greatest decrease in AUC (approximately 0.17), followed by AMEDA Left (approximately 0.06), and visual-vestibular smooth pursuit (approximately 0.05).

An Explain (SHAP) Model analysis on the test set confirmed AMEDA Right and AMEDA Left as the top contributors to model output, with AMEDA Right exhibiting the greatest impact (Fig. 4).

3.3. Aim 3 – classification probability distribution via lift curve analysis

Lift curve analysis on the held-out test set ($n = 18$) examined the distribution of classification probabilities generated by the calibrated Logistic Regression model. The lift curve exhibited an area of 1.84, indicating non-uniform distribution of podium-level athletes across ranked model outputs. At a P-Rate of 0.33 (top 33% of ranked athletes, approximately six athletes), podium-level athletes were concentrated at approximately three times the baseline rate, corresponding to a model-derived classification score of 0.277. These findings describe the distribution of classification probabilities within this sample rather than defining an optimal selection threshold (Fig. 5).

4. Discussion

This cross-sectional study demonstrates that selected visual-vestibular-somatosensory measures differ between current podium-level athletes and a Come and Try group in Olympic diving. However, it does not establish predictive validity for future talent identification.

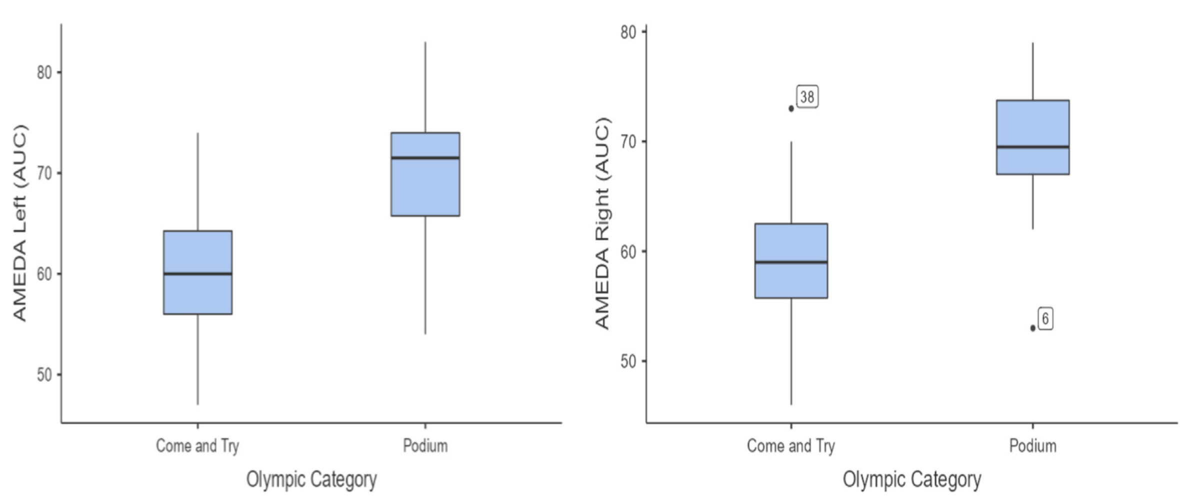

Fig. 1. Somatosensory assessment: Left and right ankle proprioception (AUC).

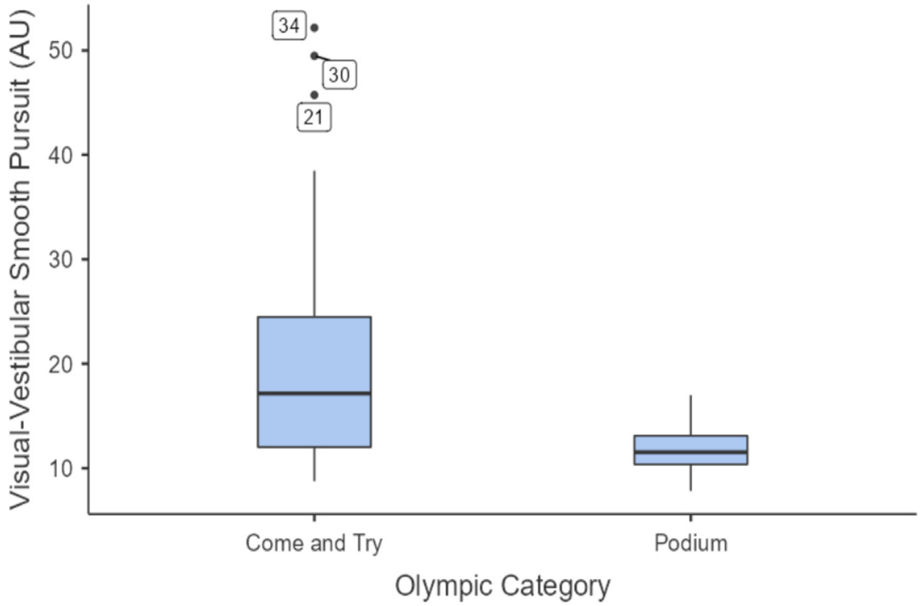

Fig. 2. Visual – vestibular smooth pursuit [visual tracking error (AU = arbitrary units)].

Whilst coach-led assessments emphasising anthropometric, physiological, and technical characteristics have successfully identified the current cohort of podium athletes in this sample, such approaches face limitations regarding long-term validity and bridging junior-to-senior performance gaps.[7,31] Within this context, VVS-A assessment may provide complementary insight into sensorimotor characteristics associated with current performance level, rather than serving as a standalone selection tool.

Elite divers demonstrated superior somatosensory ankle proprioception bilaterally, reflecting the precise sensory feedback required for diving's dynamic movements involving single-leg and double-leg take-offs. This proprioceptive advantage supports neuromuscular control and joint stability,[12,13] aligning with sensory reweighting theories that emphasise proprioceptive integration for postural control (i.e., upright stance via corrective torque).[15] Jaworski et al.[32] reported positive correlations between measures of postural sway and performance in elite badminton players, particularly in one-foot tests, paralleling diving's need for precise ankle positioning. Similarly, Han et al.[14] found that ankle proprioception strongly predicted competition level in football and gymnastics, suggesting its critical role for TID. Dowse et al.[33] demonstrated that elite surfers exhibited enhanced ankle proprioception, enabling precise foot-surface interactions akin to diving's requirements. These findings highlight ankle proprioception's pivotal role in elite diving performance.

Visual vestibular smooth pursuit (visual tracking error) was also significantly lower in elite divers, consistent with findings from high-performance sport research. van der Veen et al.[18] demonstrated that elite gymnasts exhibited superior vestibular ocular reflex (VOR) suppression during multi-axial rotations, enabling stable gaze control. Lower visual tracking errors correlated with enhanced performance in acrobatic tasks, directly relevant to Olympic diving, where divers must maintain precise gaze control to execute complex aerial manoeuvres.

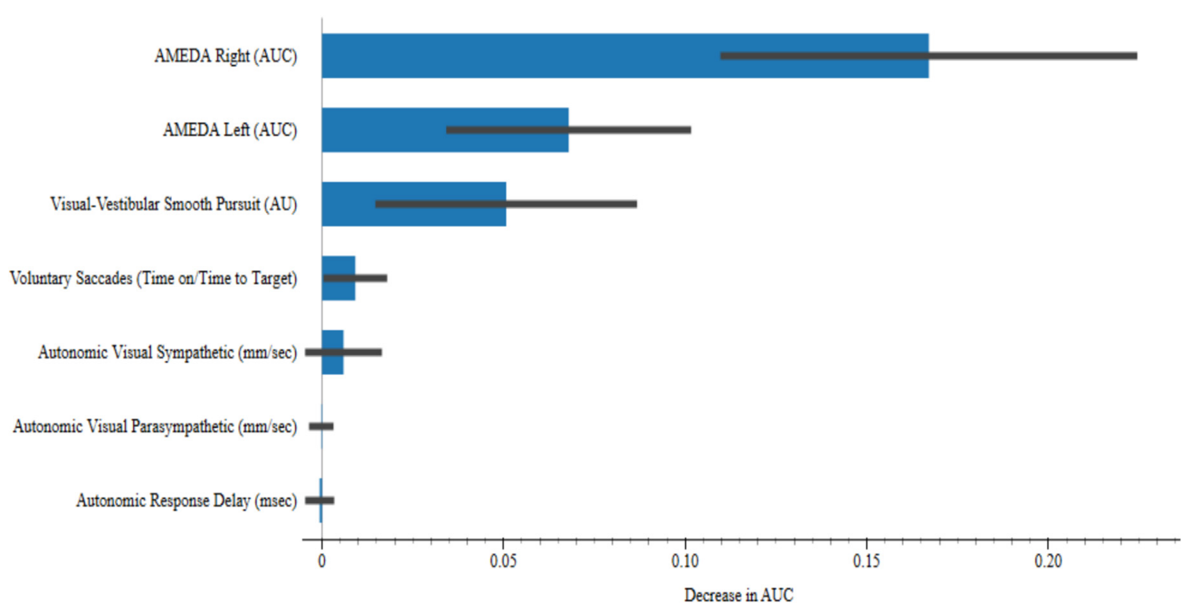

Fig. 3. Training dataset ($n = 42$) feature importance of VVS-A variables in logistic regression model (based on decrease in AUC).

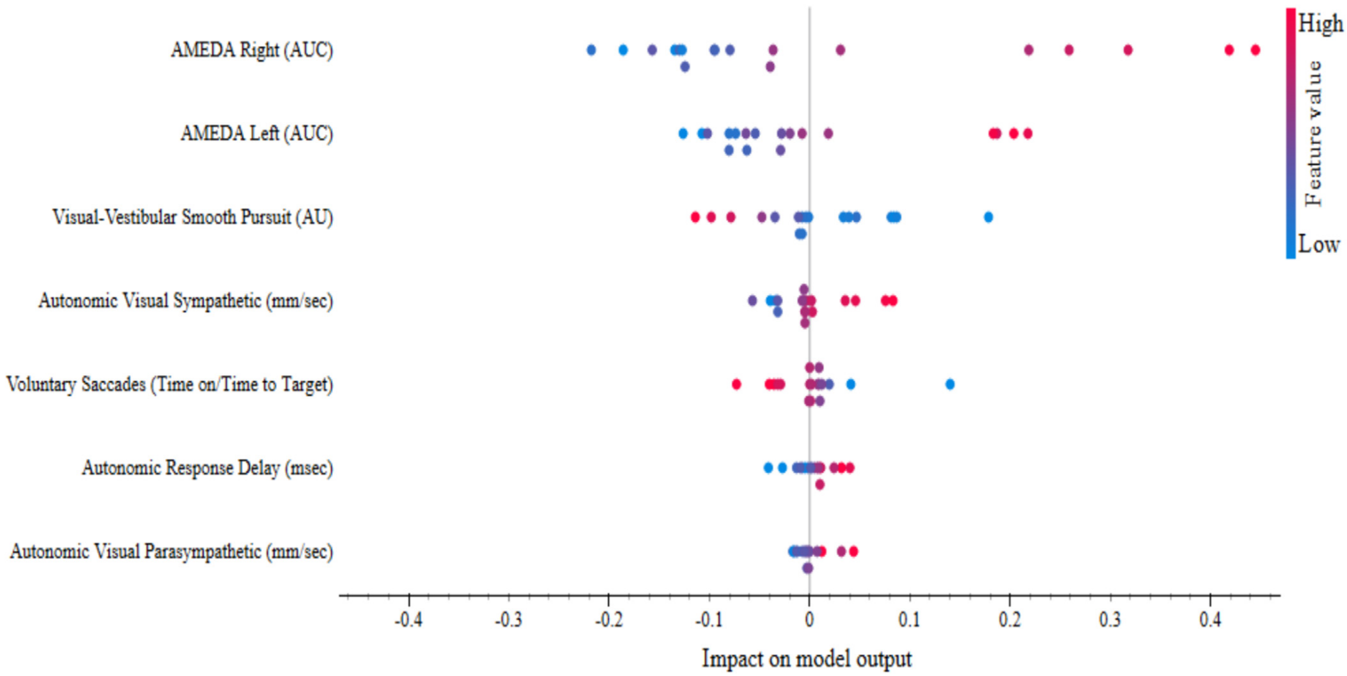

Fig. 4. Graphical representation of the "explain model" analysis of feature impacts (SHAP values) on calibrated logistic regression predictions (held-out test set).

This supports the inclusion of visual tracking metrics in TID protocols for high-performance sports requiring rapid spatial judgement.

The lack of significant differences in PLR latency suggests that autonomic reflex responses, driven primarily by parasympathetic and sympathetic pathways, do not distinguish podium-level divers from the Come and Try group in this context. This finding aligns with research indicating that PLR latency is a reflex measure unaffected by cognitive loading, suggesting that other factors, such as age or accumulated subconcussive injuries, may influence autonomic metrics in athletes.[34]

Further supporting the role of visual attention in high-performance diving, Aoyama et al.[35] found that spatial accuracy of predictive saccades was pivotal for success in a continuous visuomotor task simulating table tennis. Accurate saccadic approaches preceded effective motor actions, with post-saccade visual feedback enabling online

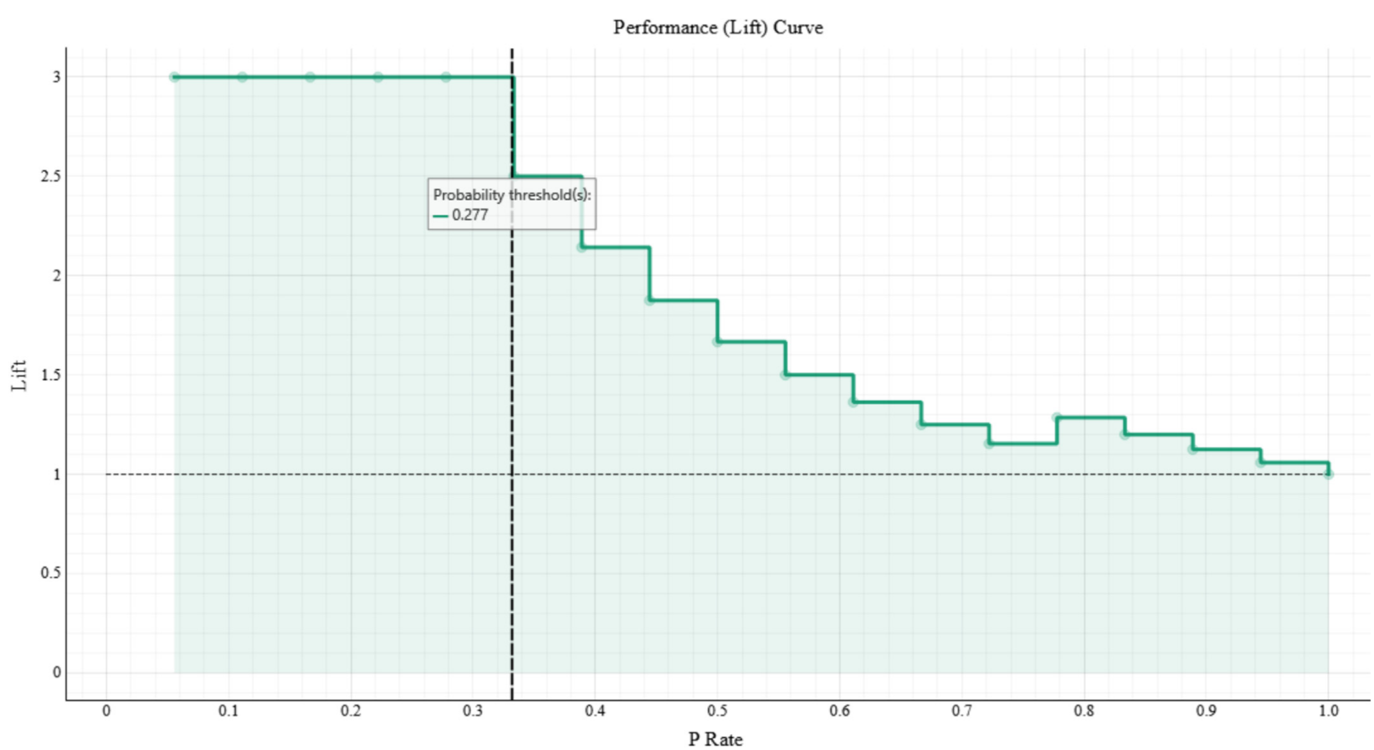

Fig. 5. Calibrated lift curve illustrating the distribution of podium-level athletes across ranked model outputs.
Athletes were ranked by similarity of multisensory profiles to current podium-level athletes. Podium-level athletes were concentrated towards higher-ranked outputs, occurring approximately three times more frequently than expected by chance within the top third of the ranking. The lift curve (area = 1.84) indicates non-uniform distribution across ranked outputs. This descriptive analysis does not define a selection threshold.

corrections. In diving, similar gaze precision is essential for calibrating movements during take-off and entry, aligning with our finding of reduced visual tracking errors in elite divers. This suggests that efficient visual search strategies are hallmarks of elite athletes, enhancing motor precision in sports like diving where split-second adjustments are critical.[35]

Proprioception integrates with visual-vestibular inputs to enhance precision in complex movements,[36] consistent with sensory reweighting principles.[15] Elite gymnasts demonstrate this integration through superior VOR suppression during rotations,[18] paralleling our findings of enhanced ankle proprioception and visual-vestibular efficiency in elite divers. By incorporating these integrated sensory metrics into our machine learning model, we illustrate a preliminary analytical approach for examining sensorimotor–autonomic characteristics associated with diving performance.

The model misclassified one current podium-level athlete (16.7% of the Podium group), highlighting important limitations. If VVS-A measures cannot perfectly differentiate current elite performance, their capacity to predict future potential is necessarily constrained. Possible explanations include compensatory strengths not captured by VVS-A, trainability of these measures, or individual variability in measurement sensitivity. This reinforces that VVS-A profiling should complement, not replace, multifactorial assessment frameworks. Accordingly, interpretation of machine learning outputs in this study must be situated within the broader developmental, maturational, and contextual factors that shape athlete progression.

Potgieter and Ferreira[37] demonstrated that visual skills were trainable in rhythmic gymnasts, with higher-level athletes showing greater improvements in eye-hand coordination and spatial awareness post-intervention. These skills parallel diving's requirements for visual tracking during aerial manoeuvres, suggesting that targeted training could enhance TID, though diving-specific trainability requires confirmation. Similarly, expert basketball players exhibit longer quiet eye durations and more efficient gaze behaviours under pressure,[38] highlighting visual attention as a potential TID marker across sports requiring split-second decisions. Their integration of mobile eye-tracking with artificial intelligence complements our machine learning approach, though sensory metric importance may vary across sports, necessitating sport-specific validation.

4.1. Practical applications

The integration of VVS-A profiling with machine learning offers a preliminary approach worthy of further scientific investigation within Olympic diving. By quantifying these metrics, coaches and sport organisations can objectively assess athletes' sensory and motor capabilities associated with current performance level. This concentration effect may assist programmes in prioritising monitoring and support within resource-constrained development environments rather than distributing resources across all participants. These metrics, supported by studies in gymnastics, badminton, and rhythmic gymnastics,[18,32,39] can be incorporated into training programmes to enhance visuomotor skills and motor control, pending further research on their trainability in diving and other sports. This machine learning approach demonstrates potential as an exploratory analytical tool to support further investigation of sensorimotor characteristics relevant to performance. Practitioners should apply this framework cautiously, recognising that other sports may require different VVS-A profiles. Importantly, given the cross-sectional design and age differences between groups, these findings should not be interpreted as evidence for selection or deselection decisions, and longitudinal validation is required before any implementation within talent identification systems can be justified.

Prospective follow-up outcomes demonstrate how machine-learning-derived rankings can be contextualised alongside coaching evaluation within this sample. Of the 25 athletes selected through traditional coaching methods, the highest-ranked Come and Try athlete (ranked 1st by machine learning) demonstrated a model-derived probability of podium classification and was subsequently selected for a national talent squad 18 months post-assessment. However, five athletes ranked in the top 10 predicted podium candidates by the ML model were not selected through traditional methods, potentially missing future podium-level divers. This illustrates how objective measures may complement decision-making when interpreted alongside coaching evaluation in a multidisciplinary approach. Importantly, traditional methods also identified talent that initially ranked lower in our model: one athlete ranked 25th of 40 Come and Try participants (6% initial predicted podium probability) was selected by coaches and also achieved national squad selection 18 months later. Upon reassessment three months post-initial testing, this athlete's VVS-A derived probability increased dramatically to 58%, demonstrating the importance of developmental trajectories and suggesting that athletes with certain baseline potential may respond rapidly to targeted training. This highlights the value of both traditional coaching evaluation and objective measures in creating a comprehensive talent identification framework.

4.2. Limitations

Several limitations should be acknowledged. First, the laboratory-based visual-vestibular and autonomic assessments do not fully capture the ecological complexity of high-performance diving environments. Whilst the AMEDA has demonstrated ecological validity,[29] incorporating mobile eye-tracking technology could enhance VVS-A ecological validity in future studies.[38] Second, the machine learning model was developed on a limited sample ($n = 20$ podium, $n = 40$ Come and Try participants), which constrains generalisability and model robustness. Whilst our held-out test set provides internal validation of model performance, external validation on an independent cohort of divers from different talent pathways is required to assess model generalisability beyond our specific sample characteristics. The small sample size (n = 60) and single organisation recruitment further limit generalisability of these findings. Additionally, the cross-sectional design prevents assessment of how these multisensory markers develop or remain stable over time. Longitudinal studies tracking VVS-A development could validate the predictive stability of these measures.[40] Third, the trainability of diving-specific VVS-A metrics remains unexplored, limiting understanding of whether these capabilities can be developed through targeted interventions.

4.3. Future directions

Future research should employ longitudinal designs to track how adolescent growth, maturation, and training influence VVS-A development, assessing whether observed group differences represent stable individual characteristics or training-related adaptations. Establishing normative VVS-A benchmarks by age, gender, and performance level across sports would support systematic athlete monitoring over time. Intervention studies should also evaluate whether targeted training can enhance specific VVS-A features, such as VOR suppression and proprioceptive accuracy, noting that diving-specific validation remains essential despite supportive evidence from other sports.[18,38]

Expanding ML models using larger, more diverse samples and additional data modalities (e.g., psychosocial or training history variables) may help determine whether VVS-A measures provide incremental value beyond existing assessment approaches. Such work could clarify whether VVS-A profiling contributes meaningfully within multifaceted talent identification frameworks and under what conditions it may inform applied decision-making, pending robust longitudinal validation.

5. Conclusion

International elite sport has grown increasingly competitive, with national achievements driving substantial investment in talent identification (TID) programmes.[41] A persistent challenge within some talent systems is the potential overreliance on decontextualised assessments at single time points, which may mischaracterise athletes who possess the potential to succeed at elite level despite lacking certain measurable attributes at a given moment.[7] This challenge applies equally to coach-led evaluation and objective measurement approaches when implemented without appropriate developmental sensitivity. This preliminary cross-sectional study shares the same single-time point limitation but demonstrates that somatosensory ankle proprioception and visual-vestibular smooth pursuit distinguish current podium-level from entry-level ('Come and Try') divers, with machine learning classification achieving high accuracy on our specific sample. These findings suggest that VVS-A assessment warrants further scientific investigation as one potential component within multifaceted talent identification frameworks. The key applied question is not whether VVS-A assessment should replace coaching evaluation, but how it might be integrated alongside informed coaching expertise within developmentally sensitive frameworks, and under what conditions such integration adds value without distorting decision-making. However, our cross-sectional design, age confounding between groups, and small sample size prevent claims about predictive validity for future talent identification. Longitudinal research tracking VVS-A development whilst controlling for maturation is essential to determine whether these measures predict future success or simply reflect current performance capabilities. VVS-A profiling may complement existing assessment protocols when interpreted alongside experienced coaching evaluation; however, it should not be used independently for selection or deselection decisions until robust longitudinal evidence demonstrates incremental value beyond established practice.

CRediT authorship contribution statement

Stephen MacGabhann: Conceptualization, Methodology, Investigation, Writing – original draft, Project administration. **Gordon Waddington:** Writing – review & editing. **Jeremy Witchalls:** Writing – review & editing. **Stephen Cobley:** Writing – review & editing. **Rebecca Dowse:** Writing – review & editing. **Phillip Newman:** Methodology, Writing – review & editing.

Confirmation of ethical compliance

This study was approved by the University of Canberra Human Research Ethics Committee (Project ID: 13350). The research team analysed de-identified data provided by the New South Wales Institute of Sport (NSWIS). Participants, and parents of children under 18 attending the 'Come and Try' diving talent search, provided informed consent through statements included in the NSWIS online registration process.

Funding information

The author(s) received no financial support for the research, authorship, and/or publication of this article.

Declaration of interest statement

The author(s) declared the following potential conflicts of interest with respects to the research, authorship, and/or publication of this article: Professor Gordon Waddington is a founding shareholder in Prism Neuro Pty Ltd.

Acknowledgements

We would like to thank all participants for their time and contribution to this study. Your involvement has been invaluable to our research.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jsams.2026.03.011.

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