A Novel AI-Driven Framework for Talent Identification in Cricket Batting Skills to Leverage Immersive Virtual Reality Performance Analytics

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Abstract: The proposed study will utilize machine learning to create a model to predict the potential of cricket batsmen with the help of the combined and objective evaluation process. The conventional talent discovery approaches used in the field of cricket may be limited by weather changes, subjectivity, and poor evaluation on perceptual-cognitive skills. To limit these shortcomings, the current study suggests a hybrid model that would integrate technical skill assessment, field-based target-based testing of performance, immersive virtual reality (VR) simulations, and machine learning (ML) classification. The number of right-handed batsmen in the study was 50, at the Under-19 district level. Assessment of players was done through standardized technique test, Cricket Australia Centre of Excellence (CACOE) batting test and a customized VR-based perceptual-cognitive task. Thirty-two performance variables were obtained and they were employed to train a Random Forest classification model. Statistical analyses involved the comparison of the performance with different ball speeds, correlation analysis and ML-based categorization. Findings showed that a decrease of 23-28% in on-field performance was observed in an increased ball speed (110 km/h to 130 km/h; $p < 0.001$), with VR-based tests showing a higher level of consistency and accuracy on shots (81% vs. 57%). Random Forest model had a total classification accuracy of 87.4%. It is

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important to note that VR speed of decision-making (r = 0.79) and dealing with short pitched high-speed deliveries (r = 0.58) stood out as the primary predictors of batting potential. The results indicate that VR combined with ML will make the objectivity, reliability, and scalability of the cricket talent identification systems more effective..
Keywords: Cricket Talent Identification, VR Simulation, ML Classification, Batting Performance Assessment, Perceptual-Cognitive Skills, Sports Analytics.

Introduction

Researchers have discussed the matter of talent identification in sports, using both the older traditional and the newer scientific model of assessment. The basic components of modern virtual reality are full input and output of the senses as well as immersion in a computer-generated environment. Virtual reality is one of the kinds of computer-based technologies - it began to receive some serious attention in the 1980s. It is the integration of the software system, 3-dimensional hardware and various sensor-based devices to interact among the users into a simulated virtual world (1). In recent years, machine learning (ML) has proven to be a powerful computational tool in cricket analytics, leading to applications such as umpire-gesture recognition, team performance evaluation and match outcome prediction. Given that cricket is one of the most widely followed sports in the world, especially in the South Asia region, there has been an increasing interest in using data-driven models for optimizing performance analysis and decision-making processes. However, despite this progress, much of this existing research is more focused on the use of match analytics and outcome prediction than structured multi-dimensional talent identification frameworks based on scientific assessment of player potential (2). Therefore, there is an important need for developing an integrated talent identification model using both objective performance metrics and also using advanced machine learning techniques to systematically evaluate the emerging players in cricket. Talent in its widest sense is the special natural abilities possessed by individuals (3). These types of skills help to determine the level of a person's proficiency. Various scholars have defined talent in discipline specific ways. The interpreter understands talent as extraordinary achievement of skill or expertise acquired from successful learning experiences. View the talent a general term used to characterise capable individuals while talent emphasise the fact that talent comes forward when the abilities of an individual are put in knowledge, dedication and meaningful contribution by the individual (4). Cricket's global importance is also shown by its base of 2.5 billion fans, according to estimates, mostly in India, Pakistan, Sri Lanka and Bangladesh. The ubiquity of the sport has led to researchers studying cutting-edge developments in player evaluation and development (5). Similarly, an ML-based framework is suggested to find the potential talent in the field of archery. In the case of soccer, talent identification was studied as an adaptive filtering process (6). Despite major breakthroughs in cricket analytics (performance prediction using machine learning applied to biomechanical analysis for e.g), little evidence about effectiveness of cricket analytics for identifying batting talent at an early stage. (7). Most of the current models have shown success when it comes to the prediction of match results, as well as the evaluation of players' performances at an elite level; however, structured talent identification frameworks aiming to find young batters still lag behind (8). Identifying batting talent is especially important because batting performance plays a decisive role in match results and pathways to sustainable player development especially in a competitive cricket playing system where early selection has an impact on access to professional coaching and pathways to higher levels. In addition, batting demands a specific set of perceptual-cognitive skills, reaction time, decision-making under pressure and biomechanical coordination that might not be properly measured using generalised or community-level assessment methods (9). Therefore, there is need to have a focused model built on batting specific rather than focusing on overall team performance metrics. Virtual Reality (VR), an immersive simulation technology that allows athletes to experience realistic game situations in a controlled and repeatable environment, has recently attracted attention in sports training in promoting perceptual and decision-making abilities (10). However its integration with machine learning in terms of structured cricket batting talent identification is largely unexplored. Addressing this gap the current study introduces and tests a machine learning aided VR based model aimed to objectively evaluate and identify potential batting talent within a defined age class in youth.

METHODS

2.1. Study Design

This research paper used an experimental type of research design that attempted to develop a virtual-reality-based ML model to identify talent within the context of cricket batting. The model aimed to examine technical and mental features of Under-19 right-handed batsmen and with the help of the sophisticated digital environments, finite accuracy of the performance measure was improved. The experiment was done on half a hundred registered cricketing players of the Jalandhar District Cricket Association (JDCA) and Patiala District Cricket Association (PDCA) of Punjab, India, and of the age group of at least two years of professional training in cricket. Ethical permissions of the study were received through both association Refrance No- [PDCA/DPCS/ 206 and JDCA / JDC / 261]. All the participants fulfilled the inclusion criteria since they were all right-hand-dominant batsmen and none had suffered any big injuries in the recent past to provide accurate and credible performance data in the study. The study subjects comprised of male aged between 16 and 19 years old district-level cricketers aged between 16 to 19 years (mean age +SD). There was no complex anthropometric profiling except with reference to age and playing experience was documented on descriptive basis.

2.2. Tools

The research employed both a set of immersive hardware and a set of analytical software to produce high-quality performance data. The main apparatus was the Oculus Quest 2 Advanced VR Headset, Meta Platforms Inc., Menlo Park, California, USA, that offered six-degree-of-freedom motion tracking and visual simulation of high resolution. These attributes enabled the virtual environment to depict the situation in cricket in a realistic manner, which is congruent to previous research stating that VR is valuable in performance measurement. All trials were done on a SS VA 900 Blaster English Willow Cricket Bat (2022 edition), which has integrated iB Cricket sensors that record the bat motion and swing mechanical values. The iB Cricket Companion Software ProYuga Advanced Technologies Pvt. Ltd., Hyderabad, India was used to record the performance of the players and produced the finer details of the performance in terms of bat speed, swing angle, reaction time, timing percentage, shot selection efficiency and scoring patterns. To complement the automated data, the Wirecast live streaming program, Telestream Inc., Nevada City, California, USA, was employed to capture every batting session in high definition so that the researcher could verify that the VR-generated metrics are correct and ensure that their observation would remain intact.

2.3. Procedure

Data collection was done on a structured cricket batting skill-test which was aimed at imitating actual conditions of baseball in a simulated environment. All the participants received a ten-minute familiarisation before the actual trials to decrease the novelty effects and limit VR-imposed errors. This cricket batting skills test was firstly created at Cricket Australia Centre of excellence (CACOE), after which it was recreated in the VR setting to be utilized as a collection of player data, and the situation of a single player in the game was also simulated in the real environment to provide a comparative analysis of the performance in VR versus on-field conditions (11). This started with full length deliveries at 110 km/h with each batter striking seven balls of a row to seven areas of pre-set targets that were in a fixed clockwise rotation, starting at Mid-Off and ending at Wide Mid-On. Once this stage was done, it progressed to a series of conditions of delivery, where ball length was good (110km/h), short (110km/h), full-length (130km/h), good (130km/h) and short (130km/h). Each of the participants was exposed to two complete rounds each of the conditions of delivery. They each tried the seven-target sequence with each type of delivery i.e., full, good length and short length delivery at 110km/h and 130km/h so that there was consistency in collecting the data at all testing conditions. Six practice trials were also given to the batters before every new condition commenced so that they could properly adapt to each new length of delivery.

Figure 1 Batsmen Hit Cover Area at 130 Km/h Ball Speed

Once all of the trials are completed, raw data was exported into a unified dataset. Model performance was measured based on the accuracy, precision, and recall. Using the ib Cricket software's companion software, the amalgam of biomechanical, perceptual and performance features, the final model separated out the players into three degrees of batting talent: high potential, moderate potential and low potential. Written consent was received from all participants and legal guardians of minors. Data confidentiality was ensured throughout the study, no harmful or invasive intervention was used. Overall, this methodology blended the science of batting assessment with VR and machine learning methodology more inspired by prior research in sports analytics but with an original contribution in the context of cricket specific talent identification.

2.4. Model Design

The suggested Talent Identification Model for batsmen is based on a progressive five-step approach to assess a player's technical, tactical and cognitive performance skills in a virtual cricket environment. The use of training virtual reality (VRT) in physical and tactical sessions has contributed to the achievement of important improvements in the psychological state of athletes and the sport ability to function as a team. (12). The first stage, Coaching & Practice, presents players with basic training modules that contain fundamental training like coaching analysis, net practice, and virtual practice at the stadium that can help the players become familiar with the virtual set-up while refining the basic batting mechanics. In the second phase, Quick Start, players compete in controlled batting scenarios with controllable match parameters such as pitch conditions (normal, bounce, dry, green), over formats (2, 5 or 10 overs) and bowling difficulty levels (easy or medium hard). This phase provides a point of reference of precision of flexibility and stability in performance under diverse game conditions. Challenges is the third stage and presents the players with certain specialized tasks that are set to assess specific batting skills. These are the Strick Challenge to a precise hitting, the Wagon Wheel Challenge to directional control, the Team Chase to pressure handling and decision making, and a challenge to survive that is produced by continuous hardship in bowling. Once past the challenge-based section of the game, the player is then able to proceed to the Tournament phase, in which the player is allowed to engage in the structured competitive gameplay of Classic, Pro, or entirely Custom tournaments. This stage measures consistency, performance within the situation and match temperament within the longer game situations. The last step is the Player vs Player (PVP) where the batsman finds himself in a competitive situation with real players and iB Cricket Real Match mode that offers maximum level of performance test with unpredictable conditions in existence. The general five step model of talent identification is presented in Figure 2.

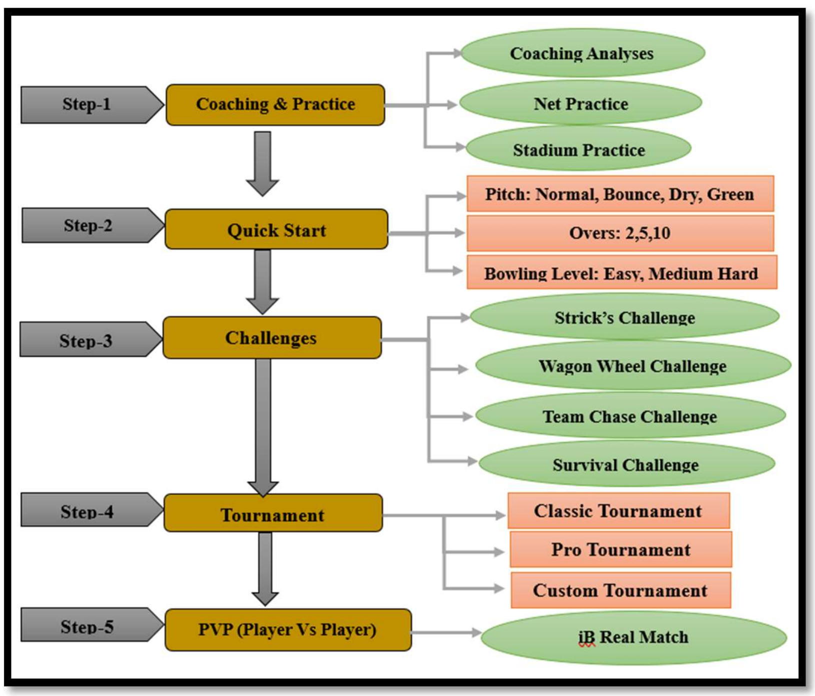

Figure 2 Talent Identification Model for Cricket Batsmen

The time taken per step is 45 min and there are several stages in each step. The between-testing stages were separated by a standardised rest period of 2-3 minutes to alleviate fatigue. Before every new state of delivery, practice trials were conducted to guarantee that there was reasonable familiarity. All of these five stages combine to create a deep pool of evaluation on the assessment of the integrated skill execution, the intelligence of the game, the flexibility and competitive temperament, where the model is able to identify batting talent with greater precision with applications to the real game. Figure 3 provides the VR batting skills performance distribution.

2.4.1. Step-1 Coaching and Practice: Potentially, there is no sport in which coaching is more important than cricket. Cricket being a very complicated sport on many aspects, requires certain technical ability which players will need to be developed with the help of coaches. Working on the player's deficiencies is a common skill-based training exercise that consumes a great deal of training time. The athlete will start his general training regimen once the deficiency is coped with the help of ib cricket, training will be practiced in various roles and disciplines and simulated game situations. The player has the option to practice here in many different ways depending upon his needs.

(A) Coaching Analyses: The coaching analyses tools in iB Cricket analyze the target batsmen and report if or not the batsmen are able to hit the shot in all direction on the Cricket ground. iB Cricket makes it simple to know the skill level of a player and the category of batsman the player belongs to.

(B) Net Practice: In the game of cricket, the practice on a net is very important. Batsmen develop the skills by making use of them more often. By repeatedly practising their specific techniques in the iB cricket net practice environment, batsmen are able to improve their abilities.

(C) Stadium Practice: The consistency of how batsmen will perform the competitive conditions can also be predicted with regard to the stadium practice features of iB cricket. The batsmen get confused after hearing the spectator and hutting his heated presence in the actual stadium when they experience this condition while using iB Cricket stadium practice tool. However, the gamer is capable of controlling themselves if the feature is utilised frequently.

2.4.2. Step-2 Quick Start-In case of competitive conditions, quick start is a feature that is added in iB cricket where batters are required to make a particular target in 2,5 or 10 over. whereby mental toughness of the player is developed

2.4.3. Step-3 Challenges: In today's highly developed type of cricket, the competitor team comes up with a very unique strategy to carry out the job of eliminating each of the players of the opponent team. Additionally, batsmen should have to contend with a number of challenges and those players can practice it by playing iB cricket.

(A) Streak's Challenge: A modern cricket field is prepared especially for every player in order to speedily take the batsman's wicket. To protect his wicket during this period it is important for the batsman to wheel the strike. Batsmen are given a platform by iB cricket Strick challenge feature in which they can change Strick by hitting strict the ball into the gap in fielding area.

(B) Wagon Wheel Challenge: Wagon Wheel is also known as battling shot placement. It is a graphic representation of the cricket field as well and especially the top view. From the position of the batsman, lines are drawn towards the field. These lines are the paths of the balls which were hit by the batter. The pre-determined batting shot placement area is included in the Wagon Wheel Challenge function in the iB cricket.

(C) Team Chase Challenge: Cricket chasing was always a very challenging task. It is particularly hard to survive an inning even without scoring any runs in Asia as the pitch wears out, the surface has turn and irregular bounce and the ball starts to reverse. Therefore, iB Cricket Team Chase Challenge feature to provide the batsmen with various pieces of pitches and ball deliveries for them to practice therein for the betterment of their skill in chasing in a competitive environment.

(D) Survival Challenge: When wickets of the batsmen in top order are falling very quickly. Every player in this position have an extremely difficult to survive. Therefore, iB Cricket has the Cricket Survival Challenge feature so that the batters can create the real competitive scenario under VR and practice it. This way, the batsmen's can survive presented with such a circumstance in a real match.

2.4.4. Step-4 Tournament: In series of particular match activities called a cricket tournament, one team eventually wins while the other competing teams lose. Batsmen can plan their game strategy under the iB cricket so that they can claim victories.

(A). Classic Tournament: In the case of a single league tournament or a double league tournament, every team plays once against every other participating team. This is called the classical tournament. The experience with the league tournaments that the ib Cricket Classic Tournament includes helps in preparing the batsmen's mind for the championship.

(B). Pro Tournament: The Pro Tournament is the same as the Knockout tournament, it is a tournament in which any team that gets defeated once gets eliminated from the entire tournament. ib Cricket Pro Tournament feature provides batsmen with the knockout tournament experience in which batsmen set their mindset for winning the tournament.

(C). Custom Tournament: A tournament is organised whenever there are many teams and the combination tournament is similar to Custom Tournament offered by ib Cricket. This aspect of IB Cricket gives batsmen the opportunity to take part in both League and Knockout Cricket.

2.4.5. Step-5 PVP (Player Vs Player): The PVP (Player Vs Player) competition offered by ib Cricket is the same as the challenge tournament. PVP is proposed to provide a measure of which of the two batsmen has the best batting prowess. In this competition, a one-on-one competition or one player for one side. The challenge is accepted after being issued by the first person to the other player.

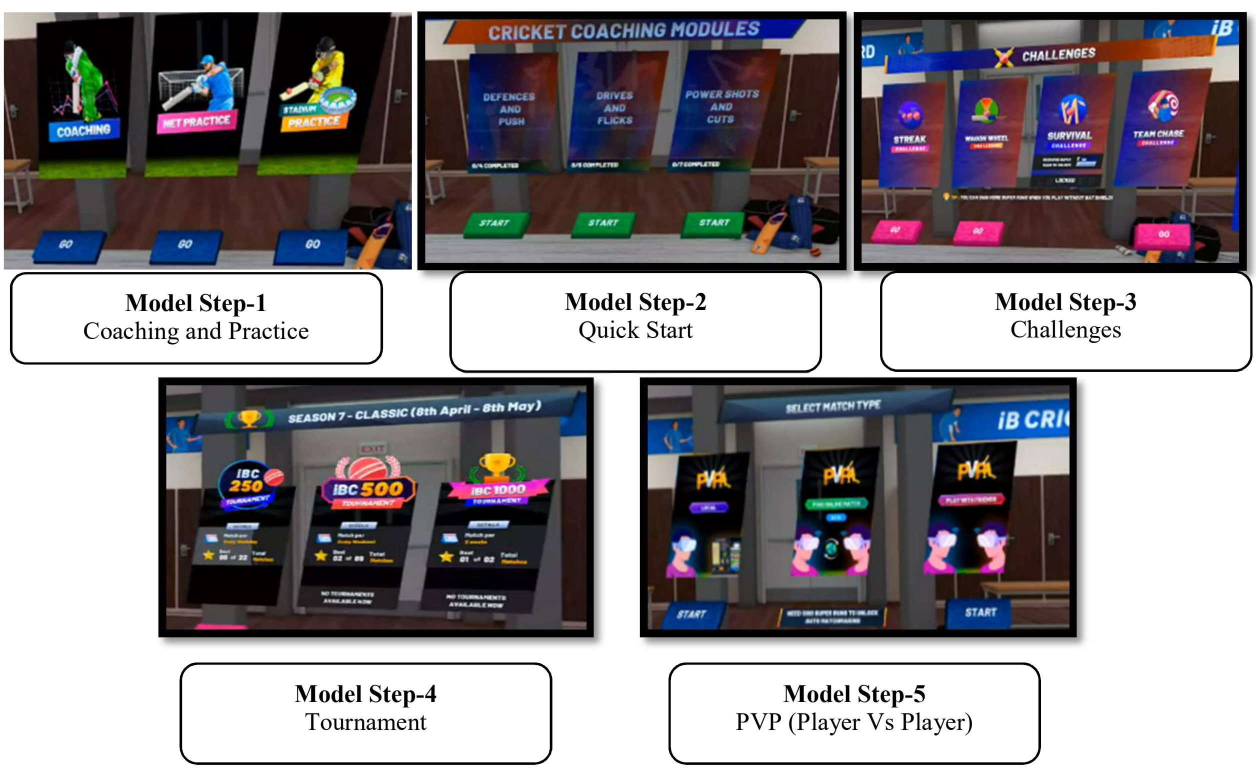

Figure 3: Steps of the Talent Identification Model for Cricket Batsmen

Note: The figures are developed by the authors with the help of the iB Cricket companion software.

2.5. Real Time Cricket Batting Skill Performance

When the talent of a batsman is manually assessed on a cricket pitch by applying a talent identification model. Traditional methods of on field talent identification in cricket are time-consuming, resource intensive, and limited in their capacity to identify perceptual-cognitive skills under controlled conditions. Factors such as variability of pitch, environmental factors and logistical constraints make manual assessments less objective and less scalable (13). In the manual talent identification model, batsmen can under no circumstances be given a competitive setting prior to the tournament, so they get in the right frame of mind of a competitive situation. Score: Batting skill test 5 different items 8 marks each item The batsmen's talents are spotted by the expert evaluation of these five skills which leads to a final score out of 40. The evaluation of manual batting skill based on the technique assessed five basic elements of cricket batting. The first one, Grip, was evaluated by looking at whether the batsman held the wrists in the right position on the handle of the bat and the batsman will be able to get a maximum of 8 marks. The second component, Stance, required that the legs and shoulders be evenly spaced and parallel to one another and had a maximum score of 8. The third of these was Initial Movement and was concerned with making the bat as close to the body as possible at all times, having a backswing path from the wicketkeeper or slip area; this too had 8 marks. The fourth skill, Back Lift, examined if the right hand did not stiffen, the left wrist stayed straight and the bat pointed to the point region due to preparation for the shot, again out of 8 marks. The last component was Completion of Shot in which the batter had to finish with the front foot pointing to the ball, the bat near the front heel, head stable and aligned with the ball and the left elbow in follow through completion assessed with another 8 marks. Also, this cricket batting skill test, originally developed by the Cricket Australia Centre of Excellence (CACOE) was utilized in the identification of the batsman's ability in striking specific of the ground area target at on-field conditions. The test started with full length deliveries, bowled at 110 km/h during which each batter had to hit seven consecutive deliveries to seven predetermined target areas in a fixed clockwise order, beginning at Mid-Off and ending at Wide Mid-On. After passing this stage, a further series of delivery conditions were used to assess the bat, including good-length balls at 110 km/h, short-length balls at 110 km/h, full-length balls at 130 km/h, good-length balls at 130 km/h and finally short-length balls at 130 km/h. All participants went through two complete rounds of each delivery condition. Each batsman played to hit the seven-target sequence twice for each of the different types of delivery such as full, good-length and short deliveries at both 110 km/h and 130 km/h to ensure consistency in the data collection in each of the testing conditions. To assure adjusting to the new delivery length, batters were also given six practice trials before the beginning of each new condition. Score: The test was designed to provide a replication of the three lengths of deliveries found in competitive cricket full, good and short delivered at two different speeds, 110 km/h and 130 km/h. Target zones were strategically located to represent typical scoring zones or "gaps" that the batters would attempt to hit in a real game situation. Each target was made up of 4 cones and scoring was done based on how precisely the ball was placed: a score of 4 was achieved when the ball went cleanly between the central two cones of the intended target, while a score of 1 was attained if the ball went via the outer two cones. Additionally, a competency score of 0.5 was assigned if the batter hit an appropriate and technically sound stroke that led the ball close to the target area even if the ball did not pass through the cones directly. The on-field batting performance was assessed with a standardised test developed by CACOE for batting development, which involved hitting seven consecutive balls at seven predetermined scoring areas in three different deliveries (with the ball) and two different bowling speeds. At 110 km/h, batters performed sequences for the full length, good length and short length deliveries yielding a total technical execution score of 3.5 marks with a possible target accuracy score of 28 marks. The same protocol was then repeated at a higher velocity of 130 km/h where players were again challenged to take seven consecutive strokes for full, good, and short lengths with an identical scoring structure of 3.5 technical points and 28 accuracy points for each delivery category. This combined approach to scoring gave the option of a consistent scoring method for precision, adaptability and quality of stroke for different ball speeds and lengths.

2.6. VR Cricket Batting Skills Performance

In a simulated environment of VR, players will have the freedom to set the level of difficulty of the targeted score, line of the ball to be played, variety of pace and the target score to chase by the batsmen (i.e., practice and Coaching features will provide the opportunity to improve batting skills). By using virtual reality headsets and gloves with motion tracking technology, users can achieve a high degree of immersion in virtual environments and effectively interact with digital tools. (14). It prepares the mindset of the batsman on which ball the player can play which shot. and under this, the batsman can also improve his decision-making skills, in which he makes the target score and chases it (e.g., 110 runs in 10 overs, 45 runs in 5 overs, and 24 runs in 2 overs) can create such a target score himself. It is very easy to create the environment of VR, it does not require a cricket ground like manual and VR simulation can be organized inside four walls. Through VR, talent identification of any batsman can be done in one place or at one time, Talent identification by VR is quite easy as compared to manually, and VR take very less time for talent identification of batsmen compare to the traditional method. Score: The aim of the VR Model is to assess the batting ability of the batsmen depending on these elements. The batsmen are advised to score the strokes in certain parts of the field; the short scoring is determined using these. The virtual reality batting assessment measured six main performance indicators, each of which was given one mark, to quantify the technical precision in the simulated environment. The first parameter named Eye Level reviewed whether the batter maintained a proper and stable line of sight throughout the delivery. The Head Status criterion was the second criterion and it was used to determine the stability and alignment of the head during the batting. Watching the Impact was the third indicator and evaluated the skill that the player has to track the ball in the eye until the point of collision. The fourth factor evaluated the distance between the head and the point of contact, whereby the distance is the best to track the ball. The fifth factor, Bat Impact Region, verified whether the ball will be in contact with the part of the bat that is wanted. Lastly, the sixth criterion was Ball Hit into the Given Region and it assessed the precision of placing the ball into the given scoring area, which was 1 Run. This combination constituted an overall depiction of batting performance in the VR system. Also, Cricket Australia Centre of Excellence (CACOE) batted skills test was also reproduced in VR setting to observe the degree to which batters can be doing in VR as accurately as they can do in real-world conditions. Manual batting skill test by Stretch in 1984 and CACOE batting performance test have been broadly used in research and in coaching practice of cricket and it has been established that they have acceptable content validity and practical reliability. The VR-based assessment was developed using familiar perceptual-motor performance measures such as head stability, tracking and shot placement in visual tracking, which had been measured before in VR-based sports performance research. Regular testing procedures and standardised equipment were used in an effort to enhance reliability.

RESULTS

This part will include detailed examination of the batting performance of 50 right-handed district-level cricket batsmen in three assessment format Manual Skill Assessment, On-Field Target-Based Batting Skill Test (CACOE), and VR-Based Batting Skill Assessment, which is supported by an ML Talent Classification Model. Combined, these findings present a multi-dimensional interpretation of batting skill, perception-cognitive capacity and game-specific adaptability, which allow proper categorisation of talents.

3.1. Manual Batting Skill Assessment (Stretch): the Stretch test was used to test five underlying variables of batting: grip, stance, first movement, back-lift and shot completion. Back-Lift had the highest mean score (6.60 +- 0.88) and the lowest scores were in Initial Movement (5.74 +- 1.21) meaning that participants were not that good at early trigger movement and reaction preparation.

Table 1 Manual Batting Skill Assessment

Skill Component	**Mean ± SD**	**Minimum**
Grip	6.42 ± 0.81	5
Stance	6.18 ± 1.02	4
Initial Movement	5.74 ± 1.21	3
Back Lift	6.60 ± 0.88	5
Completion of Shot	6.04 ± 1.13	4
Total Score	**30.98 ± 3.42**	**22**

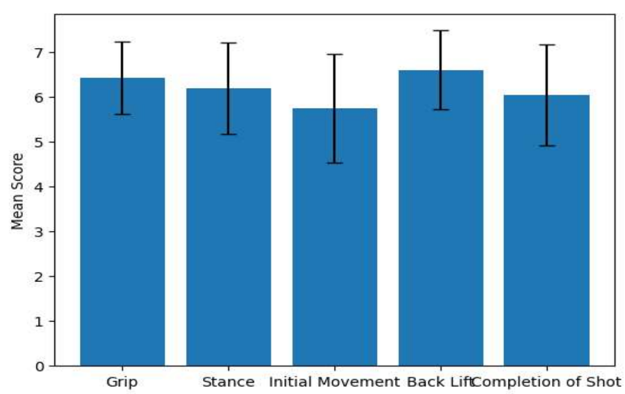

Figure 4 Mean of Manual Batting Skill Assessment

Sixty eight percent of the respondents had a score of more than 30 hence satisfactory technical competency. Figure 4 shows the mean of the manual batting assessment of skill. Mean scores on manual assessment of batting skills on five technical aspects (Grip, Stance, Initial Movement, Back Lift, and Completion of Shot). Bars are mean values; error bars are standard deviation (SD). Nonetheless, there were still basic movement inefficiencies, which give reason as to why further assessment was necessary using VR and dynamic conditions in cricket.

3.2. On-Field Batting Skill Test (Developed by CACOE): This test involved accuracy hitting a series of pre-set targets on the ground of various lengths and speed (full, good, short lengths x 110 km/h and 130 km/h). Findings indicated the definite reduction in accuracy with the pace.

Table 2 On-Field CACOE Batting Performance

Delivery Type	Mean ± SD	Minimum	Maximum
Full Length – 110 km/h	18.46 ± 3.12	12	26
Good Length – 110 km/h	17.85 ± 3.41	11	25
Short Length – 110 km/h	16.04 ± 3.58	9	24
Full Length – 130 km/h	15.62 ± 4.01	7	23
Good Length – 130 km/h	14.94 ± 3.80	6	22
Short Length – 130 km/h	13.58 ± 3.77	5	21
Total CACOE Score	**96.49 ± 11.22**	**72**	**132**

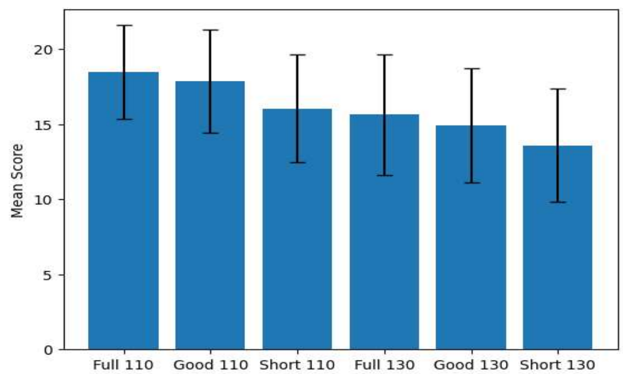

Figure 5 Mean of On-Field CACOE Batting Performance

Deliveries at 110 km/h reduced by 23-28% to 130 km/h. The poorest performance was recorded in Short Length at 130 km/h which meant that there was lack of back-foot control and less reaction time in the presence of pressure. Figure 5 shows the average of the CACOE batting performance. Mean on-field batting CACOE performance scores at the various lengths and speeds of delivery (110 km/h and 130 km/h). Bars show mean values; the error bars show standard deviation (SD). These results underline the fact that, although players have a sufficient technical base, they are not well adapted to speed and match situations.

3.3. VR Batting Skill Assessment: VR-based testing compared perceptual-cognitive and biomechanical abilities of head stability, impact watching, shot placement and bat-ball contact accuracy. VR had less variability (described by smaller SD values) than on-field tests, which suggests that the performance is consistent within controlled conditions.

Table 3 VR Batting Performance

VR Skill Parameter	Mean ± SD	Minimum	Maximum
Eye Level	0.78 ± 0.18	0.40	1.00
Head Stability	0.74 ± 0.21	0.33	1.00
Watching Impact	0.82 ± 0.20	0.40	1.00
Distance (Head–Impact)	0.70 ± 0.19	0.30	1.00
Bat Impact Region	0.76 ± 0.22	0.25	1.00
Shot Placement Accuracy	0.81 ± 0.16	0.50	1.00

Total Score (6)	**4.63 ± 0.58**	**3.20**	**5.90**

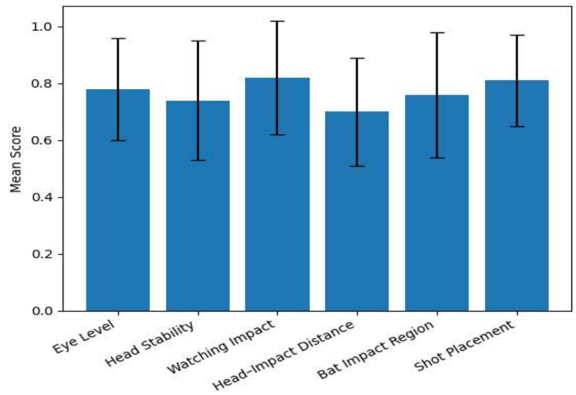

Figure 6 Mean VR Batting Performance

Almost three-quarters of the respondents (76% out of 4) had a score above 4.3/6, which shows good perceptual accuracy and consistent VR performance. The average of VR Batting Performance that was plotted in Figure 6. Average virtual reality VR performance scores based on parameters of perceptual-cognitive and technical skills. Bars are used as mean values; error bars are used to denote standard deviation (SD). VR also removed unpredictability in the pitch, thus players could respond in a more assertive and predictable way.

DISCUSSION

4.1. Comparative Evaluation VR vs. On-Field Performance: Paired samples t-test showed statistically significant difference between the VR and real-world performance results and the VR scores were higher in all parameters. Virtual reality technology has a major advantage to improving an athlete's capability in regulating the process and having a great involvement with the environment around him. (15). A comparative analysis of the batting performance in the VR environment and on-field conditions has shown significant differences between the two environments with respect to all the parameters considered. Shot placement accuracy was significantly greater in VR (81.0%) than on-field testing (57.4%) with the difference being statistically significant ($t = 8.62$, $p < 0.001$). Similarly, a significant improvement in the quality of timing was observed between VR (78.2%) and on-field performance (54.6%) with a highly significant t-value and $p < 0.001$ (9.14). In addition, the speed of the decision-making process was significantly faster in the VR situation (86.3%) compared to the traditional on-field situation (62.5%), and this difference was also statistically significant ($t = 7.88$, $p < 0.001$) (16). Collectively, these results suggest that performance scores for all key batting parameters were consistently higher when assessed using VR-based assessment. Interpretation: VR offers more visual clarity, predictive ball flight, and reduced situational stress to enable a superior performance. However, lower scores under real conditions indicate a performance gap between the proficiency at perception and match execution.

4.2. ML Talent Classification: 32 combined variables (manual + VR + CACOE metrics) using Random Forest model were used to train a model to classify the players into talent group (High, Moderate, Low). Model performance was good on all measures. The ML model proved to be very strong according to all the evaluation metrics. The model showed an accuracy of 87.4%, which is a high accuracy rate of classification overall. Its precision score of 85.2% indicates a good capacity to accurately detect the true positives, while the recall score of 88.6% indicates that it can detect all the relevant instances. The sum of these measures is quantified as an F1 score of 86.8%, which is a high and reliable score for prediction. Additionally, the model's ROC-AUC value of 0.91 gives further confirmation of excellent discriminative power in distinguishing between classes of performance. Collectively, these results indicate the effectiveness and stability of the model in the evaluation of cricket batting performance. Talent Distribution (ML-Generated) High-Potential: 14 players (28%), Moderate-Potential: 23 players (46%), and Low-Potential: 13 players (26%) It is notable that players classified as high-potential were consistently shown to have better VR decision-making skills and better adaptation to short-pitch high-speed deliveries (17).

4.3 Correlation Analysis of Actual Batting: Talent Pearson correlation coefficients were calculated to find major predictors of actual batting talent. The strongest predictor was VR Decision-Making Speed (r = 0.79), which reveals that cognitive processing speed and situational judgment is central to batting talent identification. The results of correlation analysis showed meaningful relationships among key performance variables in VR and on-field assessments. A strong positive correlation was found (r = 0.72) between VR shot accuracy and CACOE batting scores with the results suggesting that the players who played well in the VR environment also tended to play well in standardised testing on the field. An even stronger relationship was observed between VR decision-making and general talent (r = 0.79), which may indicate that cognitive speed and accuracy in the VR assessment was a very strong indicator of excellent cricketing potential. The correlation between Stretch manual skill scores and talent prediction using machine learning (r = 0.64) was moderate, representing a meaningful correlation between technical basics and predicted levels of performance. In addition, performance against short-length deliveries at 130 km/h displayed a moderate correlation with the talent level (r = 0.58), indicating that the ability to perform with faster, shorter balls is not only a relevant, but also not a distinctive sign of a higher determination of talent level (18).

CONCLUSION

The current research created and tested an integrated cricket batting talent identification model by using a combination of technical skill assessment, on-field performance assessment, virtual reality (VR) simulation and machine learning (ML) classification. The study results showed that although Under-19 players displayed a reasonable level of basic batting technique, specifically in grip and back-lift, there were limitations in early movement and trigger response that influenced their ability to adapt to higher ball speeds and dynamic conditions in a match. On-field testing showed that performance decreased significantly with an increased delivery speed, particularly for short-length balls, presenting difficulties in perceptual tracking, balance and decision making under the realistic conditions of playing cricket. These results confirm that technical proficiency is not enough for consistent match performance.

In contrast, the performance consistency or the shot accuracy of the VR-based assessments revealed significantly higher performance, indicating strong perceptual-cognitive capabilities of the players in a controlled environment. However, the difference between VR and on-field performance indicates that although players have the capacity to anticipate and make decisions effectively, it is difficult for players to transfer these skills into real-game environments characterised by variability and pressure. The classification accuracy of VR decision-making speed was predicted to be 87.4% with high-pace short-length performance and overall technical skill being identified as the most influential predictors of batting potential in the Random Forest model of classification. These results support the value of combining perceptual-cognitive measures with conventional skill measures for the more accurate identification of talent.

Overall, the proposed hybrid framework provides a scientifically robust and scalable method of modern cricket talent identification. By addressing limitations of conventional selection systems by incorporating VR simulations to capture perceptual-cognitive attributes, on-field testing to ensure ecological validity, and ML techniques to improve objectivity and predictive accuracy, the model addresses key limitations of conventional selection systems. This multidimensional approach allows for a more well-rounded assessment of player potential and has practical applications for academies, coaches, and talent development programs looking to enhance the efficiency and reliability of player selection processes.

FUTURE RESEARCH

The next step in research ought to be the improvement of the ecological validity and analytical thoroughness of the suggested model. This can involve installing ball tracking radar and simulation of highly developed bowler behaviour in virtual reality to come up with virtual reality environment that is closer to a real match environment. Inclusion of elite and professional players in the data would enhance generalisability of results. Also, real-time physiological monitoring (e.g. heart-rate and fatigue) may be included, which may shed more light on the performance during pressure. The integration of the state-of-the-art wearable biomechanical sensors and the use of deep learning to identify the stroke automatically are also the strong pathways of future research.

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