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The Identification of "Game Changers" in England Cricket's Developmental Pathway for Elite Spin Bowling: A Machine Learning Approach

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Abstract
Research exploring the development of expertise has mostly adopted linear methods to identify precursors of expertise, assessing statistical differences between groups of isolated features (variables) by way of attaching importance; e.g., deliberate practice hours (Ericsson et al., 1993). However, confining the complex nature of expertise development to linear investigations alone may be overly simplistic. Consequently, to better understand the multidimensional and complex nature of expertise development, we applied (non-linear) pattern recognition analyses to a set of 93 features obtained from a sample of 15 elite (International) and 13 sub-elite (First Class County) cricket spin bowlers. Our study revealed that a subset of 12 developmental features, from a possible 93, discriminated between the elite and sub-elite groups with very good accuracy. The 12-feature subset forms a holistic development profile, reflecting the elite's earlier engagement in cricket, greater quantity of domain-specific practice and competition, and superior adaptability to new levels of competition. Evidence for the external validity of this new model is offered by its ability to correctly classify data obtained from 5 unseen spin bowlers with 100% accuracy. After consideration of these quantitative findings, the content of qualitative data provided by the cricketers was subsequently analyzed to obtain a deeper understanding of the features that discriminate between the elite and sub-elite groups. Supplemental online material is provided here: https://www.journalofexpertise.org/articles/volume2_issue2/JoE_2019_2_2_Jones_SM.pdf

Keywords
talent identification, talent development, pattern recognition, feature selection, deliberate practice, resilience.

Introduction
The development of expertise is complex, and therefore requires a holistic approach to fully explore its multifaceted nature (Pearson, Naughton, & Torode, 2006; Abernethy, 2013). Despite this, investigations of expertise have mostly focused on isolated domains of expertise, likely accounting for only part of what is important. This approach lacks an appreciation of the more complex interactions between the domains, necessary for a holistic understanding of expertise development (Güllich et al., 2019). Past research has often restricted investigations to comparing the

volume of practice undertaken by performers with distinct levels of expertise (e.g., Ericsson et al., 1993), overlooking the potential moderating effect of wider developmental features (variables). This, combined with limited use of complex statistical analyses within the sport science field, has typically resulted in isolated analysis of independent features, producing one-dimensional findings (Schorer & Elfering-Gemser, 2013). Despite these limitations, independent features have been amalgamated to produce theoretical models of expertise development, e.g., deliberate practice and deliberate play in the DMSP (Coutinho. Mesquita, Fonseca, 2016; Côté, Baker, & Abernethy, 2007). Considering these limitations, the primary aim of the present study was to apply machine learning techniques, to identify the multifaceted pattern of developmental features that discriminate between elite and sub-elite cricket spin bowlers most accurately.

Elite sport organizations have experienced difficulties in implementing research findings historically, possibly because some studies have not provided applied recommendations, or lack context specificity in their approach. Generic recommendations often prevent research from positively impacting on sporting talent pathways, likely due to the mismatch between these generic recommendations, and the unique and highly complex demands of each sport, and their positions/disciplines (Holt et al., 2018; Jones, Lawrence, & Hardy, 2018). This historic imbalance likely reflects the production and advocation of blanket "optimal" sport performance models within the expertise development literature (Phillips, Davids, Renshaw, Portus, 2010).

Existing sport performance models, such as the Differentiated Model of Giftedness and Talent (DMGT) (Gagné, 2004), do advocate a multi-disciplinary approach to developing expertise, but nevertheless promote a standardized approach. The DMGT's conditional innate (genetic) basis for developing expertise differs to the DMSP stance (Côté et al., 2007), where possessing "superior" innate factors is not necessarily conditional for the development of expertise. Instead, this model stipulates that the "sampling stage" (stage 1 of 3), between the ages of 6 and 12, should promote deliberate play; activities which are fun, free from specific focus and provide immediate gratification (Côté et al., 2007). The final stage, known as the "investment stage" (age 16+), focuses on undertaking specialized practice in the primary sport. This stage is consistent with research denoting that 10,000 hours of deliberate practice (activities which are effortful, focused, goal directed, and not inherently enjoyable) leads to the development of expertise (Ericsson et al., 1993). The "investment stage" is contingent on the preceding inter-sport "specialization stage" (ages 13-15).

Specialization describes the prioritization of personal resources towards a sport (Côté et al., 2007), and is suggested to accelerate the development of expertise (Ericsson et al., 1993; Ford, Ward, Hodges, & Williams, 2009; Ward, Hodges, Williams, & Starkes, 2004). Existing development models encompassing specialization, such as the DMSP, do not consider intra-sport differences, i.e., differences between positions/disciplines, meaning that intra-sport specialization is not currently recognized as a valid construct of specialization. The impact of diversification within sports (i.e., intra-sport diversification) is largely unexplored, and less well understood among researchers and coaches, and thus intra-sport differences may have been overlooked historically (e.g., Voigt & Hohmann, 2016). Current standardized sport specialization guidelines, coupled with the lack of consideration for intra-sport specialization, limits our current understanding of "desirable" sport and discipline-specific development environments (Güllich et al., 2019; Rees et al., 2016).

Emerging research comparing the multi-disciplinary biographies of serial medaling (super-elite) athletes against those of elite athletes has made significant advancements in the area of expertise development (The Great British Medalists Study; Güllich et al., 2019, Hardy et al., 2013). This study analyzed the predictive power of a large pool of features,

relative to each other, producing a smaller subset of the practice and psychosocial-related features containing the highest predictive power. However, the coarse-grained approach employed in The Great British Medalists Study sacrificed detail in favor of breadth of exploration. Merging multiple sports within the analysis meant that the discriminating power of features relating to practice was diminished due to differences between sports. In the sport of cricket, the physical, technical, tactical, and psychological requirements of the disciplines are so fundamentally different, that they are considered as different sports (Jones et al., 2018). Consequently, there exists a need for pathway-specific research in cricket that considers disciplines/positions as separate entities to better understand precursors of expertise in cricket and to provide context-specific recommendations for the England and Wales Cricket Board's (ECB) talent pathway.

The difficulties of developing elite cricketers in England, and the spin bowling discipline in particular, are well documented, not least due to the historical scarcity of spin bowlers competing at international level (Richardson, 1934; Coyne, 2016). The severity of the issue is perhaps highlighted by the overrepresentation of other nations in the bowling world player rankings (International Cricket Council World Rankings, 2017). The dominance of these spin bowlers is often attributed to the warmer climates of their development origins; warmer climates are shown to aid the mechanics of applying revolutions on the ball using the fingers or wrist, and lead to drier wickets that are receptive to lift and turn, cumulatively fostering the development of spin bowlers (Nodehu, Moghadam, Rahnama, Habibi, & Dehghani, 2015). This point is particularly pertinent in the Indian sub-continent, where spin bowling is considered the first line of attack (Silva, Perera, Davis, & Swartz, 2016). Very different are the colder climates of England and Wales, where the wickets are flat offering little lift and turn, which means that pace, rather than spin, is inherently considered the first line of bowling attack. This disparity in climates poses environmental challenges for the subsequent progression of spin bowlers. That is, while the development structures within warmer climates appear to facilitate and encourage the development of "pure" spin bowlers, multidiscipline spin bowlers who possess batting (all-round) potential may be favored over pure spin bowlers within the talent pathway in England and Wales. Spin bowling is an art; producing spin, rhythm, control and flight on the ball are all fundamental aspects, taking years of craft to develop a repeatable action and consistent bowling outcomes (Such, Felton, & King, 2012). Unlike pace bowling, where generating pace and bounce are key, spin bowling demands sound technique to deceive batsmen, along with a degree of patience and resilience.

The documented talent pathway in England and Wales begins with County cricket academies. Players progress through the age groups before graduating to become Second XI and, eventually, First XI County senior professionals. Players demonstrating greatest potential the earliest will likely be selected for prestigious regional tournaments along this course, before entering the Young Lions (international U19s team). The Lions senior team represents the final stage along the pathway to becoming an international player. The structured nature of talent pathways makes it increasingly important for talent identification processes to function optimally, especially when assessing spin bowling potential during the early stages of development. In this regard, it is important that players who are deselected from talent development programs are continually reconsidered for selection, in light of the differential rates of development that occur in prospective international cricketers (Barney, 2015). At present, the developmental trajectories of English spin bowlers are not empirically known, owing to the scarcity of expertise development research in cricket. Furthermore, it could be hypothesized that the development of spin bowlers differs from that of neighboring cricket disciplines (i.e., batting, pace bowling and wicket-keeping), given the spin bowling discipline's emphasis on

technique, for example. In this regard, a study exploring the development of spin bowlers will likely lead to the identification of desirable practice environments and subsequently inform the production of elite spin bowlers from academies.

A study of Cricket Australia's spin bowling development structure at junior, state, and international levels found that the development of spin bowlers is delayed, relative to other cricket disciplines (Mann, 2014). This was demonstrated by a later peak in spin bowlers' performance, and was attributed to flaws within talent development environments, perhaps best illustrated by the low volumes of spin bowling-specific practice and competition bowling identified. For this reason, it is deemed particularly difficult for "genuine" spin bowlers to break into Cricket Australia's talent pathway. The prevalence of setbacks during development was a commonality shown across the development of these spin bowlers. Setbacks were most prevalent when transitioning from junior to senior cricket, suggesting that there may have been an imbalance across the technical, physical or psychological development of these Australian spin bowlers.

Research comparing the conversion rates of County academy cricketers who graduate to the senior international team in England and Wales, against the prevalence of the relative age effect (RAE), concluded that the development of cricketers reflects a complex and non-linear journey (McCarthy, Collins, & Court, 2016). RAE refers to an overrepresentation of relatively older players within age-group teams and academies, and is attributed to advanced physical maturation (Barney, 2015; McCarthy et al., 2016). However, a reversal favoring relatively younger players was observed for those selected for the senior international team, suggesting that these prospective senior international players may have benefited from overcoming the challenge of training and competing with peers of a greater physical size throughout development. Relatively younger spin bowlers who overcome the RAE likely demonstrated resilience, among other psychological characteristics required to become an elite spin bowler (Jones et al., 2018). Moreover, adaptability to new levels of performance has been identified as a key predictor of progression along various stages of the cricket talent pathway (Barney, 2015) supporting the notion that the journey to expertise attainment is non-linear.

Previous investigations of isolated features of development have disregarded their potential interactive effects (Güllich et al., 2019). Consequently, there is a need for researchers to identify features that *make the difference* between relatively synonymous groups of experts, reflecting the multifaceted and complex nature of expertise development, rather than solely demonstrating differences between isolated features, such as practice hours (Abernethy, 2013). Machine learning methods, such as artificial neural networks, have been used to examine the extent which subsets of features predicts the optimization of talent recruitment and development processes, demonstrating far superior accuracy than offered by linear discriminant analysis (Edelmann-Nusser et al., 2002; Pfeiffer & Hohmann, 2012; Pion, Hohmann, Liub, Lenoira, & Segersa, 2016). However, like in much of previous research, these studies share the assumption that *all* features initially identified possess importance, due to the absence of "feature selection" procedures; these procedures can mitigate for the fact that feature inclusion could be due to chance, caused by a type 1 error (see Güllich et al., 2019).

The present study addresses existing limitations by employing state of the art non-linear pattern recognition techniques to explore the complexities behind *"what makes the difference?"* in the developmental trajectories of elite cricket spin bowlers setting them apart from the sub-elite. Furthermore, a qualitative component was employed to enable deeper understanding of any features that may discriminate between the elite and sub-elite groups, identified in the quantitative analyses, constituting a mixed method approach. It was hypothesized that this mixed method approach would produce a holistic and fine-grained profile containing the strongest precursors of

elite spin bowling expertise, by discriminating between elite and sub-elite spin bowlers, and thereby informing the ECB's talent identification and development framework.

Method

Participants

The sample comprised 15 elite and 13 sub-elite past and present spin bowlers with an age range of 24 to 75 years. Elite spin bowlers (M_{age} = 43; *SD* = 14.32) had represented the England international team in test and/or limited over formats (M_{caps} = 37; *SD* = 43). The sub-elite spin bowlers (M_{age} = 40.62; *SD* = 7.30) had endured a prolonged career in domestic (professional) County cricket (M_{caps} = 261; *SD* = 47) but had not represented England at senior international level, and were deemed unlikely to do so beyond reasonable doubt, owing to their age, coupled with the professional opinion of the ECB's National Lead Spin Bowling Coach. The clear distinction in spin bowlers' level of expertise allowed for an accurate examination of developmental features[1] that may precede elite (international) expertise, and addressed inconsistencies shown across existing criteria used to define levels of expertise in previous research (Baker et al., 2015; Coutinho et al., 2016; Swann et al., 2014).

Measures

Spin Bowling Development Interview Schedule. For this study, the researchers developed an interview schedule based on methodologies that had been successfully used in previous research (e.g., Hardy et al., 2017) (*see* Supplementary Information). Prior to the development of the schedule, there was a consultation process between the researchers and the National Lead Spin Bowling Coach. Specifically, the authors outlined the aspects of development that were of theoretical interest to the study, and the National Lead suggested aspects of development that were of interest to the ECB for the practical development of spin bowlers. The resulting interview was sub-divided and ordered into quantitative and qualitative questions.

Quantitative Measures. The data obtained from the quantitative section of the interview was input into Microsoft Excel during the interview across each of the four sections outlined below (see Supplementary Information for all features collected):

1. Demographics: Birth quarter, birthplace, sibling order effect, type of schooling, educational milestones.
2. Structured sporting history: Quantity of organized coach-led cricket practice/training, quantity of unsupervised cricket practice, "spin bowling-specific" organized practice, competition experience, competition time spent bowling, early cricket specialization or diversification, quantity of organized practice and competition in other sports across defined age periods.
3. Cricket developmental milestones: Highest level of cricket representation within defined age periods, age first selected for each representation level, level of challenge encountered, age of spin bowling specialization, age became teams' best spin bowler, age thought about becoming professional cricketer, perceived quality of coaching and facilities, injury time across defined age periods.
4. Unstructured cricket activity: Quantity of unorganized cricket play, time spent reading about cricket, time spent watching cricket.

Qualitative Measures. A relatively unstructured interview schedule was designed to obtain a deeper understanding of any quantitative discriminating features relating to the development of elite spin bowlers. To explore key developmental milestones, five qualitative questions were included in the interview. The questions are noted below:

1. What were your biggest challenges along your pathway to becoming a spin bowler?
2. If applicable, how did you overcome such challenges?
3. What had the single biggest influence on your development as a spin bowler?
4. Was there a significant learning experience/key moment that took place

during your development that eventually contributed to the career you had?

5. Is there anything else of significance that we have not touched on that would be helpful in understanding your journey to becoming a (County or international) spin bowler?

In preparation for analysis, all verbatim obtained from the qualitative component of the interview was recorded for transcription and coding purposes.

Procedure

After the study received institutional ethics approval, participants were recruited by the ECB's National Lead Spin Bowling Coach. Once participants had agreed to take part and had provided written informed consent, they were interviewed using the specified interview schedule. All interviews were conducted by the same experimenter, and all participants were asked the quantitative set of questions first, immediately proceeded by the qualitative section. Each interview lasted approximately two hours and was recorded to back up the data. Once all interviews had been completed, the quantitative data collected was subsequently standardized and analyzed using pattern recognition approaches[2], with the primary aim of determining which developmental features discriminate between elite and sub-elite spin bowlers. Transcription of the qualitative data was outsourced to UK Transcription and was subsequently coded and analyzed by the fifth author (who was blind to the quantitative findings), with the primary aim of identifying any discriminating themes between elite and sub-elite spin bowlers.

Analytical Strategy

Quantitative Design. Previous talent identification research has often identified isolated features of theoretical interest, and subsequently examined statistical differences by way of attaching importance (e.g., Ericsson et al., 1993). Improving upon the use of such traditional statistical procedures, the present study adopted pattern recognition analysis by way of increasing predictive power. Pattern recognition analysis has been developed in bioinformatics to solve the problem of classifying objects on features that they possess (for example, see Duda, Hart, & Stork, 2001). The essence of this solution is that modern computational power is used to analyze large numbers of features and find which features best distinguish between two different classes of objects. In the present case the features are the characteristics that have been recorded from our sample of elite and sub-elite spin bowlers, and these two groups constitute the classes of objects that we want to be able to identify. In very simple terms the computer programs that run these analyses can select features (characteristics) and classify which objects (spin bowlers) belong to which classes (groups) using several different criteria. Unlike discriminant function analysis, which predicts group membership based on linear functions of a set of variables (features), pattern recognition analysis is performed on a machine learning workbench that uses algorithms and data pre-processing tools with non-linear predictive modelling and data analysis capabilities (WEKA; Witten, Frank, & Hall, 2011). Results produced from pattern recognition analyses reflect multiple and complex interactions, which take place between the features, not the sum of multiple "main effects" as in more traditional approaches. A 3-staged pattern recognition approach was adopted in the present study, a protocol advocated by Jones, Hardy, and Kuncheva (2017) and Güllich et al. (2019): Feature Selection, Initial Classification, Final Classification – Recursive Feature Elimination (these staged approaches are briefly described below).

The present dataset is termed "wide" because there are far more features than there are objects. Therefore, robust *feature selection* protocols should be applied to prevent spurious results. A vast number of different procedures can be used for feature selection (Dash & Liu, 1997; Liu & Motoda, 2007; Guyon, 2003; Kohavi & John, 2011; Larran & Saeys, 2007). Four were used in the present analyses: Support Vector Machine (SVM; Burges, 1998), Relief-F (Kira & Rendall, 1992), Fast Correlation Based Filter (FCBF; Yu & Liu, 2003), and Correlation Attribute Evaluation (Hall, 1999). Each of these procedures uses very different criteria to select features. However, the

most important points for the reader to note are that the four procedures used are well established and the selection of features using numerous selection methods is a conservative approach which helps prevent features being awarded high importance due to chance (Visa, Ramsay, Ralescu, & van der Knaap, 2011). The more times a feature is selected by different procedures, the greater the confidence that can be placed in the predictive power of the feature. As such, features selected by more than one procedure are selected for initial classification in the present study having been identified as possessing the greatest predictive power.

In order to evaluate the cumulative predictive power of the feature subset selected, four different classifiers were adopted for the *initial classification* of the features. Like feature selection procedures, there are many different classifiers, and like feature selection, one can place greater confidence in results that can be replicated across different classification procedures. All classifiers were applied using the default parameter settings in Weka. The classifiers used were the SVM classifier (as used in the feature selection; Burges, 1998), Multilayer Perceptron classifier (MLP; Bishop, 1995), Naïve Bayes classifier (NB; Hand & Yu, 2001), and Nearest Neighbour classifier (Lazy learner, IB1; Duda et al., 2001).

To account for the fact that we are working with a wide dataset, we chose the leave-one-out (LOO) cross-validation protocol for feature-selection and classification analyses. This protocol removes one participant before allowing the classifier to learn how to discriminate between the two groups and then tests the classifier on the participant removed. This cross-validation process is carried out 28 times in total, with each of the participants used once as the "testing data" (28-fold cross-validation). This training-and-testing protocol reduces the risk of overfitting and thereby gives a more realistic prediction of the classifier's performance on unseen data (the generalization performance). The classification accuracy of the cross-validation experiment is a concept equivalent to "goodness-of-fit" and may serve as a measure of it.

Final Classification. Next, the Recursive Feature Elimination method (RFE) (Guyon, Weston, Barnhill, & Vapnick, 2002) was employed, using the SVM classifier, as this has been adopted as the state-of-the-art standard for feature selection (Bolon, 2015), especially in the area of bioinformatics (Zhang et al., 2006; Zhou & Tuck, 2007). RFE identifies the subset of features that predicts the class labels with higher classification accuracy, allowing us to provide the user with the optimal solution for a given dataset.

This is the first time that pattern recognition analysis has been used in cricket talent research, allowing investigation of the multifaceted—yet holistic—nature of expertise development concurrently. Following the collation of the interview data, a total of 93 features were left to be analyzed. The results produced from the aforementioned 3-staged process are outlined in the Results section.

Qualitative Design. The ontological position adopted by the researchers was a critical realism position (Braun & Clarke, 2013), and the epistemological position taken was the pragmatic paradigm (Doyle, Brady, & Byrne, 2016). The qualitative analysis was based on a combination of traditional inductive content analysis (Weber, 1985) and the principles of inductive grounded theory analysis (Glaser & Strauss, 1967). The transcriptions were analyzed using QSR International's NVivo 10 (2012) qualitative data analysis software. For themes to be classified as discriminating between the two groups of spin bowlers, they needed to be largely represented by at least four participants from the elite or sub-elite groups. Results were considered commonalities when the number of quotes were similarly represented across the two groups, with specifically no more than a difference of two participants between the groups. Last, in instances where there was an insufficient number of participants from either group of spin bowlers represented in a theme (for it to constitute a discriminator or a commonality), we considered there to be no clear consensus and regarded these themes as additional answers.

Results

Quantitative Findings: Pattern Recognition Analyses

Feature Selection. The top 20 features (variables) for the four feature selection methods are numbered in Table 1, ranked from best to worst. Features which are selected by more than one feature selection method are color coded. White cells represent the unselected features (selected by just one feature selection method).

Table 1. Top 20 feature rankings across the four feature selection methods

Rank	SVM	Relief-F	CFS	CAE
1	30	1	30	30
2	73	71	56	48
3	56	57	37	57
4	54	58	1	43
5	48	67	57	56
6	1	26	49	1
7	57	24	48	41
8	41	43	42	45
9	62	30		31
10	25	68		37
11	67	6		59
12	38	34		62
13	37	66		25
14	55	75		68
15	22	76		7
16	50	33		32
17	53	64		54
18	87	9		76
19	43	73		74
20	93	4		24

Note. Labels of features selected only once: **4** – No. of older siblings; **6** – Primary school principle place for sport practice?; **7** - Primary school a designated sport school?; **9** – Went to higher education?; **22** - Organized practice hours intensity up to First XI County debut; **26** - Proportion of spin bowling-specific practice up to age 14; **31** – Number of cricket competition hours up to age 14; **32** - Cricket competition hours intensity up to age 14; **33** - Number of cricket competition hours up to age 17; **34** – Cricket competition hours intensity up to age 17; **38** – Cricket competition hours intensity up to age of international debut; **42 –** Age of first cricket involvement playing family/friends; **45** - Age first thought about becoming professional cricketer; **49** – Age of specialization in cricket; **50** – Age of specialization in spin bowling; **53** - Age of first close relationship with a coach; **55** – Age first selected for ECB training squad; **58** - Highest level cricket competition by age 20; **59** – Age of senior club cricket debut; **64** – Age of senior Second XI Cricket debut; **66** – Level of Challenge senior Second XI Cricket debut; **71** – Level of challenge senior First XI Cricket debut; **74** – Age became regular senior First XI Cricketer; **75** - Age regular involvement in any unstructured sport; **87** - Unsupervised cricket practice hours intensity up to age 17; **93** - Unsupervised cricket practice hours intensity up to age of international debut.

On viewing Table 1, it is apparent that a total of 36 out of 93 features appear in the top 20 rankings cumulatively across the four selection methods. In the present analyses, features were selected if they were ranked in the top 20 discriminatory features by at least two out of the four feature selection methods used, which led to the initial retention of 16 features, shown in Table 2.

Table 2. The 16 selected features common across at least two of the feature selection methods

Feature Number	Feature Labels
1	Birth Quarter
24	Age of First Organized Spin Bowling-Specific Practice
25	Proportion of Spin Bowling-Specific Practice up to Age 14
30	Proportion of Competition Overs Bowled up to First XI Debut
37	Cricket Competition Hours up to Age of Senior International Debut
41	Age of First Regular Involvement in Cricket
43	Age of First Involvement in Unsupervised Practice
48	Age Decision Made to Become Professional Cricketer
54	Age First Joined a County Cricket Academy
56	Highest Level of Cricket Competition by Age 14
57	Highest Level of Cricket Competition by Age 17
62	Years to Achieve a First Significant Performance in Senior Club Cricket
67	Years to Achieve a First Significant Performance in Second XI County Cricket
68	Years to Become Best Spinner in Second XI County Cricket
73	Years to Become Best Spinner in First XI County Cricket
76	Cricket Play Hours up to Age 14

Initial Classification. The initial classification accuracy (percentage of correctly classified players) of the four different classifiers for the dataset of 28 players described by the 16 selected features was as follows:

- Support Vector Machine (SVM) Classifier: 78.6%
- Multilayer Perceptron (MLP) Classifier: 82.1%
- Naïve Bayes Classifier: 85.7%
- Nearest Neighbour (Lazy learner, IB1) Classifier: 85.7%

Initial classification revealed that all four classifiers discriminated between the two classes with accuracies greater than that expected by chance (50%). Further analysis of the dataset was used to return a subset of features with the *greatest* ability to discriminate between elite and sub-elite spin bowlers.

Final Classification – Recursive Feature Elimination (RFE). The 16 feature scores returned by SVM were ranked, and the feature with the lowest score was removed. An SVM was trained and tested again using the LOO protocol. The *new* 15 feature scores were ranked, and the feature with the lowest score was removed. This process was repeated until classification accuracy no longer improved upon removing the next lowest weighted feature, meaning that there was no statistical basis for further removal of features. This led to the removal of four features and the retention of a predictive model containing 12 features (see Table 3).

The final classification accuracy (percentage of correctly classified players) of the four classifiers for the dataset of 28 players described by the 12 features was as follows:

- Support Vector Machine (SVM) Classifier: 92.9%
- Multilayer Perceptron (MLP) Classifier: 89.3%
- Naïve Bayes Classifier: 82.1%
- Nearest Neighbour (Lazy learner, IB1) Classifier: 78.6%

Table 3. Individual SVM feature weightings before and after features with low weightings were removed and the protocol was re-run.

Feature	Weighting Before Extraction	Weightings After Extraction
Highest Level of Cricket Representation by Age 14	+ .7127	+ 1.4684
Age First Joined a County Cricket Academy/Junior Representative Cricket	+ 1.1889	+ 1.2423
Years to Become Best Spin Bowler in First XI County Cricket	- 1.1137	- 1.1445
Competition Overs Bowled up to First XI County debut	+ 1.1857	+ 1.1258
Age Decision Made to Become Professional Cricketer	- .8822	- 1.0851
Cricket Competition Hours up to England Senior International Debut	+ .8138	+ .8796
Age of First Involvement in Unsupervised Practice	- .8554	- .7966
Years to Achieve a Significant Performance in Senior Club Cricket	- .621	- .8769
Age of First Regular Involvement in Cricket	- .714	- .8317
Birth Quarter	+ .9816	+ .8206
Spin Bowling-Specific Practice up to Age 14	+ .6389	+ .6964
Years to Achieve a Significant Performance in Second XI County Cricket	- .6652	- .6541
Age of First Organized Spin Bowling-Specific Practice*	- .2745	-
Highest Level of Cricket Representation by Age 17*	+ .5285	-
Years to Become Best Spin Bowler in Second XI County Cricket*	- .3993	-
Cricket Play Hours up to Age 14*	+ .2842	-

Note. Number of Instances = 28. Positively weighted features reflect a positive relationship with the elite class - where a *higher* number is associated with elite group membership. Negatively weighted features reflect a negative relationship with the elite class - where a *lower* number is associated with elite group membership.

*Removed due to low importance weightings.

Quantitative Findings: Summary

The final classification analysis highlights that the SVM classifier produces the greatest accuracy (92.9%) and observes the largest increase in classification accuracy from initial classification to final classification (+14.4%). Consequently, we can conclude that this classifier discriminates between the elite and sub-elite with *very good* accuracy, supporting the findings of Pfeiffer and Hohmann (2012), who conclude that pattern recognition approaches are excellent tools to predict competitive performance categories using developmental features. The analysis confirmed that the predictive model containing the following developmental features discriminated between elite and sub-elite spin bowlers with the greatest classification accuracy: highest level of cricket representation by age 14, age first joined a County cricket academy, years taken to become best spin bowler in First XI County Cricket, proportion of competition overs bowled up to First XI County debut, age decision made to become professional cricketer, years taken to achieve a significant performance in senior club cricket, cricket competition hours up to senior international debut, age of first involvement in unsupervised cricket practice, age of first regular involvement in cricket, birth quarter, years taken to achieve a significant performance in Second XI County Cricket, and proportion of spin bowling-specific practice up to age 14. The 12 features discriminate as a combination and as such should be interpreted as a holistic profile. The stereotypical profiles of the elite and sub-elite are visualised in Figure 1. The descriptive statistics of the features are shown in Table 4.

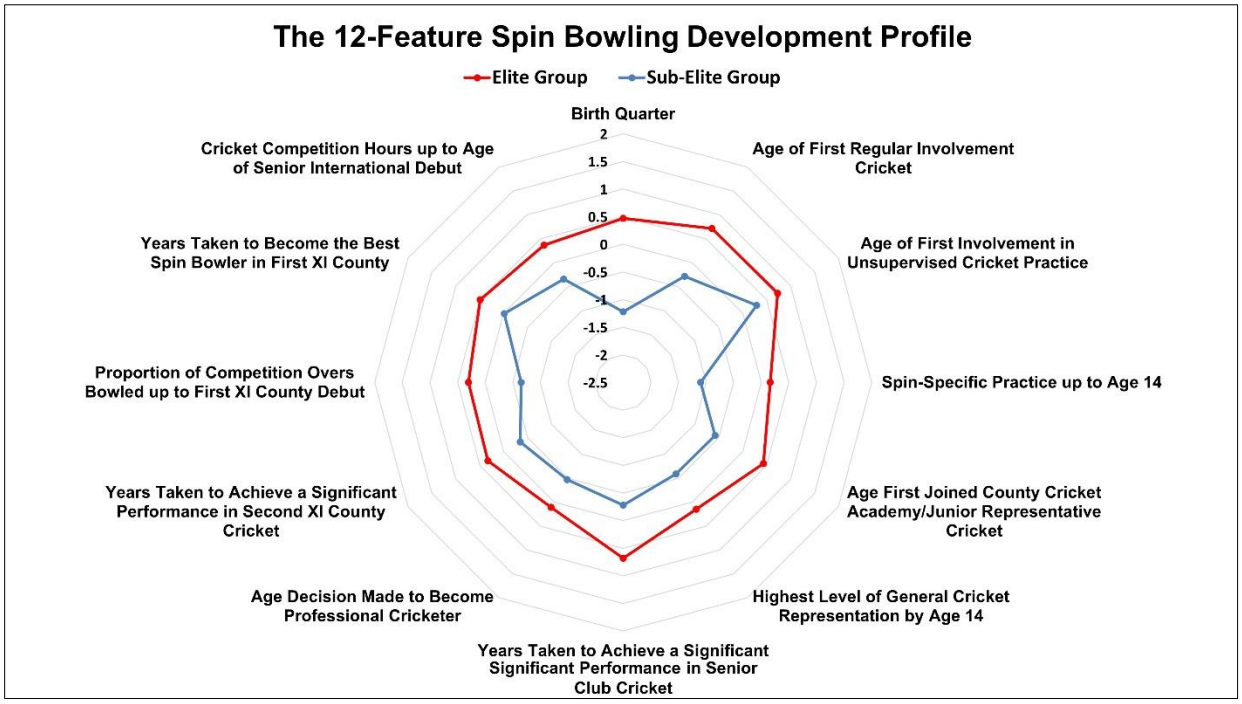

Figure 1. The 12 developmental features that discriminate between elite and sub-elite spin bowlers.
Note. Data points reflect the standardized median values for each expertise class. A higher number is associated with the elite group. membership. The values of negatively weighted features (outlined in Table 3) are reversed, in order to present the discrimination of the elite/sub-elite development profiles through visual means.

Table 4. Unstandardized descriptive statistics of the 12 developmental features that discriminate between elite and sub-elite spin bowlers.

#	Feature	Elite Group					Sub-Elite Group				
		Mean	**Median**	**SD**	**Min**	**Max**	**Mean**	**Median**	**SD**	**Min**	**Max**
1	Highest Level Cricket Representation by Age 14*	5	4	1.60	1	6	4	3	0.60	2	4
2	Age First Joined County Cricket Academy/ Junior Representative Cricket	13.60	14	2.77	8	17	12.23	11	2.52	8	17
3	Years to Become Best Spin Bowler in First XI County Cricket	1.33	4	3.62	0	14	6.87	6	4.44	1	17
4	Proportion of Competition Overs Bowled up to First XI County Debut (%)	29.40	28	9.87	12	55	21	20	3.37	16	27
5	Age Decision Made to Become Professional Cricketer	15.60	17	3.33	7	19	17.96	18	1.65	15	22
6	Cricket Competition Hours up to Senior International Debut	11,016	11,340	5,507	4,524	26,718	11,382	8,317	1,670	6,140	11,382
7	Age of First Involvement in Unsupervised Cricket Practice	8.27	7	2.91	5	14.50	10.92	10.50	3.51	6	20
8	Years to Achieve a Significant Performance in Senior Club Cricket	0.47	0	0.55	0	1.5	1.04	1	1.39	0	5
9	Age of First Regular Involvement in Cricket	7.37	6	2.94	2	12	9.23	9	2.85	4	14
10	Birth Quarter	2.80	3	1.08	1	4	2.00	1	1.22	1	4
11	Spin Bowling-Specific Practice up to Age 14 (%)	51.47	50	39.56	0	100	30.77	0	37.02	0	90
12	Years to Achieve a Significant Performance in Second XI County Cricket	1.33	1	1.23	0	4	1.77	2	1.74	0	5

Note. *Cricket Representation Levels: 1 = Junior Club Cricket, 2 = Senior Club Cricket, 3 = Junior County Cricket, 4 = Regional Cricket, 5 = Second XI County Cricket, 6 = International Youth, 7 = First XI County Cricket

An important disclaimer must be made here. The classification accuracy which we report above for the set of 16 features, and even more so for the set of 12 features may be slightly optimistically biased. This is because Weka's protocol for feature selection (LOO or not) is followed by another round of using the same data in order to train and test the classifier (LOO). In other words, the object set aside for testing has been "seen" during the training stage when feature selection was carried out; this is the so-called "peeking" (Kuncheva, 2014; Smialowski, Frishman, & Kramer, 2010). The effect of this peeking is indirect and ignored in many studies. Nonetheless, one cannot make the claim that the classification accuracy on unseen data will match the one achieved for this dataset until this has been directly tested as part of a model validation (as performed below).

Confirmatory Model Testing. The 12-feature model discriminates between elite and sub-elite spin bowlers with very good accuracy; the next required step was to test the model's ability to generalize (and thus predict) unseen datasets, i.e., spin bowlers who were not included in the original analysis. This follows the training-and-testing protocol previously adopted during feature selection and classification. To do this, we utilized the interview data of five additional spin bowlers, three of whom met the were elite (international cricketers), having represented England, Pakistan and New Zealand international cricket boards, and two of whom were English sub-elite (professional County) spin bowlers. The selected classifier used to test the model (SVM) predicted the true expertise class of elite and sub-elite spin bowlers with 100% accuracy, thus lending support to the model's generalizability on unseen data. A future prospective replication study would allow further scrutiny of the model's external validity.

Qualitative Findings: Content Analysis

The analysis comprised three stages. The first two stages were conducted independently by the fifth author, whereas the first, second, and fifth author conducted the final triangulation stage. During the first stage, common themes were categorized as lower order. The lower-order themes were subsequently grouped into higher–order themes, until all similarities between themes were saturated and no further higher-order themes could be determined. The final stage involved a triangulation process, to verify, validate, and reduce any systematic bias during the analysis. This involved a discussion that challenged the initial interpretation of the data, and disagreements were resolved by reference to the original transcripts and further discussion until full consensus was reached. Discussion of the extensive verbatim quotes that comprised each higher order theme led to the identification of five discriminating themes between the elite and sub-elite, along with four commonalities.

Qualitative Findings: Summary

The commonalities identified between the elite and sub-elite indicated the following: The biggest developmental challenge was getting selected for the team, and avoiding being de-selected; the spin bowlers successfully overcame challenges by seeking advice and feedback from experienced bowlers and coaches; they would filter out any unnecessary information when listening to advice, so as to only take away information that had relevance to them; and reported that significant others (i.e., family, captains, and coaches) had a big influence on their development. The discriminating themes indicated that sub-elite spin bowlers were more likely to have experienced difficulties in overcoming their development challenges; these were attributed to nervousness about performance, a fear of failure, feeling unequipped to cope with high-level expectations, and a lack of support from others. The elite spin bowlers, however, were more likely to overcome such challenges they faced during their development by deliberately engaging in hard work and training, which discriminated the elite (see Supplementary Information for the extended qualitative findings). The complementary nature of the qualitative and quantitative discriminating findings allowed for the conceptualization of four developmental themes, discussed below.

Discussion

The present study sought to identify the developmental features (variables) that discriminate between elite and sub-elite spin bowlers. We conducted a detailed examination of development within the sport of cricket and adopted distinct criteria to discriminate between levels of spin bowling expertise, spin bowlers who had competed at senior international level (elite), and spin bowlers who had been professional cricketers but only at the domestic First Class County level (sub-elite). The adopted mixed method approach, which included the application of pattern recognition analyses, addresses a number of methodological limitations of previous expertise, thus allowing the authors to adopt a holistic approach to modeling the multifaceted and complex nature of expertise development. In the authors' opinion, this novel approach is a strength of the study. Furthermore, the advanced pattern recognition techniques adopted in the paper offer application potential for the identification of precursors of expertise across different sports.

The 12-feature classification model produced from the quantitative analyses discriminated between the elite and sub-elite classes with very good accuracy. Subsequent validation analysis of the final 12-feature model, using an unseen dataset of five players, revealed a perfect (100%) classification fit of this testing data. Results of this validation analysis highlight that the 12-feature model can be generalized to spin bowlers outside the original sample, and can be extended to spin bowlers worldwide. The external validity demonstrated in the present study may prompt international cricket boards to examine their own development structures by way of maximizing the development of spin bowlers and other cricket disciplines.

The qualitative component of the study added depth to our understanding of the features that discriminate between the elite and sub-elite groups identified in the quantitative analyses and produced an additional five discriminating themes. Four commonalities between the elite and sub-elite were also identified, alongside the additional answers; these are reported in full within the Supplementary Information.

To facilitate discussion of the findings in relation to existing theoretical framework and the temporal sequence of spin bowler development in England and Wales, the 12-feature model was subdivided across four areas of development (Early Development; Pathway Milestones; Domain-specific Activity; Pathway Performance Indicators). This framework allowed the emergent themes derived from the qualitative findings to be integrated into the discussion.

Early Development

Early cricket development is unsurprisingly linked to birth quarter and age of regular exposure to cricket (Barney, 2015). However, our findings suggest that the interplay between birth quarter and age of exposure to cricket may not be as linear as previously suggested (for a review see Cobley et al., 2009). First, the findings revealed that elite spin bowlers were born later in the year than their sub-elite counterparts. This supports existing cricket research demonstrating differential RAEs contingent on expertise level and discipline (Barney, 2015; Jones et al., 2018). McCarthy et al., (2016) similarly reported that a significantly greater proportion of graduate players from the ECB's talent pathway who become senior international players were born later in the year (Q4 RAE). Many of the elite spin bowlers in the present study were attached to a different discipline during their formative years**,** and RAE bias is confounded by the significant weighting placed on physical requirements for some disciplines, e.g., pace bowling. Furthermore, de-selection due to physical maturation bias is suggested to result in a resurgence of young players with greater psychological resilience re-entering youth sport programs (Lewis, Morgan, & Cooper, 2015). Qualitative analysis emphasized the need for spin bowlers to be resilient in the face of adversity, as was explained by an elite spin bowler: "You've got to be resilient, you've got to be tough and you've got to be strong to keep bouncing back" (P21). Furthermore, becoming a spin bowler provides opportunity for relatively younger players to remain viable and excel in cricket due

to the emphasis placed on technique rather than physical development (P. Such, ECB National Lead Spin Bowling Coach, personal communication, September 27, 2016).

Our second finding highlighted that elite spin bowlers became regularly involved in cricket earlier than sub-elite bowlers. The benefits of early participation within a sport are denoted by the "sampling stage" of the Development Model of Sport Participation (Côté et al., 2007). This stage denotes the benefits of early sport participation, through engagement in playful activities which harness learning through trial and error and develop young players' intrinsic motivation towards a sport. Considering the fundamental differences that exist between the cricket disciplines (Jones et al., 2018), coupled with the current knowledge that neither group of spin bowlers typically specialized in the spin bowling discipline until early in their teenage years (M_{age} = age 14), we can infer that the early cricket experiences of both groups of spin bowlers were somewhat diverse. The present finding suggests that elite spin bowlers may have specifically benefited from the earlier (regular) engagement in these diverse sport experiences. Earlier engagement is shown to develop intrinsic motivation towards a sport, promoting self-regulation and an internal drive to succeed (Cope, Bailey, & Pearce, 2013). Furthermore, self-regulation is a positive predictor of elite group membership in sport (Bartulovic, Young, & Baker, 2017). Thus, a greater drive to succeed could mean that prospective elite spin bowlers are more likely to undertake greater volumes of practice, contributing to their development of spin bowling expertise (McCardle, Young, & Baker, 2017; Rees et al., 2016). The benefits of these earlier diverse sport experiences appear partly indicative of the early engagement hypothesis, which suggests that prolonged exposure to play and practice activities in a sport, aided by early sport specialization, facilitates the subsequent expertise development in the field (Ford et al., 2009); however, there is no evidence of early sport specialization in the present study. Moreover, elite spin bowlers' earlier engagement in diverse cricket experiences was likely important in developing the required fundamental motor skills for cricket, and spin bowling technique specifically, to perform at the highest level (Goodway & Robinson, 2015).

Third, elite spin bowlers also engaged in unsupervised practice sessions earlier than the sub-elite, suggesting an earlier shift in focus from regular (recreational) cricket participation, to targeted unsupervised practice. The benefits of early sampling are now likely reflected in the behavior of the prospective elite spin bowlers, who appear to be acting on their developing inner drive for the sport (Cope et al., 2013; Côté et al., 2007), and likely extends the benefits of the early engagement hypothesis (Ford et al., 2009). The present finding also demonstrates that prospective elite spin bowlers' actions *outside* of competition are in fact distinguishable from prospective sub-elite bowlers during the earliest stages of development. Elite bowlers' earlier engagement in unsupervised practice is likely an additional indicator of self-regulation, as they begin to take control of their behavior, in pursuance of their developmental goals (McCardle et al., 2017). Continued development and progression of self-regulated learners could have a positive bearing on the success of the ECB talent pathway. The lack of observable performance indicators during the earliest stages of development makes the early identification of talent difficult, especially for sport officials who place primary emphasis on current performance level. In fact, the present findings illustrate that these formative experiences are likely catalysts for the subsequent development of performance, as spin bowlers evolve.

Pathway Milestones

Analysis revealed that elite spin bowlers joined a County cricket academy later than the sub-elite, but made the decision to become professional cricketers earlier. The later entry of elite bowlers into an academy is mirrored in the developmental trajectories of Olympic athletes (Hardy et al., 2013; Rees et al., 2016), and may be the result of an overrepresentation of relatively older and physically mature players in

age group cricket (Barney, 2015). This early bias likely affects spin bowlers who transition from a different discipline due to the distinct differences between spin bowling skill demands and other disciplines. Consequently, prospective elite bowlers may not have demonstrated sufficient spin bowling potential in their performances in early development to warrant earlier selection into an academy.

The impact of elite bowlers' early participation in cricket may have influenced the timing of their decision to become professional, as early intrinsically rewarding experiences have been proposed to kindle players' inherent attachment towards a sport (Côté et al., 2007). However, elite athletes have also been shown to possess greater levels of extrinsic motivation and lower levels of intrinsic motivation than their sub-elite counterparts (Fortier, Vallerand, Briere, & Provencher, 1995). While there is ambiguity surrounding *what* motivates young players to become elite, the present findings, along with previous research (Rees et al., 2016), suggest that elite performers may possess greater inner drive than the sub-elite. This is supported by an investigation assessing the discriminant validity of the ECB's scouting process, revealing that inner drive was the only variable (across psychological, physiological, technical and tactical awareness categories) that discriminated between cricketers who remained shortlisted and those subsequently selected onto the England Development Programme (Barney, 2015). The findings relating to "Early Development" in the present study also support the notion that elite spin bowlers may have developed a degree of resilience. That is, through demonstrating exceptional inner drive to overcome significant obstacles during development, such as the challenges associated with RAE. Indeed, the motivational benefits of the elite's earlier participation in cricket may prepare them for the challenges ahead, kindling an earlier desire to become professional (Cotè et al., 2007). The drive to succeed was evidenced further by the elite in the qualitative findings, whereby data indicated that elite spin bowlers were more likely to have overcome the challenges faced during development with less difficulty than their sub-elite counterparts, often citing failure as their driver for success: "I think not getting selected just created the hunger more for me. Like failing" (P7). The sub-elite group, however, identified "fear of failure" (P23), as one of the biggest difficulties that they endured during their development.

Domain-Specific Activity

Despite there being no difference between the elite and sub-elite's quantity of organized practice, elite spin bowlers undertook a greater proportion of organized spin bowling-specific practice. While the elite's greater quantity of spin bowling-specific practice is consistent with the theory of deliberate practice, where an abundance of domain-specific practice is reported to lead to the development of expertise, it does not support the 10,000 hours benchmark (Ericsson et al., 1993). In fact, the total cricket practice hours (organized and unorganized) within the present study was notably under 10,000 hours for both the sub-elite group (M_{hours} = 5,561, SD = 3,262) and the elite (M_{hours} = 5,697, SD = 2,285) groups, up to the age at which they became elite, and is consistent with a study of elite Australian spin bowlers (Mann, 2014). That said, the present finding mirrors the conclusions of recent studies demonstrating that high volumes of domain-specific practice increase the probability of developing expertise (*see* Rees et al., 2016). This was supported by the majority of elite spin bowlers who explained that they overcame the selection challenges by "working hard, practicing hard" (P16; P20), coupled with the clear distinction in the elite and sub-elite's proportion of spin bowling-specific practice. Furthermore, accumulation of domain-specific practice during formative years allows for trial and error, and subsequent acquisition of fundamental spin bowling movements, enabling translation into competition concurrently (Pinder, Davids, Renshaw, & Araújo, 2011; Rothwell, Stone, Davids, & Wright, 2017).

The elite had also bowled a larger proportion of their teams' overs up to the age of their First XI County debut. The frequency of competition overs bowled may serve not only to indicate current performance level but is also likely a

hallmark of potential. The inherent difficulty facing developing spin bowlers in achieving a repeatable action demands resilience; further resilience is required for players challenged by RAE, who are met with a "lack of knowledge from captains…and coaches" (P23) and unresponsive "flat pitches" (P17), all of which are likely to impact on the selection of spin bowlers (Mann, 2014). The findings suggest that it is those resilient spin bowlers who overcome such challenges that are likely trusted to bowl and subsequently go on to become elite (McCarthy et al., 2016). Bowling a substantial amount of competition overs by the age of their First XI County debut appears paramount for developing spin bowlers, particularly given how the time constraints associated with the senior cricket competition schedule often reduces time available to practice, meaning that recurring flaws identified must often be addressed "on the job" during competition (A. Strauss, former ECB Director of Cricket, Personal Communication, April 11, 2016).

In addition to the greater proportion of competition overs bowled before their First XI County debut, the elite had also accumulated a greater quantity of cricket competition hours up to the age of their international debut, compared to the sub-elite[3]. It is likely that this finding is partly a biproduct of the elite's early exposure to additional higher-level competition and more time spent bowling during competition. Upon reaching First XI County Cricket, the elite are selected for competition more regularly, likely owing to their developed competencies and a strong track record. In fact, the most marked difference in competition experience exists once spin bowlers reach the First XI County game. As such, it appears paramount that spin bowlers consistently demonstrate the successful transfer of spin bowling-specific practice into competition overs and cope with the psychological demands of spin bowling by the time they reach the pinnacle of the domestic County game. Since the sub-elite had experienced less spin bowling-specific practice, less competition overs, and less general competition time during their development, it can be inferred that the sub-elite were not equipped to deal with the concurrent technical and psychological demands of competition. Consequently, the sub-elite may have lacked the required skill level and/or visual-perceptual-motor skill to reproduce high-level performances consistently during competition (for a review *see* Müller & Rosalie, 2019; Rosalie & Müller, 2014).

Despite the revelation that the elite had undertaken significantly more spin bowling-specific practice, it is important to note that age of specialization in the sport of cricket (elite: M_{age} = 16.73, sub-elite: M_{age} = 17.61) and spin bowling as a discipline (elite: M_{age} = 14.07, sub-elite: M_{age} = 13.62) were also explored in the present study, but did not discriminate between elite and sub-elite spin bowlers. Consequently, the present finding is not indicative of the pre-existing positive and linear relationship between early specialization (at neither an inter nor intra-sport level) and volume of domain-specific practice (for a review *see* Rees et al., 2016). In fact, in the case of both elite and sub-elite spin bowlers, the ages reported in the present study appear most indicative of later, rather than earlier sport specialization, which is contrary to data reported across a number of historic studies denoting the benefits of early sport specialization (e.g., Ericsson et al., 1993; Ward et al., 2004). Clearly, there is a need for future research to measure both inter and intra-sport specialization as separate constructs to advance understanding of the complexities of specialization.

The present findings support previous research outlining the benefits of early diversification, facilitated by early engagement in sport (Güllich, 2014; Rees et al., 2016). Furthermore, it appears that the spin bowlers sampled in the present study benefited from early diversification *within* the sport of cricket, *coupled with* (domain-specific) spin bowling practice. That is, the elite's early investment in prolonged spin bowling-specific practice, while simultaneously developing wider skills from a diversified cricket development, appears an important foundation in their pursuance of becoming elite (Mann, 2014). The development of a wider skill repertoire enhanced by a

diversified cricket development is likely to lead to a roundedness that makes spin bowlers viable acquisitions for academies, subsequently maximizing one's chances of becoming an elite spin bowler (Mann, 2014). Furthermore, several sub-elite bowlers highlighted that being a "one-dimensional cricketer" had often caused them to be overlooked for selection during their development; "I didn't bat, and I was a really average fielder, so I was either bowling well, or I wasn't in the team" (P30). Specifically, the perceptual benefits of prior engagement in batting may assist spin bowlers in attempting to deceive batsmen resulting from a form of self-modeling, (Zetou, Kourtesis, Michalopoulou, & Kioumourtzoglou, 2009). Further, given that conditions in England and Wales may not always be receptive to spin bowling, multidiscipline spin bowlers who also demonstrate prowess as batters are likely to be favored during selection. Similarly, a previous attachment to pace bowling may assist spin bowlers to develop a foundational strong physique enhancing their physical ability to produce a repeatable action in the long-term (Such et al., 2012).

Pathway Performance Indicators

Elite spin bowlers had competed at a higher level of cricket representation than the sub-elite, up to the age of 14; only prospective elite players had competed at the highest of levels of competition (international youth cricket) by age 14. The most parsimonious explanation for this finding, is that the highest potential players demonstrate ability early, and progress to higher forms of the game. The finding coincides with a statement made by an elite spin bowler during the interview: "When I was 14, I was playing the top men's league, first team with the club" (P1); however, the bowler also went on to voice his concerns about youth players in England and Wales competing at lower levels of competition: "A lot of guys now are having to play school's cricket and then suddenly get dropped in the deep" (P1). This would suggest that youth spin bowlers who are confined to school team representation may face substantial difficulty when progressing to higher levels in future owing to the marked difference in competition standards during early development. However, owing to the wide range of representation levels shown across both expertise groups by age 14, a note of caution also exists, meaning that prospective elite spin bowlers could conceivably come from a diverse playing background at this age.

Superior adaptability to new environments is likely an important attribute in prospective elite spin bowlers representing 3 of the 12 discriminating features and perhaps should be considered an important criterion for cricket selection, such as in making the transition from junior to senior cricket (Barney, 2015). Elite spin bowlers achieved an earlier first significant performance in both senior club cricket and Second XI Senior County Cricket, compared to the sub-elite. These elite spin bowlers appear to have the skills to cope with the increase in physical, psychological, and technical demands at senior level having previously been exposed to the highest level of competition from an early age. They also likely demonstrated resilience in successfully bridging the gap between junior and senior cricket (Jones et al., 2018). This finding extends previous research highlighting that the ability to adapt to senior (Second XI) cricket, by taking wickets soon after debut, predicts subsequent performance at international level (Barney, 2015).

The elite's superior adaptability is further emphasized upon reaching the pinnacle of domestic cricket (First XI County Cricket), where adaption becomes more gradual; elite spin bowlers become the best spin bowlers in their respective teams in fewer years than the sub-elite. There was an acknowledgement of the benefit of such troughs in development from one elite spin bowler, who explained as follows: "Sometimes you would get there, and all of a sudden your progress would stop, and you needed to play at that level for a while before you actually started to move up again" (P19). This finding is consistent with Barney (2015) who concluded that bowlers need the experience of First XI County Cricket to develop technical skill before performing in international cricket. Indeed, elite spin bowlers had accumulated a

greater volume of competition hours experience up to the age of their senior international debut. Here, we suggest that it is those spin bowlers who develop the desired skills quickest who are likely to become (elite) international cricketers. Of course, becoming the best spin bowler within a team is contingent on the performance levels of other spin bowlers in the team. In this way, one elite spin bowler explained the benefits and drawbacks of being in the shadow of an (already) elite spin bowler during his development: "It was great to play with him but I got to a stage where I wasn't playing anywhere near as much cricket as I felt to ought to or would like to do so I moved County" (P20). In light of this, it is likely that a number of aspiring elite spin bowlers go unnoticed by selectors. This is particularly problematic given how the number of spin-bowled overs are declining in the County game (Coyne, 2016). It appears crucial that spin bowlers who have demonstrated consistency and a robustness up to this point experience regular competition time, which may require a change in County team. Importantly, the present finding also suggests that County cricket *does* offer spin bowlers with the necessary attributes a route to international level, on the condition that they receive sufficient opportunity to demonstrate their prowess (Vaughan, 2015).

Limitations

The critical reader may relate a number of limitations to the present study. First, as with all retrospective research, there is a risk of error in recall. To mitigate this, we drew a comparator sample who were (on average) the same age, also possessing similar standard deviations (*see* Method). Consequently, it was inferred that any recall inaccuracies owing to age would be approximately equal for both groups. Second, the 12-feature model was tested on five unseen participants to gain some idea of the model's potential generalizability. While a five-participant test-set could be construed as being somewhat underpowered to be considered a genuine standalone replication, the training-and-testing protocol adopted by the Leave-One-Out (LOO) protocol during feature selection and classification ensure that the features are continuously tested on each participant independently. Regardless, the present study contained the entire spin bowling sample in England who fit the specified criteria. It is therefore conceivable that researchers would have to wait approximately 20 years before a comprehensive replication study could be conducted, by which time the development landscape would have likely changed again. The multiple classification indices used to test the model provide an early indication of the model's generalizability, which, at the very least, is more informative, than not testing the model for 20 years. Last, the interpretation attached to the present findings are theoretically driven, reflecting the authors' understanding of contemporary research in their specialized fields of expertise, but are largely speculative because of the descriptive nature of the research design (i.e., we have not explicitly manipulated any variables, but rather used advanced machine learning techniques to classify expertise based on developmental biographies).

Summary

Prospective elite spin bowlers develop an early passion for cricket, participating both recreationally and in targeted unsupervised practice from an early age. However, the development trajectory that follows is indicative of a complex, non-linear journey to becoming senior internationals. They appear to keep their playing options open early on, either through choice, or owing to the maturational effects of being relatively younger within their playing cohort, perhaps in an attempt to remain viable and follow their passion for cricket. Before being selected for an organized County academy program, prospective elite spin bowlers take longer to illustrate that they are high potential. Fulfilment of potential is likely delayed further by the "expensive" nature of spin bowling, compared to pace bowling, when considering the sheer number of runs conceded. Therefore, it is conceivable that a significant proportion of prospective elite spin bowlers do not appear as valuable acquisitions for cricket academies until later, once they demonstrate all-round ability.

However, while both groups tend to specialize in cricket and spin bowling relatively late, crucially, the elite become exposed to more spin bowling-specific practice and competitive experience compared to their prospective sub-elite counterparts (who were already attached to a County academy program). Early performance indicators demonstrate that while elite spin bowlers may come from varied competition backgrounds, only prospective senior elite players played at the highest levels by an early age. Furthermore, upon playing at senior levels, elite spin bowlers adapt to club and Second XI County formats quicker, thereby demonstrating resilience. This may explain why the elite bowl a considerable number of their teams' competition overs up to their First XI County Cricket debut. Prospective elite players gradually become the best spin bowler in their First XI County team quicker than their sub-elite equivalents over a period of years before likely coming to the attention of selectors for the senior (elite) international team.

Implementation

The pattern of 12 features that discriminate between elite and sub-elite groups emerged from a total pool of 93 features. Thus, it was essential that the remaining 81 features were interpreted (alongside the qualitative data) as either being *equally important* or *equally irrelevant* in becoming a sub-elite spin bowler. For better understanding the complexities of the feature profiles of both elite and sub-elite spin bowlers, a research working group was formulated and overseen by the corresponding author. The group included five ECB officials whose roles were directly aligned with the talent pathway: Performance Director; Head of Science, Medicine and Innovation; National Talent Pathway Manager; National Lead Spin Bowling Coach; and Player Identification Lead. The implementation and dissemination phase included three steps, and the initial stages focused on the quantitative data. First, elite and sub-elite spin bowlers were combined into a single group, where the remaining 81 relevant features were assessed by comparing the pattern of skewness to extant expertise research literature in sport. Next, bimodally distributed features were then removed, leaving 33 features that could be regarded as true commonalities from analyses of the quantitative data. The four commonalities identified between elite and sub-elite bowlers during the qualitative analysis (*see* Results) were then disclosed to the working group during this stage, alongside the 33 commonalities obtained from the quantitative analyses. Expert opinion was sought in the second stage to assist with identifying the commonalities that hold equal importance in achieving sub-elite status. This led to identification of 19 equally important commonalities (Table 5).

The commonalities are also depicted in Figure 2, alongside the 12 discriminators previously identified. The final stage involved applying the most likely explanation to the collective quantitative and qualitative findings informed by the expert opinion of the working group and extant literature. Applied implications were produced by the working group and converted into recommendations which were disseminated nationally to maximize spin bowler identification and development in England and Wales (presented below).

Table 5. The 19 commonalities identified by the ECB's research working group as possessing equal importance to the discriminators (in achieving sub-elite status initially).

#	Commonality Labels
1	Age of First Organized Cricket Competition *(-)*
2	Number of Organized Sports Played Across Development *(+)*
3	Age Started Spin Bowling in Competition *(-)*
4	Age of Senior Club Cricket Debut *(-)*
5	Physical Size at Age of Senior Club Cricket Debut *(-)*
6	Level of Challenge upon making Senior Club Cricket Debut *(+)*
7	Age Became the Best Spin Bowler in Senior Club Team *(-)*
8	Age of Second XI Senior County Cricket Debut *(-)*
9	Physical Size at Age of Second XI Senior County Cricket Debut *(-)*
10	Level of Challenge upon making Second XI Senior County Cricket Debut *(+)*
11	Age of Specialization in Cricket *(+)*
12	Age Became the Best Spin Bowler in Second XI Senior County Team *(-)*
13	Age of First XI Senior County Cricket Debut *(-)*
14	Cricket Competition Hours up to Age of First XI Senior County Debut *(+)*
15	Unsupervised Cricket Practice Hours up to Age of First XI Senior County Debut *(+)*
16	Cricket Play Hours up to Age of First XI Senior County Debut *(+)*
17	Organized Cricket Practice Hours up to Age of First XI Senior County Debut *(+)*
18	Proportion of Spin Bowling-Specific Practice up to First XI Senior County Debut *(+)*
19	Age Became Regular Choice Spin Bowler in First XI Senior County Team *(-)*

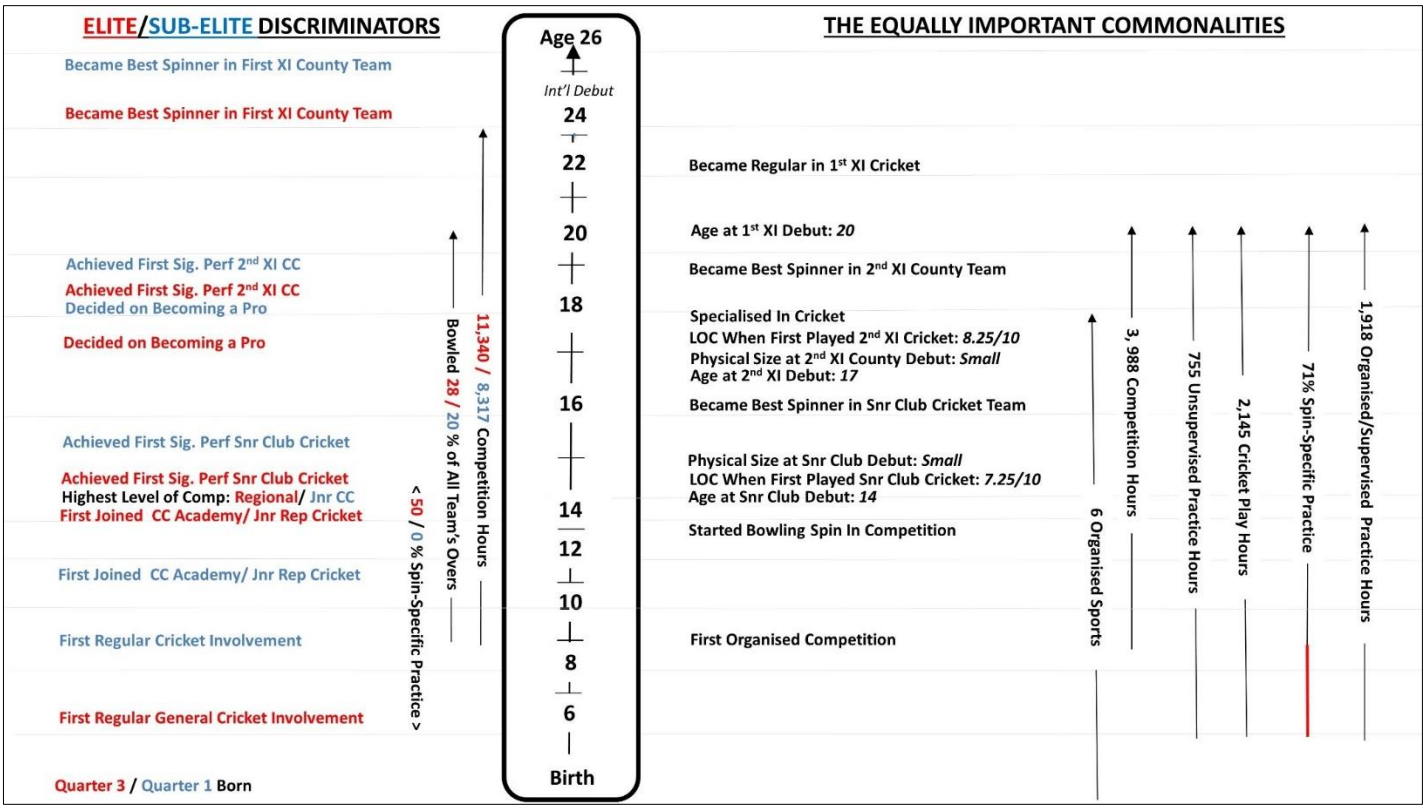

Figure 2. A timeline of the 12 developmental discriminating features between elite and sub-elite spin bowlers (left), and the 19 equally important commonalities identified (right).
Note. Data points reflect the unstandardized median values of each feature

FINDING #1
International spin bowlers appear to demonstrate an early keenness towards cricket during their development, because they:

(a) Became regularly involved in cricket, and spin bowling, from an earlier age than the County spin bowlers (~ Age 6 vs. Age 9).

(b) Accumulated considerably more spin bowling-specific practice than the County spin bowlers up to the age of 14 (~ 50% vs. 0% of practice sessions).

(c) Decided on pursuing a career in cricket sooner than the County spin bowlers (~ Age 17 vs. Age 18).

Actions:	Pre-Pathway (8-12)	Early Pathway (U13-15)	Mid Pathway (U16-18)	Late Pathway (18-21)
What to do? (*Talent Development Coaching Tips*)	Create opportunities to explore and experiment spinning the ball during practice, making it fun and explorational.	Promote and provide opportunity for prolonged "spin-specific" practice, alongside multidiscipline practice, during early pathway practice sessions.	Continually encourage and offer opportunity for prolonged "spin-specific" practice.	
What to look for? (*Talent Identification Tips*)	The emerging "spin bowling badger" - the kid who has a passion for cricket and spinning the ball.	The flourishing "spin bowling badger"- the player who takes the bag of balls by himself and practices hard.	The evolved "spin bowling badger" - the spin bowler who makes cricket, and spin bowling, a priority.	
What to find out? (*Intelligence*)	When did spin bowlers take up cricket/spin bowling, and why?	How much self-directed spin bowling practice do the players do in their spare time? How much "spin-specific" practice do they do across all environments?	Begin to explore the spin bowlers' cricket aspirations; who does he/she want to be?	Are the spin bowlers' aspirations resilient and enduring; do they "stick at it"?
Pathway Implications (*Pathway Strategy*)	Instill the principle of spin bowling exploration and experimentation, among multidisciplinary cricket practice, into the talent development framework, pathway reviews, coach education resources and coach development programs.	Coach development and resources for early specialized spin bowling practice.	Use the research to highlight the developmental journeys of high potential (international) spin bowlers to the wider cricket workforce.	

FINDING #2

International spin bowlers achieved their success by overcoming early challenges, specifically they:

(a) Were younger within their age-groups, and therefore likely physically immature (~ Q3 Born vs. Q1 Born).

(b) Were typically selected onto the County talent pathway program later than the County spin bowlers (~ Early teens; ages 13-14 vs. Age 11).

(c) Played to a higher standard of cricket competition up to the age of 14 (**International**: Junior club cricket to International youth; **County**: Senior club to Regional).

Actions:	Pre-Pathway (8-12)	Early Pathway (U13-15)	Mid Pathway (U16-18)	Late Pathway
What to do? (*Talent Development Coaching Tips*)	Ability to spin the ball may be hampered by physical immaturity. As such, create opportunities to explore and experiment spinning the ball during practice, making it fun. Strategies for achieving this may include extended use of smaller balls during development (i.e., 4.75oz or 5oz), and manipulation of surfaces/net manipulation to validate spinning the ball.	Physical immaturity may hamper spin bowlers' ability to spin the ball or land the ball 22-yards during competition. Smaller hand size, associated with physical immaturity, may also prompt spin bowlers to bowl leg spin, rather than finger spin, initially. Long-term spin bowling potential should therefore be considered relative to current stage of maturity, along with a combination of: 1. Snap and energy in the action; evidence of shape in the air and spin off the pitch. 2. The demonstration of perseverance and creativity in practice & competition to "find a way". 3. Ability to adapt to new challenges. 4. Resilience to deal with setbacks. Given this possible later onset of physical maturity in spin bowlers, decision-makers should explore opportunities to play players down age-groups, where selection is restricted due to immaturity. Maturational differences or injury may cause pace bowlers to transition to spin bowling later in development. Facilitate this transition by offering multiple pathway entry points, and through fostering a spin-friendly environment, providing specialized spin bowling coaching at point of entry.		
What to look for? (*Talent Identification Tips*)		Potential in spin bowling action, regardless of ability to spin the ball (*relative to stage of physical maturity*). Perseverance and creativity to stay viable. Behaviours reflecting adaptability and resilience.		
What to find out? (*Intelligence*)	Is there an underlying reason why the spin bowler(s) are not currently the standout "talented" players (performances aside)? Birth quarter & biological maturation status.	Is there an underlying reason why the spin bowler(s) are not currently the standout "talented" players (*performances aside*)? Birth quarter & biological maturation status. Do spin bowlers adapt to the competitive challenges, and opportunities of the County pathway quickly?		
Pathway Implications (*Pathway Strategy*)		Profiling and monitoring systems. Specialized spin bowling coaching. Increased emphasis on method and ability to spin the ball when judging spin bowling potential (by way of reducing emphasis placed on youth competition performances solely). Ensure that an agreed structure exists for 'playing spin bowlers down' age groups. Multiple pathway entry points.		

FINDING #3:

(a) **International and County spin bowlers typically "specialized" in cricket, and in spin bowling later, rather than earlier in development** (Cricket specialization ~ Age 16-17; Spin specialization ~ Age 13-14).

(b) So, our research shows that international spin bowlers did both spin bowling-specific practice *and* multi-dimensional cricket practice to around age 14.

Actions:	Pre-Pathway (8-12)	Early Pathway (U13-15)	Mid Pathway (U16-18)	Late Pathway (18-21)
What to do? (*Talent Development Coaching Tips*)	Provide multi-disciplinary cricket experiences in practice and competition. Encourage multi-sport participation.			
What to look for? (*Talent Identification Tips*)		Prioritization of spin bowling (*discipline specialization*).	Prioritization of cricket (*sport specialization*).	
What to find out? (*Intelligence*)		Whether spin bowlers are committed to developing their second/third disciplines. Whether spin bowlers are engaged in other complimentary sports/activities.		
Pathway Implications (*Pathway Strategy*)	Multi-sports exposure Multi-discipline cricket exposure			

FINDING #4:
International spin bowlers demonstrated superior adaptability to County spin bowlers, by typically:
(a) Achieving a first significant performance within a year of making their senior club and Second XI County debuts (i.e., first 3fer, 5fer to 10 wicket haul).
(b) Becoming the best spin bowler in their First XI County team within fewer years (typically 4 years following debut).

Actions:	Pre-Pathway (8-12)	Early Pathway (U13-15)	Mid Pathway (U16-18)	Late Pathway (18-21)
What to do? (*Talent Development Coaching Tips*)		Enable as much challenging scenario and performance-specific practice as possible throughout development, to develop adaptability in bowlers.		Expose high potential spin bowlers to senior-elite performance environments, to: 1. Give spin bowlers an opportunity to "settle" and demonstrate adaptability in unfamiliar and challenging elite environments. 2. Provide spin bowlers with an insight into the demands of elite cricket, consequently highlighting areas for further development. 3. Allow opportunities for cricket officials to challenge and confirm beliefs surrounding the potential of a spin bowler, both within and outside of competition.
What to look for? (*Talent Identification Tips*)		Spin bowlers who demonstrate superior adaptability; typically achieving a first significant performance in their senior club cricket and Second XI County teams within a year of debut.		Spin bowlers who become first-choice for their First XI County team within a few years of debut. Spin bowlers who adapt to new and unfamiliar surroundings quickly pre-First XI County debut, and gradually becoming assured and comfortable, once in the First XI environment.
What to find out? (*Intelligence*)		When spin bowlers achieve their first significant performance for their senior club and Second XI County teams.		When spin bowlers achieve their first significant performance for their senior club and Second XI County teams. How quickly spin bowlers become the "frontline spin bowler" at their First XI County.
Pathway Implications (*Pathway Strategy*)		Promote adaptability. Foster "safe to fail" challenging practice environments.		Provide appropriate "step-ups" in challenge by exposing high potential spin bowlers to elite cricket environments (training, competition environments).

FINDING #5:
International spin bowlers had greater match experience than the County spin bowlers, specifically they:

a) **Bowled a significantly greater proportion of match overs than the County spin bowlers, up to the age of their First XI County debut (around age 20)** (~ 28% vs. 20% of team overs).

b) **Experienced greater game time up to the age of their international debut *at* around age 24** (~ 11,000 vs. 8,000 hrs; approximately 400 full days of cricket difference, with the biggest difference occurring from when the spin bowlers arrive into First XI County Cricket).

Actions:	Pre-Pathway (8-12)	Early Pathway (U13-15)	Mid Pathway (U16-18)	Late Pathway (18-21)
What to do? (*Talent Development Coaching Tips*)		Provide spin bowlers with as many competition overs as possible, particularly up to their First XI County debut. If spin bowlers cannot get regular match time in the team, then try and source additional playing opportunities elsewhere alongside providing ongoing scenario and performance-specific practice volume.		
What to look for? (*Talent Identification Tips*)				
What to find out? (*Intelligence*)		The proportion of match overs that spin bowlers bowl in all environments. The type and number of matches that spin bowlers play within a typical week.		
Pathway Implications (*Pathway Strategy*)		Build and make use of external links to source alternative competition for non-regular spin bowlers. Instill scenario and performance-specific practice volume into the curriculum.		

Conclusion

To conclude, the key findings from the present study revealed a combined pattern of 12 features of development that discriminate between sub-elite and elite spin bowlers with very good accuracy. The discriminating features materialize to produce a development profile encompassing four major areas of development (Early Development; Pathway Milestones; Domain-Specific Activity; Pathway Performance Indicators). Follow-up analysis/testing on unseen data led to perfect classification, providing evidence of the model's generalizability. The study serves to highlight the importance of adopting a holistic approach in expertise research to enable the examination of the multifaceted and complex nature of expertise development, *and* the study offers sophisticated analysis methods to achieve this, thus producing a series of applied recommendations in collaboration with the ECB. We suggest that priorities in England and Wales Cricket now lie in profiling youth spin bowlers against the model to identify potential areas for development. To that end, it is equally important to address current development processes in academies that appear to hamper or discourage development areas across the 12 features highlighted. A prospective replication study of these modern-day spin bowlers will indicate any similarities or differences in the pathways over time and will serve to increase the probability of producing an oversupply of future international spin bowlers. To obtain a greater understanding of what likely constitutes "desirable" practice environments, extended research exploring the precursors of sporting expertise would benefit most from investigating the microstructure of practice.

Endnotes

1. The term "features" is used to describe groups of variables within the present study.
2. As pattern recognition analysis was not in wide use at the commencement of the present study, the first, second, and fourth authors developed a guide containing procedural guidelines for its application in the field.
3. The average age of the elite's international debut was calculated and then used to determine the quantity of competition hours that the sub-elite had experienced by the age of this milestone.

Authors' Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

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