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Research article

Evaluating a computer based skills acquisition trainer to classify badminton players

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Abstract
The aim of the present study was to compare the statistical ability of both neural networks and discriminant function analysis on the newly developed SATB program. Using these statistical tools, we identified the accuracy of the SATB in classifying badminton players into different skill level groups. Forty-one participants, classified as advanced, intermediate, or beginner skilled level, participated in this study. Results indicated neural networks are more effective in predicting group membership, and displayed higher predictive validity when compared to discriminant analysis. Using these outcomes, in conjunction with the physiological and biomechanical variables of the participants, we assessed the authenticity and accuracy of the SATB and commented on the overall effectiveness of the visual based training approach to training badminton athletes.

Key words: Skills acquisition, badminton, neural networks, discriminant analysis.

Introduction

In recent years, extensive research has been carried out to analyse the physiological and biomechanical factors that characterise racket sport athletes (Manrique and González-Badillo, 2003), especially with tennis and squash players. There is however, limited data to assess which factors are desirable in competitive badminton (Huynh and Bedford, 2010; Manrique and González-Badillo, 2003). Despite its inclusion as an official sport in the 25th Olympic Games, research in the field of performance optimisation, mental and visual training, and skill acquisition for badminton remains scarce (Blomqvist et al., 2001; Huynh and Bedford, 2010; Manrique and González-Badillo, 2003).

In attempting to train and improve badminton players, Huynh and Bedford (2010) argue that the cognitive components of badminton must not be underemphasised. The authors suggest that in attempting to optimise skill proficiency, athletes need to incorporate a combination of both physical and cognitive aspects into their training program. They introduced a new visual based training (VBT) method of identifying and improving a badminton player's reaction time and awareness: the Skills Acquisition Trainer for Badminton (SATB). This program however, is still fairly immature in nature, and additional studies and research are required to assess its accuracy.

Previous research involving VBT has shown that the ability to detect and utilise advanced visual cues allows players to predict their opponent's actions more accurately. A classic example of this can be found in Abernethy and Russell's (1987) study regarding the differences between the ability of experts and novice to discriminate visual cues. The research suggested that novice badminton players were unable to detect information regarding advanced cue sources, which is the ability that provides experts with superior anticipatory skills. Specifically, the researchers stated that experts would utilise the visual cues from their opponent's *racket and arm placement* to predict stroke direction and speed, whereas novices were only capable of extracting advance information from the racket itself.

Renshaw and Fairweather (2000) utilised a visual based method to examine expertise among cricket players by assessing verbal discrimination when faced with five different types of bowling deliveries. They showed that expert batters were more successful than novices in identifying different types of deliveries made by an expert wrist-spin bowler. The overall detection rates in this study were significantly different between national, regional and club cricket players. National players correctly identified 63% of deliveries, regional players identified 56%, and club players correctly identified 48% of overall deliveries. However, when examining this discrimination capability for types of delivery, the authors found that batters were less able to discriminate deliveries that were similar in nature, regardless of expertise. Renshaw and Fairweather (2000) explained this poor discrimination ability due to the deliveries that were similar in nature to the legspin delivery (i.e. topspin and backspin). Similarly in badminton, the many different shot types used have similar appearances in execution, and may generally only be differentiated during the last few milliseconds prior to the racket making contact with the shuttle.

These research studies lead us to predict that perceptual training early in an athlete's skill development will prove beneficial for their anticipatory skills in the long run. However, this is not to say that VBT methods would be more efficient than, or that they should replace the standard training regimines of physical training. In a practical sense, adapting a perceptual strategy which emulates an expert will not bring a novice to that level simply by forcing the model onto them. From a dynamic systems approach, these types of visual imagery training would be insufficient (Renshaw and Fairweather, 2000) unless coupled with a form of physical practice. Ideally, it is the combination of both visual training and motor practice that will enhance overall perceptual performance. Furthermore, with the digital age constantly developing, and the nature in which Gen-Z children are raised and taught through digital means (Mitchell, 2008; Tapscott,

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2008; Howe and Strauss, 2008), the use of a VBT method to train athletes (e.g. the SATB program) should prove not only effective but also stimulating for athletes of the future.

Heazlewood and Keshishian (2010) used perceptron neural networks in conjunction with discriminant analysis to identify the variables that characterise karate athletes into high and low performance groups. Their study revealed that both perceptron neural networks and discriminant function analysis yielded a high percentage of accuracy in categorising karate athletes into high and low performance groups. The authors of the present study attempted to replicate Heazlewood and Keshishian's (2010) study, and apply both neural networks and discriminant function analysis to Huynh and Bedford's (2010) SATB program.

Derived from studies of brain functioning, the definition of a neural network varies depending upon the field in which it is being examined. In a statistical sense, a neural network applies to a loosely related family of models, characterised by a parameter space and flexible structure (SPSS Inc., 2007b).

Neural networks are made up of numerous artificial neurons (modelled after biological neurons), each having their own associated weight. Buckland (2002) states that the weights in most neural sets can be both positive and negative, therefore providing excitory or inhibitory influences to each input. As each input enters the nucleus, it's multiplied by its weight. The nucleus then sums all these new input values which gives us the activation (refer to Figure 2). If the activation is greater than the threshold value , the neuron outputs a signal. If the activation is less than the threshold value, the neuron outputs zero. This is typically called a step function.

If we consider the number of inputs a neuron can have as n, and the corresponding weights each input can have as w, then the equation for the activation value can be represented by:

$$a = \sum_{i=0}^{i=n} w_i x_i \tag{1}$$

The Multilayer Perceptron (MLP) procedure produces a predictive model for one or more dependent variables based on the values of the predictor variables. What makes a multilayer perceptron unique is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain (Haykin, 1998). This function is modelled in several ways, but must always be normalizable and differentiable. The two main activation functions used in current applications are both sigmoids, and are described by:

$$\phi(y_i) = tanh(v_i) \tag{2}$$

$$\phi(y_i) = (1 + e^{-vi})^{-1} \tag{3}$$

Function 2 is a hyperbolic tangent which ranges from -1 to 1, while function 3 is equivalent in shape but ranges from 0 to 1. Here y_i is the output of the ith node (neuron) and v_i is the weighted sum of the input synapses.

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result (Haykin, 1998). This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron.

The error in output node j in the nth data point can be represented by $e_j(n) = d_j(n) - y_j(n)$, where d is the target value and y is the value produced by the perceptron. We then make corrections to the weights of the nodes based on those corrections which minimize the error in the entire output, given by:

$$\mathcal{E}(n) = \frac{1}{2}\sum_j e_j^2(n) \tag{4}$$

The advantage of utilising a neural network is that it can approximate a wide range of statistical models without requiring the researcher to hypothesise in advance certain relationships between the dependent and independent variables (Heazlewood and Keshishian, 2010; SPSS Inc., 2007b). Instead the form of the relationship is determined during the learning process. The trade-off for this flexibility is that the synaptic weights of a neural network are not easily interpretable. Thus, if you are trying to explain an underlying process that produces the relationships between the dependent and independent variables, it would be better to use discriminant analysis (Heazlewood and Keshishian, 2010).

As explained by Heazlewood and Keshishian (2010), discriminant analysis can be used to classify cases into the values of a categorical dependent variable, to predict group membership based on a linear combination of the interval variables. The procedure begins with a set of observations where both group membership and the values of the interval variables are known (Stockburger, 1998). The end result of the procedure is a model that allows prediction of group membership when only the interval variables are known. A second purpose of discriminant function analysis is an understanding of the data set, as a careful examination of the prediction model that results from the procedure can give insight into the relationship between group membership and the variables used to predict group membership (Stockburger, 1998).

The aim of the present study was to compare the statistical ability of both neural networks and discriminant function analysis on the newly developed SATB (Huynh and Bedford, 2010). Using these statistical tools, we will attempt to identify the accuracy of the SATB in classifying badminton players into different skill level groups (e.g. beginner, intermediate, advanced). Finally, using these outcomes, in conjunction with the physiological and biomechanical variables of the participants, we will assess the authenticity and accuracy of the SATB and comment on the overall effectiveness of the VBT approach to training badminton athletes.

Methods

Forty-one participants, classified as advanced, intermediate, or beginner skilled level, participated in this study. Participants in the advanced skill level group (*n* = 10) were athletes who had played badminton for a number of years and were comfortable with coaching/teaching their skills and knowledge to others. Participants in the intermediate group (*n* = 16) were those who had played badminton for at least one year and were semi-confident with their skills and competencies. Participants in the beginner group (*n* = 15) had very little badminton knowledge and minimal game experience.

The measure used to compare neural networks and discriminant analysis was the SATB. The SATB is a VBT program that consists of five visual questions per session (over ten sessions). Participants would first watch different clips of badminton rallies being played, with sequences running for 2 – 30 seconds. This was followed by a still frame for 1 second after which participants would be asked to answer (on screen) what type of shot was about to take place (e.g. drop shot), as well as the location that shot would be played (e.g. middle right). An example of this is shown in Figure 1with the corresponding answer options.

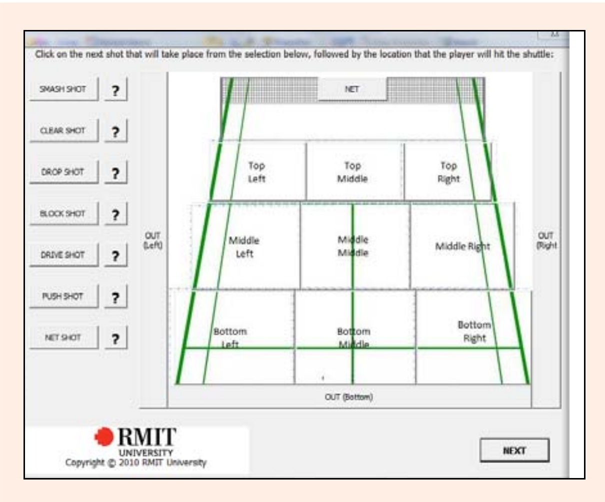

Figure 1. An example of the SATB answer selection screen

The SATB was based on a weighted system, with the assistance of experts' judgement and opinion (coaches and trainers who have played and taught for many years). Two points were awarded for the correct shot type response, one point for other possible shot types in that situation, and no points for any other shot types. Similarly, two points were given if participants chose the correct location the shuttle would land, one point if it was adjacent to the shuttle location, and no points for any other location selection. Participants were also timed from the point the rally sequence finishes' to the point they input all their responses in order to examine response time. With five questions per session, the maximum score a participant could acquire was 20, with an optimal time of 11.9 seconds. Hence, the equation for the SATB score is given by:

$$SATB = \frac{11.9}{TIME} \times SCORE \qquad (5)$$

From equation 5, *TIME* is the combined time it took participants to answer all five questions regarding shot type and shuttle location. The value of 11.9 was based on Jorgensen et al.'s (2002) study "*Using mouse and keyboard under time pressure: preferences, strategies and learning*" (a click response time = 1.1 ± 0.08 s), in conjunction with expert opinion that it would take two seconds to select both location and shot type. *SCORE* is the combined score of each correct response from the five questions. Therefore the maximum score an individual can acquire on the SATB is 20.

Skill level served as the dichotomous classification variable. The dependent variables in both the neural networks and discriminant analyses were represented by three different groups of factors: anthropometric factors, motor fitness factors and SATB factors. The anthropometric factors were: height (cm), weight (kg), age (years), and experience (years); the motor fitness factors were: 20m sprint (secs), vertical jump (cm), and beep test (score); and the SATB factors were: shot type (score), court placement (score), and response time (secs).

Results

The neural network solution based on the training data set and testing (holdout) data set classified at 100% accuracy badminton ability (advanced, intermediate, beginner) examining the SATB specific tests for the training and testing samples (refer to Table 1).

Table 1. The neural network solution based on the training data set and testing (holdout) data set classified at 100% and 57.9% accuracy respectively for skill level (beginner, intermediate and advanced) for the SATB specific tests.

	Predicted			
	1	2	3	% Correct
Training				
1.Beginner	9	0	0	100.0%
2.Intermediate	0	5	0	100.0%
3.Advance	0	0	8	100.0%
Overall Percent				
Testing				
1.Beginner	5	1	0	83.3%
2.Intermediate	3	6	2	54.5%
3.Advance	2	0	0	0.0%
Overall Percent	52.6%	36.8%	10.5%	57.9%

Diagrammatic representation of the neural network architecture for SATB specific tests with one hidden layer using a hyperbolic function and the output layer a softmax function are represented in Figure 2.

The classification accuracy for the motor fitness tests was 95.5% for the training and 73.7% for the testing sample respectively (refer to Table 2).

Table 3 and Figure 3 indicate the most important discriminating variables in the neural network analysis are shot type and location selection. Similar analysis using the general motor fitness data, which classified 95.5% correctly from both ability groups indicated the 20m sprint test (100% normalised) and vertical jump test (74.6% normalised) were the most important discriminators for the motor fitness tests.

Discriminant analysis was equally effective in classifying ability level when using the SATB specific tests, however slightly less accurate when using the motor fitness tests. The motor fitness tests produced 73.2% (Wilks' Lambda = 0.394, $p < 0.001$) and SATB specific tests produced 80.5% (Wilks' Lambda = 0.23, $p < .001$) correct classifications, respectively. The means and standard deviations for the 20m sprint, beep test, and vertical jump tests are displayed in Table 4, with higher skilled level participants displaying higher scores on the vertical jump and beep tests, and lower scores on the sprint tests.

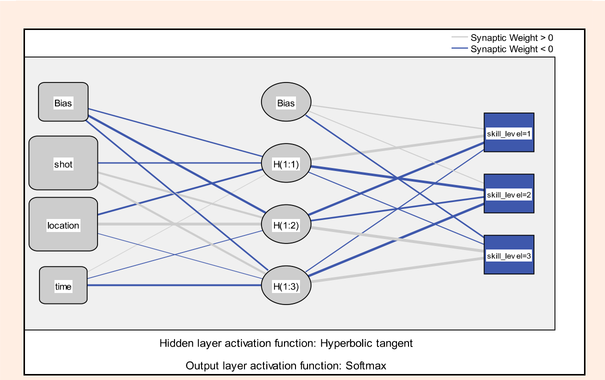

Figure 2. Diagrammatic representation of neural network architecture for SATB specific tests

Table 2. The neural network solution based on the training data set and testing (holdout) data set classified at 95.5% and 73.7% accuracy respectively for skill level (beginner, intermediate and advanced) for the motor fitness tests.

	Predicted			
	1	2	3	% Correct
Training				
1.Beginner	8	0	1	88.9%
2.Intermediate	0	5	0	100.0%
3.Advance	0	0	8	100.0%
Overall Percent	36.4%	22.7%	40.9%	95.5%
Testing				
1.Beginner	9	1	0	90.0%
2.Intermediate	3	2	1	50.0%
3.Advance	0	0	3	100.0%
Overall Percent	63.2%	15.8%	21.1%	73.7%

Table 5 indicates the accuracy of classification based on motor fitness constructs. In this model 73.2% of all three ability groups were classified correctly. In this context the classification was marginally lower (22.3%) than the neural network solution.

Table 3. Independent variable importance and normalised values for SATB specific constructs.

	Independent variable importance	
	Importance	Normalised importance
Shot type	.409	100.0%
Location placement	.407	99.5%
Time response	.183	44.7%

The means and standard deviations for the SATB specific tests: shot type, court placement and response time are displayed in Table 6. Once again, the scores are higher for those of a higher skill level when compared to those of a lower skill level.

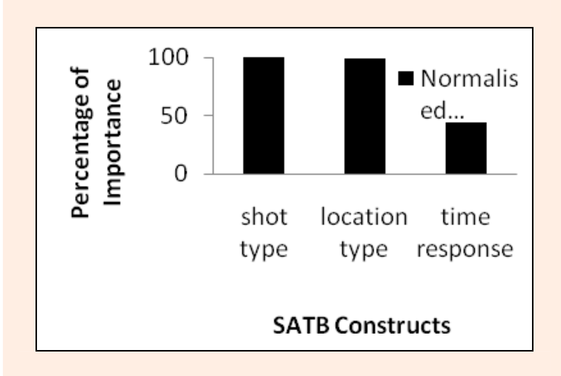

Figure 3. Normalised importance of the SATB constructs.

Table 4. Means and standard deviations for beginner, intermediate and advanced badminton athletes based on motor fitness variables. Data a0re means (±SD).

	Sprint test	Beep test	Vertical jump test
Beginner	4.34 (.37)	7.77 (1.98)	58.67 (9.31)
Intermediate	3.86 (.29)	8.61 (1.84)	64.88 (6.84)
Advance	3.41 (.19)	9.82 (1.25)	68.1 (6.61)

Table 5. Classification results were 73.2% of original group cases correctly classified for the motor constructs.

	Predicted Group Membership			
	1	2	3	Total
Count				
1.Beginner	12	3	0	15
2.Intermediate	2	10	4	16
3.Advance	0	2	8	10
Count %				
1.Beginner	80.0%	20.0%	0.0%	100.0%
2.Intermediate	12.5%	62.5%	25.0%	100.0%
3.Advance	0.0%	20.0%	80.0%	100.0%

Table 6. Means and standard deviations for beginner, intermediate and advanced badminton athletes based on SATB variables. Data are means (±SD).

	Shot type	Location	Time response
Beginner	1.80 (.94)	.87 (.92)	89.54 (38.99)
Intermediate	5.06 (1.34)	3.38 (1.59)	72.34 (16.05)
Advance	6.20 (1.48)	4.20 (2.20)	41.08 (21.06)

The timed score for the SATB response time reflects that a lower score is equated with higher ability on these tests. Table 7 indicates the accuracy of classification based on SATB specific constructs. The classification accuracy was 80.5% (Wilks' Lambda = 0.23, $p < 0.001$) correct classifications.

Table 7. Classification results where 80.5% of original grouped cases correctly classified for the SATB constructs.

	Predicted Group Membership			
	1	2	3	Total
Count				
1.Beginner	14	1	0	15
2.Intermediate	2	12	2	16
3.Advance	0	3	7	10
Count %				
1.Beginner	93.3%	6.7%	0.0%	100.0%
2.Intermediate	12.5%	75.0%	12.5%	100.0%
3.Advance	0.0%	30.0%	70.0%	100.0%

Table 8. Correlation results examining skill level across anthropometric, motor fitness and SATB specific factors.

	1	2	3	4	5	6	7	8	9
1. Skill level	--	.44**	-.15	-.78**	.42**	.44**	.80**	.65**	-.56**
2. Age		--	-.17	-.22	.05	.03	.33*	.39*	-.28
3. BMI			--	.03	.04	.14	-.09	.10	-.16
4. Sprint test				--	-.63**	-.45**	-.65**	-.47**	.50**
5. Beep test					--	.51**	.40**	.24	-.19
6. Vertical test						--	.51**	.35*	-.25
7. Shot type							--	.56**	-.36*
8. Location								--	-.39*
9. Time									--

* and ** denote p < 0.05 and p < 0.01 respectively.

Finally, a Pearson's correlation coefficient was computed to assess the relationship between participants' skill level and the dependent variables, across all three groups (anthropometric, motor fitness and SATB specific). Table 8 summarises these results.

Discussion

The findings from this study are consistent with that of Heazlewood and Keshishian (2010), suggesting that neural networks, specifically the multilayer perceptron (MLP) networks, are more effective in predicting group membership, and displayed higher predictive validity when compared to discriminant analysis. Furthermore, our study was successful in supporting the accuracy of the SATB program with the analyses for the neural networks and discriminant analysis resulting in a 100% and 80.5% accuracy rating respectively.

Interestingly, the Pearson's correlation for the 20m sprint (r = -0.78, p < 0.001), vertical jump (r = 0.44, p < 0.001) and beep test (r = 0.42, p < 0.001) did not correlate with skill level as highly as we had anticipated. This can be accounted for however, due to the variation in age across the sample (with a range of 46 years), which resulted in higher average scores in the motor fitness tests for participants of a lower age group. Despite being in a higher skill level group, the older participants were not at the expected level of fitness as were some of the intermediate participants. As such, it is advised that future studies have samples with a smaller age discrepancy across all skill levels.

The MLP did, however, maintain a high percentage rating for correctly discriminating between motor fitness tests, which is consistent with Heazlewood and Keshishians' (2010) study. The authors found that karate specific tests were better predictors of ability level than motor fitness tests. We support this notion, with the present study suggesting that SATB specific tests (shot type, court placement, and response time) were better predictors of badminton ability than motor fitness tests. Tong and Hong (2000) suggest that due to the numerous patterns and play types in badminton (e.g. strength type, speed type, etc) knowing your opponents strategy and playing style (similar to the factors that the SATB attempts to improve) is essential for improving your skill level.

The second goal of our study was to assess the authenticity and accuracy of the SATB as a VBT program. Results indicated that the program was successful in predicting group membership with an accuracy of 100% and 80.5% neural networks and discriminant analyses respectively. These results provide implications for coaches and trainers of badminton to implement VBT methods into their own training program. Minimal research has been carried out to examine the use of VBT methods in badminton, despite the fact that quality of cognitive performance in a game situation is often as important as the execution of the motor skills (Blomqvist et al., 2001; Huynh and Bedford, 2010; Thomas, 1994). As such, these findings further support the validity and accuracy of Huynh and Bedford's (2010) SATB program, as an effective tool in developing badminton athletes.

As a further point of interest, we discovered that participants were more likely to predict the correct shot type than location placement on the SATB program. This was consistent across all three skill level groups. This can potentially be explained due to the complex nature of shot types and the varied options with location selection. Because the sequences that participants viewed were from top level badminton matches, with athletes capable of performing a variety of trick/fake shots that could land in almost any position, participants found location selection to be more challenging than shot selection. However, the same can be said about shot type with many athletes giving the impression they may perform a certain shot, yet executing a completely different shot (e.g. faking a smash shot to perform a drop shot). Additional studies are required to determine the underlying cause as to why participants are able to identify shot types more accurately than shuttle destination.

Conclusion

The multilayer perceptron neural network marginally outperformed the discriminant function analysis as a predictor of badminton skill level, specifically when incorporating the SATB system. Nonetheless, both neural networks and discriminant analysis were accurate statistical tools in predicting and classifying group membership among badminton players. The SATB program was tested and validated, and can be implicated for future research in the field of VBT training.

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Key points

- Neural networks are more effective in predicting group membership and displayed higher predictive validity when compared to discriminant analysis.
- These results provide implications for coaches and trainers of badminton to implement visual based training methods into their own training program.
- Predicting shot type was more successful that predicting location placement. This suggests implications for training badminton player's judgement of shuttlecock trajectory.

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