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# Smart Sports Recruitment: Leveraging Software for Talent Precision

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**Abstract**

This research highlights the critical role of technology in sports, particularly in identifying and developing talent more effectively. Technology enables better athlete performance analysis; however, talent identification still relies on traditional methods. Coaches and sports teachers often select athletes based solely on competition results without leveraging technology-based analysis. As a result, important biomotor components are frequently overlooked, and the manual processing of talent data is time-consuming and less effective. To develop sports talent identification software based on biomotor and anthropometric databases to accelerate the search for talented athletes and sports recommendations efficiently and accurately. Biomotor and anthropometric test items are adopted from the talent scouting test scoring system of the Ministry of Youth and Sports of the Republic of Indonesia. The development method consists of the following stages: (1) performing needs analysis through surveys and interviews, (2) designing a talent identification model with a flow diagram, (3) developing a talent identification model using the Entity-Relationship Model, (4) testing the validity of the model by material and media experts using the Content Validity Index, and (5) conducting field trials with battery tests and anthropometric measurements. Producing talent identification software called Talent Identification Development (TIDev). Expert validation showed the I-CVI validity index of 0.93 (material) and 0.90 (media), indicating the high effectiveness of TIDev in identifying potential athletes and providing sports recommendations. A trial of 40 junior high school students showed that 34 students felt that the recommendations were based on their interests and talents, covering 12 recommended sports. TIDev can accelerate and simplify athlete recruitment, providing accurate and reliable sports analysis and recommendations.

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## INTRODUCTION

In the modern sports landscape, technology plays a pivotal role in talent discovery and development. Advanced tools, such as data analytics and wearable devices, have redefined how athletes' potential is evaluated and their performance is monitored (Blobel et al., 2021; Reynoso-sanchez et al., 2023; Seçkin et al., 2023; Avcı et al., 2023). These innovations enable sports organizations to streamline talent identification processes, providing a competitive edge in athlete recruitment and training (Barraclough et al., 2022; Leite et al., 2021; Williams et al., 2020). However, traditional talent identification systems, heavily reliant on competition outcomes and subjective assessments, often overlook the nuanced potential of younger and less experienced athletes (Chmait & Westerbeek, 2021; Gray & Plucker, 2010; Persson et al., 2020; Zulfikar et al., 2022).

The urgency of addressing these limitations is increasingly recognized in fields such as physical education, sports, and talent management. Software-based talent identification systems offer a transformative approach, leveraging algorithms and statistical tools to enhance accuracy and scalability (Williams, 2020; Abbott & Collins, 2004; Pamungkas et al., 2022; Suherman et al., 2021;

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Vaeyens et al., 2008). These systems enable rapid data processing, support multi-dimensional assessments, and allow access to diverse user groups, including coaches, schools, and sports academies. This innovation is particularly relevant for countries like Indonesia, where the adoption of advanced methods in talent discovery remains limited despite significant potential in sports development (Hamid et al., 2023; Saputra et al., 2022).

The novelty of this research lies in its focus on a software-based approach to address the gaps in traditional talent identification methods. Unlike previous studies that emphasize a single sport or demographic group (Abrori et al., 2023; Nilsen et al., 2024; Leite et al., 2021), this research developed a comprehensive model that evaluated anthropometric data and motor skills across multiple sports, adopted from the Ministry of Youth and Sports of the Republic of Indonesia's talent scouting assessment system by adding talent categorization. The model categorizes aptitude into five different levels: high potential, potential, moderate potential, less potential, and no potential, offering different perspectives on athletic ability. Additionally, the model prioritizes sports of Olympic significance while accommodating popular regional preferences, ensuring broad applicability.

In East Kalimantan, talent search methods already exist by adopting methods from Australia. Still, they need to be done specifically. Adjustments to the norms for assessing body structure and physical potential still need to be improved. On the other hand, professionals, such as coaches and sports teachers, usually choose athletes who win competitions without conducting special analyses and tests using technology (Susanto et al., 2023). The motor components of athletes are rarely used in talent identification and are done manually, making it less effective and take a long time to find out the results (Irurtia et al., 2022; Koopmann et al., 2020; Leite et al., 2021; Siener et al., 2021). In East Kalimantan, for example, adopting talent scouting methods largely mirrors the approach used in countries like Australia but without sufficient customization to local conditions (Susanto et al., 2023). Current practices often rely on manual data processing and subjective evaluation, which can lead to inefficiencies and inaccuracies in identifying talented athletes (Irurtia et al., 2022; Koopmann et al., 2020). By integrating technology, this research addressed these challenges and proposed a scalable solution in line with the evolving demands of modern sports management (Marhayati et al., 2022).

The problems, if explored further, include the following aspects: 1) there is no software-based talent identification media that can see the potential talent and recommend sports based on children's motor abilities; 2) Some sports organizations have not fully integrated digital technology into the athlete recruitment process, which hinders recruitment efficiency; and 3) The low level of digital inclusion of the community in athlete recruitment, characterized by the lack of community participation and involvement in the use of digital technology in the athlete recruitment process (Chen & Dai, 2024; Cossich et al., 2023; Exel & Dabnichki, 2024; Glebova et al., 2024). Switching from conventional to software-based methods in talent identification enhances efficiency and promotes inclusivity by reaching a broader demographic. This is particularly important in emerging economies, where access to advanced training and assessment tools remains uneven (Wang & Sun, 2018; Monsees, 2024). Furthermore, early talent identification through technology can help athletes align their training with their innate abilities, leading to better performance and higher retention rates in professional sports (Alexiou et al., 2024; Zhao et al., 2024).

Athlete training and development continues to innovate, similar to the digital technology industry. Several research results show the importance of talent identification in sports, including technology-based approaches to improve accuracy in the process (Lidor et al., 2009), the contribution of technology-based data analysis in supporting the development of athletes' potential (Bangsbo et al., 2006), and how technology and data-based approaches can be used to integrate theory and practice in the talent identification process (Abbott & Collins, 2004; Attalla et al., 2024). Talent identification software can be essential for discovering new trends, finding effective training methods, and using advanced technology to improve athlete performance (Bakhtiar et al., 2023; Till & Baker, 2020; Xiang et al., 2024). In Indonesia, this software can be used to discover potential athletes in various sports from an early age, as has been initiated by several youth athlete development programs through cooperation between the government and private institutions LIKE the Garuda Select and Indonesia Youth Athlete Development programs. In addition, the software contributes to the growth of the digital economy by opening new business opportunities in the ecosystem of mobile applications and online platforms (Appelbaum & Erickson, 2018). An accurate sports talent identification model can support the sports industry in optimizing the recruitment and development process of athletes, as seen in the development of young badminton and football talent in Indonesia (Hamid et al., 2023).

This research also emphasizes the role of software in fostering collaboration between various stakeholders, such as government bodies, private organizations, and educational institutions. The Garuda Select program in Indonesia demonstrates the potential of integrating technology into youth athlete development initiatives, creating a robust pipeline for future talent (Appelbaum & Erickson, 2018). Moreover, the development of such software aligns with Indonesia's broader digital transformation agenda, contributing to economic growth by creating opportunities in the sports technology ecosystem. Beyond the immediate benefits of talent identification, the proposed model also has significant implications for future research. By introducing a standardized and scalable approach, the model provides a framework for exploring advanced algorithms, integrating artificial intelligence, and customizing assessments for specific sports or regions. This research laid the groundwork for further investigations into optimizing the talent identification process globally, emphasizing the importance of localized adaptations to meet unique demographic needs (Till & Baker, 2020; Xiang et al., 2024). Thus, this research bridged the gap between conventional and technology-based talent identification methods. By utilizing software-based tools, this research offered a comprehensive, data-driven approach to athlete recruitment and development, which addressed regional needs while aligning with global trends in sports technology. This innovation not only improved the efficiency and accuracy of talent identification but also laid the foundation for a more inclusive and dynamic sports ecosystem in Indonesia and beyond.

## METHOD

*Research Design*

This research employed the development method by Borg and Gall (2014). The stages consisted of several stages. The first stage was analyzing the model to be developed using survey and interview methods. The second stage was designing and developing the model using the Entity Relationship Diagram (ERD) in the form of a flow chart. This diagram was developed by the researchers, serving as a framework created with special symbols for the purpose of defining the relationship between database entities or to visualize data interactions. The third stage was developing a software-based talent identification model using the Entity Relationship Model (Teorey et al., 1986). There were three main components: entities, attributes, and relationships. Entities represent athletes. Attributes are information related to athlete data, such as age, school origin, anthropometric data, and motor skills. Relationships are used to describe the relationship between entities in the database, such as data on the athlete's motor skills and the sport they play. The fourth stage was validation and revision by involving media experts and material experts using the Content Validity Index (CVI) approach. Lastly, the fifth stage was the implementation and field trials using battery tests and anthropometric measurements.

*Participants*

Participants involved in this research were junior high school students whose talents were identified from various sports interests to provide diverse data. The respondents consisted of coaches, physical education teachers, and professional sports managers. They had important roles in providing context, assessing the effectiveness of software results, and implementing results in practice. The technology experts and software developers are involved in testing and validating the software. Furthermore, data analytics experts and academics are involved to ensure statistical validity and deepen the interpretation of data generated by the software.

*Population and Methods of Sampling*

This research employed purposive sampling, a non-probability sampling technique where participants are deliberately selected based on predefined criteria relevant to the research objectives. This method was chosen to ensure that the samples were highly aligned with the study's focus on talent identification and development in sports.

The trial involved 15 respondents, comprising sports coaches, physical education teachers, and sports administrators. Additionally, 40 junior high school students were selected as trial samples to assess their sports talents. The students were chosen based on several criteria. First, they were between the ages of 11 and 14 and actively engaged in sports. These specific criteria ensured that the research targeted a relevant population for effectively identifying and analyzing young sports talents.

For expert validation, the research involved two groups. The first group consisted of five expert validators who were highly competent in the field of talent development. Their expertise ensured that the tools and methods used for talent identification were effective and aligned with best practices. The second group included three expert validators with expertise in information and digital media, ensuring that the technological components of the study were validated for accuracy and applicability. The purposive sampling enabled the researchers to select participants and experts who could provide meaningful insights and ensure the reliability of the instruments and methods used in the research.

*Instrumentation*

This research used several instruments, including observation and interviews used for needs analysis and product design. The flowcharts were used to visualize the steps and sequence of implementation in the form of prototypes and specifications of talent identification development models. The entity-relationship model was used to describe the contents of the database in the form of entities, attributes, and relationships between entities. The software displayed a dependency diagram explaining the relationship between determinants, input questions, rules, values, recommendations, and questionnaires for model validation tests using the Content Validity Index (Polit & Beck, 2006), battery, and anthropometry tests for field trials (Abrori et al., 2023). In the last stage, the researchers utilized SPSS 23 to perform a reliability test with Cronbach's Alpha (Brown, 2002) and the Interclass Correlation Coefficient (ICC)(Wibowo et al., 2022).

*Procedures*

This research employed the development method of Borg and Gall (2014), consisting of five stages to create a software-based talent identification model. First, the needs analysis stage was conducted through observations and interviews with 15 respondents (coaches, PE teachers, and sports administrators). It identified the requirements for the software's prototype and specifications. Second, the design and development stage design and develop the software design, covering the tools, like data flow diagrams, databases, and dependency diagrams. It featured a web-accessible platform for coaches and teachers to input data on students' anthropometric and motor components, detect talent potential, and provide sports recommendations with graphical statistical comparisons. Third, the model development uses a procedural development model. The software incorporated four key processes: data input, talent identification, sports profiling, and information output. Built with Visual Basic 6.0 and Microsoft Access, it includes various menus, such as students' data, statistical comparisons, and test instructions. Fourth, the validation testing involved expert validators (five sports talent experts and three media experts) using the Content Validity Index (CVI) to ensure alignment with user specifications. Fifth, the implementation and field trials were conducted on 40 junior high school students (ages 11–14). The trials collected anthropometric and motor test data, which was entered into the software to evaluate its effectiveness. The process involved coaches, PE teachers, and sports administrators. The stages in this research are presented in Figure 1.

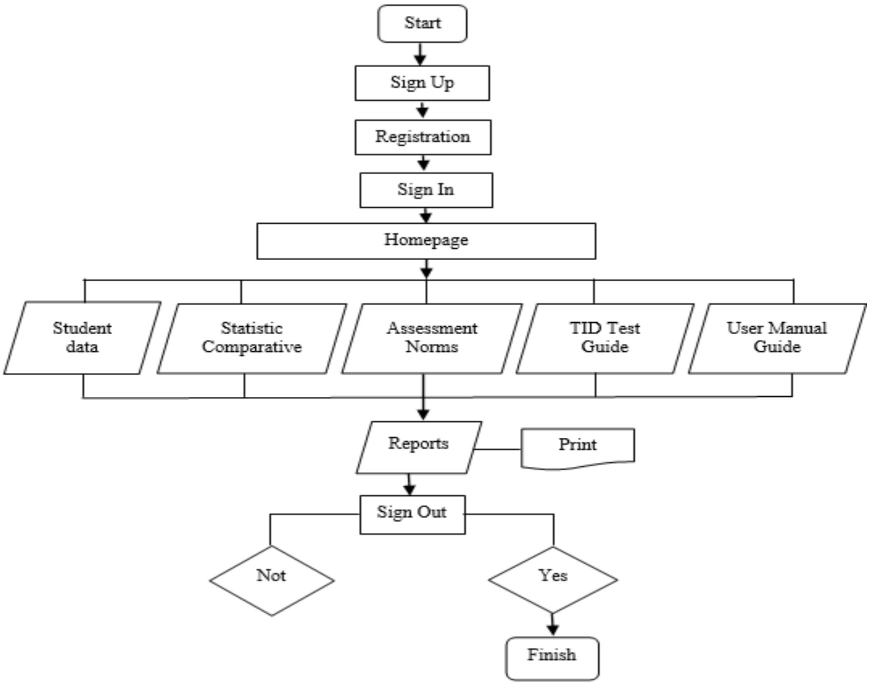


**Figure 1.** Model Flowchart Design

In detail, this research used a development method with five main stages. The first stage was conducting a needs analysis of the talent identification model to be developed, using observation and interview methods with coaches, physical education teachers, and sports instructors (15 respondents). From the needs analysis, the prototype and specifications of the software to be developed were known.

The second stage was the design and development of software, namely the data flow diagram, database, entity relationship diagram, relationship table, flow diagram, and dependency diagram. The design of the software-based talent identification development model had the following specifications: (1) could be accessed via website using a computer or laptop connected to the internet, (2) contained data material on students' anthropometric and motor components that can be inputted independently by coaches, physical education teachers, and sports administrators as users, (3) can detect potential talent and sports recommendation values based on each abilities, and (4) equipped with statistical comparisons between students in the form of graphs.

The third stage was to develop a software-based talent identification model using a procedural development model. The software development system had four main processes: 1) data input process, 2) identification process, 3) sports profile information process, and 4) sports information process. The entities used were the administrator, testee, and tester. The data flow diagram explains the relationship between entities and processes. The software was developed using the Visual Basic 6.0 programming language and the Microsoft Access database. The main display provided several program menus and submenus, adjusting to the flowchart that has been created, namely the data, the statistical comparison, the assessment norm, the test instructions, the user instructions, and the report.

The fourth stage was software validation testing using the Content Validity Index (CVI). Five experts in sports talent search materials and three media experts were involved. The validation process determined whether the software produced was to the specifications provided by the user. After calculating the percentage of items considered significant by each expert, the average value of all experts was determined (Denise F. Polit, Cheryl Tatano Beck, 2007; Wibowo et al., 2022).

The fifth stage was the implementation and field trials using battery and anthropometric tests. The test was conducted on 40 junior high school students aged 11-14. The data collected were; 1) height, 2) sitting height, 3) weight, 4) arm span, 5) throwing and catching tennis balls, 6) throwing a basketball, 7) vertical jump, 8) agility running, 9) 40-meter sprint, and 10) multilevel running (Abrori et al., 2023; Susanto et al., 2024). All of this data was entered into talent identification software to test the effectiveness of the product developed. The participants were coaches, academics, sports teachers, sports coaches, and students. The detailed stages are shown in Figure 2.

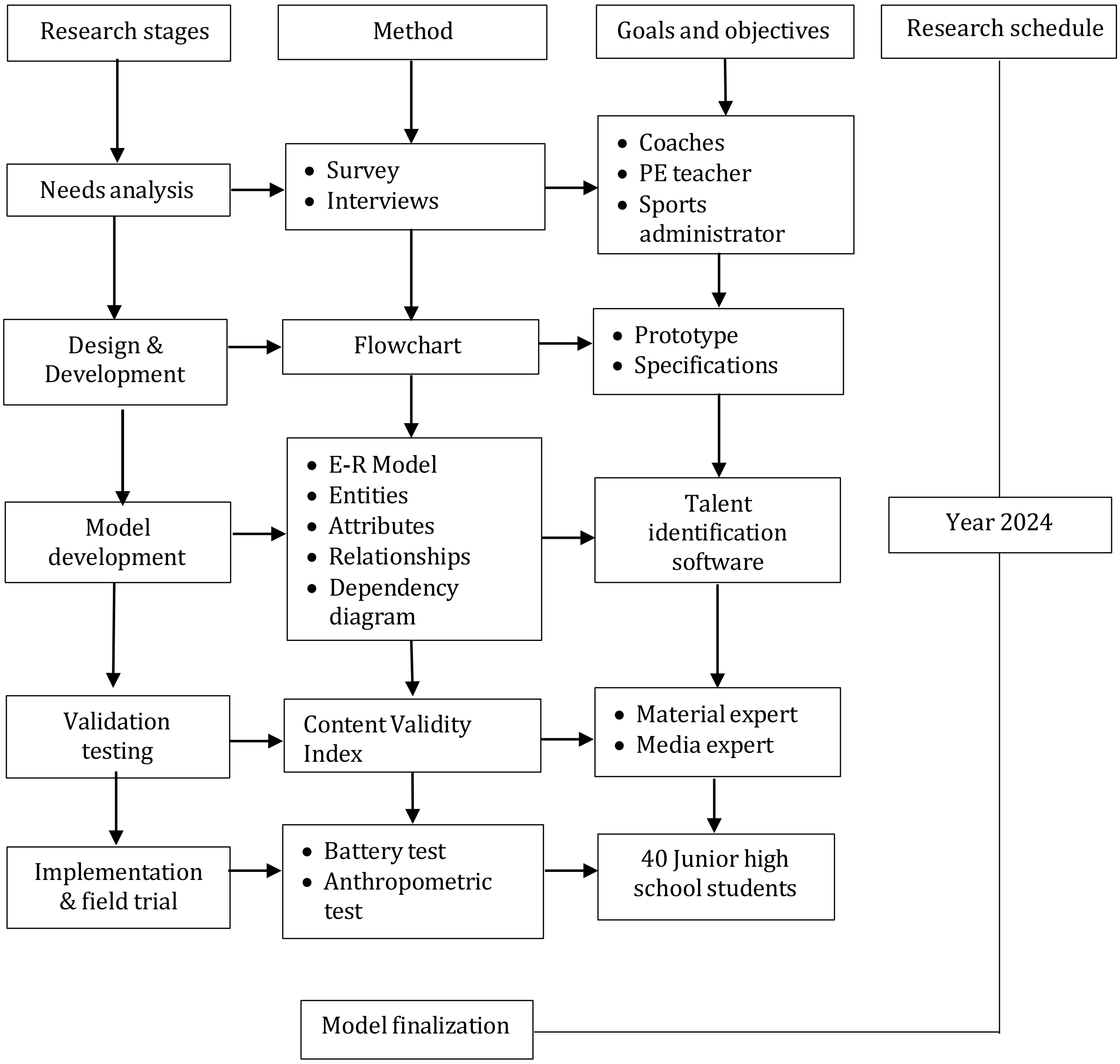


**Figure 2.** Research Flowchart

Figure 2 is a flowchart that illustrates the steps and decisions in the modeling program process. Each step is depicted with a diagram symbol and connected by a line or arrow. The software display menu contains data, comparative statistics, assessment norms, user instructions, aptitude test implementation guides, and test result reports that can be printed in Word, Excel, and PDF formats.

*Data Analysis*

Data analysis includes all activities of classifying, analyzing, using and drawing conclusions from all data collected in the action. After the data had been collected, it was processed. The research data was collected using two techniques: preliminary instrument studies and instrument development models and field trials. The quantitative data was sourced from the validation of material experts and media experts using the Content Validity Index (CVI) approach. The recommended measurement scale was a 4-point ordinal scale to avoid neutral and ambivalent midpoints. Some frequently used labels are 1 = irrelevant, 2 = somewhat relevant, 3 = quite relevant, and 4 = very relevant. Then, for each item, the I-CVI was calculated as the number of experts who gave a good assessment of 3 or 4 (thus the dichotomization of the ordinal scale into relevant = 1 and irrelevant = 0), divided by the total number of experts (Polit & Beck, 2006).

Field trials were conducted to ensure that the developed model or software can function in accordance with its main purpose, which is to support the process of identifying sports talent accurately, efficiently, and on target. This trial aimed to evaluate the model's ability to generate relevant data and analysis based on predetermined talent indicators. The evaluation includes the model's ability to identify physical and biomotor aspects, such as height, weight, agility, speed, talent detection, and sports recommendations.

## RESULTS AND DISCUSSION

### Results

The percentage of talent identification model in needs analysis is shown in Table 1.

**Table 1.** The Percentage of Needs Analysis of the Talent Identification Model

| The talent identification model needs analysis | Respondent's Answer | Percentage |
|---|---|---|
| **Anthropometric & biomotor data collection** | 19 | 95 |
| **Data analysis** | 15 | 75 |
| **Talent Categorization** | 16 | 80 |
| **Sports Recommendations** | 18 | 90 |
| **Data Reporting and Visualization** | 17 | 85 |
| **Statistic Comparative** | 19 | 95 |
| Total Respondents | **20** | **100** |

Table 1 displays the findings from the needs analysis of the talent identification model, collected through observations and interviews with academics, coaches, physical education instructors and sports administrators. They needed a talent identification model that included features such as anthropometric and biomotor data, sports recommendations, analytical data, and web-based comparative statistics. The percentage of respondents' participation was quite high, with an average of 75% to 95%.

The talent identification model developed had the following specifications: (1) software for talent identification that can be accessed via a website using a computer or laptop, (2) contains data material that includes the anthropometric and motor components that can be input independently by coaches, sports teachers, and sports administrators, and (3) can detect potential talents and recommend sports according to the abilities. The talent identification model developed is called Talent Identification Development (TIDev) and can be accessed at http://talentidentification-dev.alhaqkyramli.com. The display of the data menu in the software is shown in Figure 3.

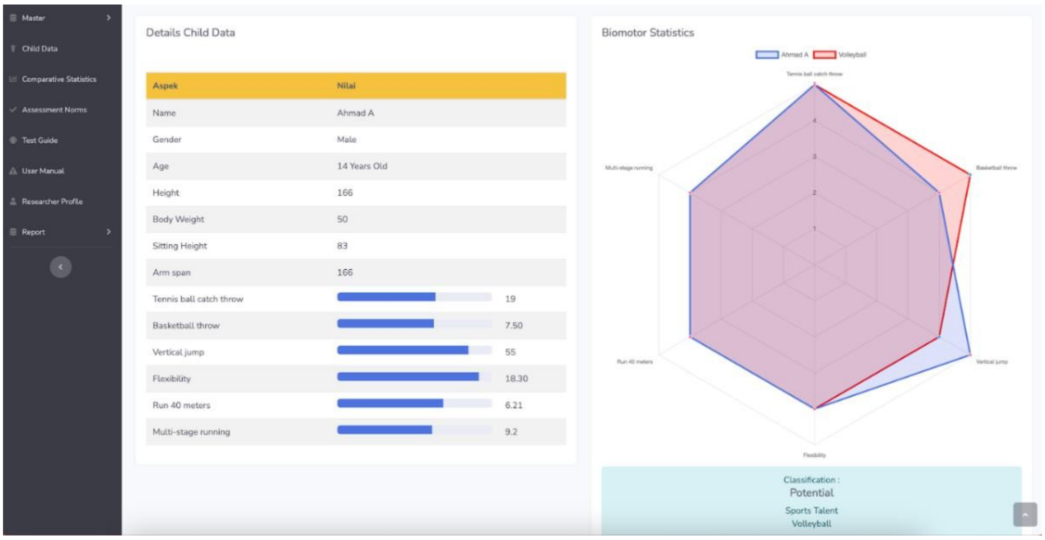


**Figure 3.** The Display of the Data Menu in the Software

Figure 3 is one of the student's data menu displays in the software. This menu is used to input data, such as creating, viewing, updating, and deleting data. It is equipped with statistics on biomotor test data and the physical needs of the sports played. The assessment method used in the automatic assessment process in this software is the Criteria Reference Assessment (CRA). CRA is used as a reference to determine the classification of a student's potential talent. Potential talent classification is listed in Table 2.

**Table 2.** Classification of Potential Talent

| Score | Classification |
|---|---|
| **> 27** | Very potential |
| **23 - 26** | Potential |
| **19 - 22** | Quite potential |
| **15 - 18** | Less potential |
| **< 14** | Not potential |

The results of the material expert validation are shown in Table 3.

**Table 3.** Material Expert Validation Results

| No | Indicator | Expert Number | | | | | Total Agreement | I-CVR |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | | |
| **1** | The software developed follows the talent identification theory. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **2** | The talent identification concept developed is appropriate to the level of children aged 11-14. | 0 | 1 | 1 | 1 | 1 | 4 | 0.80 |
| **3** | Anthropometric measurement material and motor tests are by need. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **4** | Appropriateness of talent identification assessment norms for children aged 11-14. | 0 | 1 | 0 | 1 | 1 | 3 | 0.60 |
| **5** | Conformity to norms for assessing talent in sports. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **6** | Compatibility of motor test guidelines and anthropometric measurements. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **7** | Can involve physical education coaches/teachers/sports coaches in identifying talent. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **8** | Body anthropometric data: Height, weight, body proportions, and mass index. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **9** | Motor data: Strength, speed, hand-eye coordination, agility, explosive power, and endurance can be determined. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **10** | Comparative statistical data on students is presented entirely and specifically. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **11** | Equipped with graphics. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **12** | Instructions for carrying out a complete and easy talent identification test. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **13** | The software can check the input data for all talent identification test items. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| **14** | Recommendations for sports are based on the motor requirements standards for each sport. | 1 | 0 | 1 | 1 | 1 | 4 | 0.80 |

| No | Indicator | Expert Number | | | | | Total Agreement | I-CVR |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | | |
| **15** | Talent identification data can be printed as needed. | 1 | 1 | 1 | 1 | 1 | 5 | 1.00 |
| | | **13** | **14** | **14** | **15** | **15** | **Mean I-CVI** | **0.93** |
| | **Relevant proportions** | **0.87** | **0.93** | **0.93** | **1.00** | **1.00** | | |

Table 3 displays the content validity index (I-CVI) with an average item level of 0.93. The average proportion of relevance of talent identification from the first material experts was 0.87, the second expert was 0.93, the third expert was 0.93, the fourth expert was 1.00, and the fifth expert was 1.00. According to the material experts, the software had excellent validity and only required minor revisions. The results of the Cronbach Alpha reliability analysis are shown in Table 4.

**Table 4.** The Analysis Results of the Cronbach Alpha Reliability

| Reliability Statistics | | |
|---|---|---|
| **Cronbach's Alpha** | Cronbach's Alpha Based on Standardized Items | N of Items |
| **0.798** | .798 | 5 |

Table 4 shows that the data has a value of 0.798, higher than 0.6. This result indicated that the responses of the five talent identification material experts were consistent, implying that the content of the talent identification model was reliable. The results of the reliability analysis of the Interclass Correlation Coefficient are shown in Table 5.

**Table 5.** The Reliability Analysis Results of the Interclass Correlation Coefficient (ICC)

| Intraclass Correlation Coefficient | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Intraclass Correlation[a] | 95% Confidence Interval | | F Test with True Value 0 | | | |
| | | Lower Bound | Upper Bound | Value | df1 | df2 | Sig |
| **Single agreement** | .413[b] | .194 | .681 | 4.950 | 14 | 56 | .000 |
| **Average agreement** | .779[c] | .545 | .914 | 4.950 | 14 | 56 | .000 |

Table 5 shows the ICC's reliability analysis. The single measurement agreement value is 0.413, and the average agreement value is 0.779. These results are in accordance with the criteria stating that if the agreement value is more than 0.75, then the data is reliable.
The results of the media expert validation are shown in Table 6.

**Table 6.** Media Expert Validation Results

| No | Indicator | Expert Number | | | Total Agreement | I-CVR |
|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | | |
| **1** | Visual design: Compatibility of design with branding and attractive aesthetics | 0 | 1 | 1 | 2 | 0.67 |
| **2** | Design Consistency: Consistent use of design elements throughout the Software | 1 | 1 | 1 | 3 | 1.00 |
| **3** | Responsive: Display ability to adapt to various screen sizes (desktop, tablet, and mobile) | 1 | 1 | 1 | 3 | 1.00 |
| **4** | Ease of navigation: Menus and buttons are easy to access and understand | 1 | 1 | 1 | 3 | 1.00 |
| **5** | Access speed: Fast page load times and interaction responsiveness | 0 | 1 | 1 | 2 | 0.67 |
| **6** | Clarity of information: information presented clearly and easily understood | 1 | 1 | 1 | 3 | 1.00 |

| No | Indicator | Expert Number | | | Total Agreement | I-CVR |
|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | | |
| 7 | Completeness of Features: Availability of features that support comprehensive talent identification | 1 | 1 | 1 | 3 | 1.00 |
| 8 | Reliability: Minimal bugs or technical problems that interfere with use | 1 | 1 | 1 | 3 | 1.00 |
| 9 | Integration: The Software's ability to integrate with other systems (e.g., HR systems, training platforms) | 1 | 1 | 0 | 2 | 0.67 |
| 10 | Data visualization (graphs, diagrams, tables) in reports is easy to understand and helps in data interpretation | 1 | 1 | 1 | 3 | 1.00 |
| 11 | Informative Dashboard: A dashboard display that provides important information concisely and visually | 1 | 1 | 1 | 3 | 1.00 |
| 12 | Easy to understand reports: Ability to produce reports that are clear and easy to understand by users | 1 | 1 | 1 | 3 | 1.00 |
| 13 | User Customization: The ability to customize the appearance and features to suit individual or organizational needs | 1 | 1 | 1 | 3 | 1.00 |
| 14 | Ease of Learning: New users can learn to use the app/website quickly and easily | 1 | 1 | 1 | 3 | 1.00 |
| 15 | User Feedback: The app/website provides clear and useful feedback when the user performs an action | 1 | 1 | 1 | 3 | 1.00 |
| 16 | Relevant recommendations: Relevant recommended systems based on analyzed data | 1 | 1 | 1 | 3 | 1.00 |
| 17 | Data Protection: Features to ensure user data is safe and protected | 1 | 1 | 1 | 3 | 1.00 |
| 18 | Regulatory Compliance: Compliance with applicable regulations and data security standards | 1 | 1 | 1 | 3 | 1.00 |
| | | **16** | **18** | **17** | **Mean I-CVI** | **0.90** |
| | **Relevant proportions** | **0.89** | **1.00** | **0.94** | | |

Table 6 displays the average content validity index I-CVI with an average item level of 0.90. The average proportion of relevance of digital media experts from the first expert was 0.89, the second expert was 1.00, and the third expert was 0.94. Based on the material experts, the software had a very high validity and only required minor revisions. A measuring instrument is said to be reliable if at least half of the experts consider the indicator to be important and the question items are relevant by four out of five validators with an I-CVI of 0.80. The results of the Cronbach Alpha reliability analysis are shown in Table 7.

**Table 7.** The Analysis Results of Cronbach Alpha Reliability

| Reliability Statistics | | |
|---|---|---|
| **Cronbach's Alpha** | Cronbach's Alpha Based on Standardized Items | N of Items |
| **0.829** | .838 | 3 |

Table 7 shows that the data has a value of 0.829, higher than 0.6. This result showed that the responses of the three media experts were consistent, implying that the content of the talent identification model is reliable. The results of the reliability analysis of the Interclass Correlation Coefficient (ICC) are shown in Table 8.

**Table 8.** The Reliability Analysis Results of the Interclass Correlation Coefficient (ICC)

| Intraclass Correlation Coefficient | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Intraclass Correlation[a] | 95% Confidence Interval | | F Test with True Value 0 | | | |
| | | Lower Bound | Upper Bound | Value | df1 | df2 | Sig |
| **Single agreement** | .626[b] | .367 | .822 | 5.854 | 17 | 34 | .000 |
| **Average agreement** | .834[c] | .635 | .933 | 5.854 | 17 | 34 | .000 |

Table 8 shows the ICC's reliability analysis. The single measurement agreement value was 0.626, and the average agreement value was 0.834. These results were in accordance with the criteria stating that if the agreement value is more than 0.75, then the data is reliable. Figure 4 shows the percentage of respondents' opinions regarding the software's feasibility.

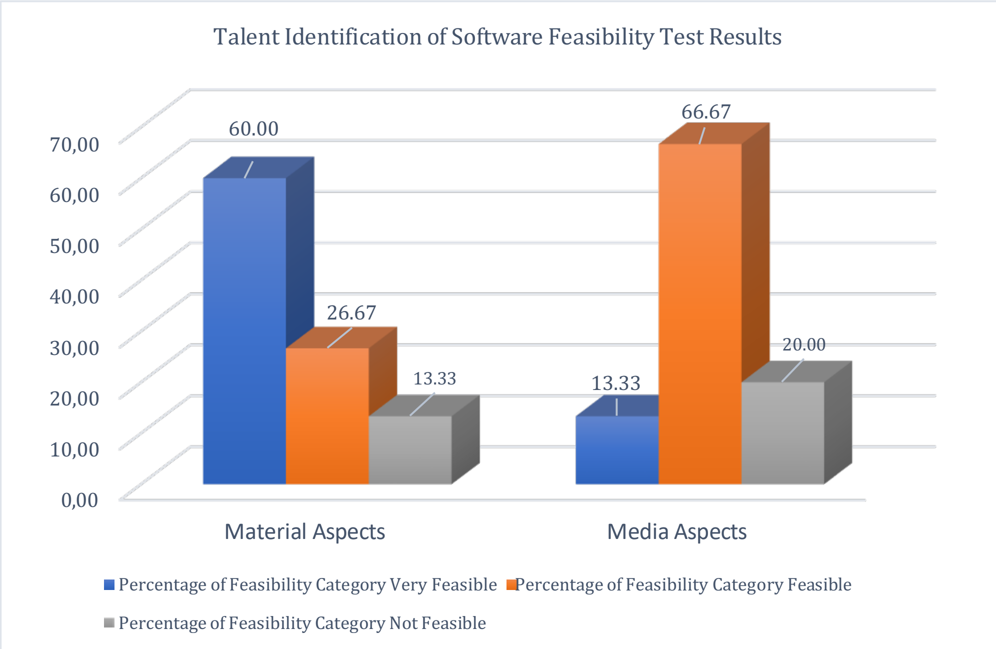


**Figure 4.** Percentage of Respondents' Opinions on Software Feasibility

Figure 4 displays the percentage of software feasibility. The results showed that 60% of respondents stated that the content of the talent identification material was very appropriate, 26.67% stated that it was acceptable, and only 13.33% stated that it was inappropriate. Furthermore, the results showed that 13.33% of respondents stated that the media content was very appropriate, 66.67% stated that it was acceptable, and only 20% stated that it was inappropriate. The percentage of talent recommendation accuracy is shown in Table 9.

**Table 9.** Percentage Accuracy of Talent Recommendations

| Recommendations | Student's response | Percentage |
|---|---|---|
| **Agree** | 34 | 85% |
| **Disagree** | 6 | 15% |
| Grand Total | **40** | **100%** |

Table 9 shows that the TIDev software was very accurate in recommending sports talents, with 85% of students feeling that the recommendations matched their interests and talents. However, 15% of students felt the results needed to be more accurate and suggested improvements to the talent analysis algorithm. The results of the user satisfaction percentage are shown in Table 10.

**Table 10.** Percentage of User Satisfaction

| Satisfaction Level | User Response | Total | Percentage |
|---|---|---|---|
| **Very easy (4)** | 2 | 8 | 13.33% |
| **Easy (3)** | 10 | 30 | 66.67% |
| **Difficult (2)** | 3 | 6 | 20% |
| **Very difficult (1)** | 0 | 0 | 0% |
| Grand Total | **15** | **44** | **100%** |
| Mean | | **2.93** | |

Table 10 shows that the majority of users found the software easy to use, with an average score of 2.93 out of 4. Still, only three of them said that using it was difficult because they did not know much about technology or because of the complex interface on some devices.

**Discussion**

This research developed a software-based sports talent identification model called Talent Identification Development (TIDev). The TIDev software was designed to overcome the constraints of time-consuming and inefficient manual talent identification methods. With big data technology and analysis, TIDev accelerated the talent identification process. Subjects' anthropometric and biometric data can be entered quickly and accurately, and the analysis results are obtained quickly, providing significant benefits for coaches, managers, and team officials in recruiting and training athletes.

Reliability is defined as the consistency of results across different users. It is another strength of TIDev. The software delivers consistent results whether used by coaches, sports teachers, or other users. Studies (Cust et al., 2019; Reyaz et al., 2022) confirm that the machine learning algorithms embedded in the software consistently produce reliable scores upon repeated tests. Moreover, in addition, this research found that software-based talent identification can reduce evaluation time by 50% compared to manual methods, overcoming the limitations of the traditional time-consuming talent identification process. By integrating big data technology, TIDev accelerates the identification process, allowing anthropometric and motor data from young athletes to be input quickly and accurately, thus providing coaches and managers with timely insights for recruitment and training.

The software's efficiency lies in its optimal use of resources. TIDev automates the collection and processing of motor and performance data, significantly reducing the need for manual input. Automated data collection improves efficiency by minimizing the time required to gather information (Khan et al., 2023). Furthermore, TIDev's machine-learning algorithms enable rapid and accurate data analysis, facilitating quicker decision-making by coaches and managers (Akgun & Greenhow, 2021; Jamil et al., 2021). The software can also update models and recommendations in real time based on incoming data, improving its accuracy and efficiency over time (Khan et al., 2023). This feature proves particularly useful in competitive environments where timely decision-making is crucial (Parra-Martinez & Wai, 2023).

TIDev has a fairly fast average response time of around three seconds, which makes it very efficient at processing data and providing talent recommendations. This speed gives it an edge in environments that require quick decisions, such as in talent identification at sporting events or while a competition is in progress (Vaeyens et al., 2009). However, there are cases where response times exceed five seconds, indicating potential performance issues. The problem occurs in devices connected to less stable networks, where latency affects software response speed (Sefati & Halunga, 2023). Improvements to algorithm optimization and the use of data compression technologies are recommended to maintain response time consistency even under non-ideal network conditions (Karras et al., 2024).

Thanks to big data and machine learning technologies, TIDev can effectively process large amounts of motor and performance data, enhancing its analytical capabilities. It allows managers and coaches to make faster and smarter decisions. For example, the software can uncover important physical characteristics and abilities contributing to an athlete's performance or find patterns and trends that are not immediately apparent through manual study. These factors can help determine which physical and motor skills are most closely related to future athletic achievement. According to Parra-Martinez and Wai (2023), the software continuously updates its recommendation models as new data becomes available, ensuring the accuracy and relevance of its recommendations. Furthermore, TIDev provides detailed and actionable advice on the most suitable sport for an athlete based on data analysis, improving the precision of talent selection and enhancing coaching programs (Priyadarshini & Veeramanju, 2023). TIDev has proven to have a high level of accuracy in providing recommendations regarding students' potential and talents.

*Research Contribution*

This research makes a significant contribution to identifying talent in students aged 11–14. The TIDev software can categorize talent more broadly than previous applications, with five categories: high potential, potential, moderate potential, low potential, and no potential. This feature helps coaches and sports management identify and prioritize athlete development in a more structured manner. Height, weight, arm span, and other physical test data are efficiently processed to provide relevant recommendations to make it easier for coaches, physical education teachers, and sports administrators to make data-driven athlete recruitment and development decisions. In addition to general talent identification, TIDev incorporates Olympic priority sports branches, allowing for more focused talent recruitment aligned with international competitive standards. The study shows that focusing on Olympic-priority sports allows for better resource allocation and structured athlete development, maximizing the chances of success at international events (Vaeyens et al., 2009). Moreover, the ability of TIDev to update recommendations based on real-time data has proven effective in optimizing training programs for athletes in these disciplines, particularly in high-pressure environments like the Olympics (Olusoga et al., 2012). This feature further validates TIDev's role in modernizing sports talent identification, especially in elite and competitive sports where timely decision-making is critical.

*Limitations*

The limitation of the study is that it did not include psychological and cognitive tests in the talent identification software. It can reduce the accuracy and comprehensiveness of the results obtained. Talent identification does not only depend on physical or motor abilities but also involves psychological aspects such as motivation, self-confidence, and stress management, and cognitive aspects, such as decision-making ability, problem-solving, and strategy. Without including these tests, the software tends to provide a partial picture and risks, ignoring individuals who have high potential beyond physical indicators. This issue can result in biased and less-than-optimal results in determining the appropriate talent development path, especially in the context of sports that require a combination of physical, mental, and intellectual abilities.

*Suggestions*

Future research should conduct validation tests with new and larger samples, apply machine learning and big data analytics to process more complex data and develop automated prediction models, integrate wearable technology and the Internet of Things (IoT) to support real-time anthropometric and biometric data collection, conduct longitudinal studies by tracking the development of identified talented athletes or individuals over a while (e.g., 3-5 years), and use qualitative and quantitative data to assess progress and success.

## CONCLUSION

This research successfully developed and validated a comprehensive and efficient software tool for sports talent identification. Talent Identification Development (TIDev) not only speeds up and simplifies the talent identification process but also provides accurate and reliable analyses and recommendations. With this software, it is hoped that the recruitment system and coaching of potential athletes in East Kalimantan can be carried out more effectively and on target, producing outstanding athletes in the future. This software also has the potential to be further developed and adapted to the specific needs of various sports and different age groups to provide more comprehensive benefits to the world of sports in Indonesia. The study successfully developed and validated the Talent Identification Development (TIDev) software, an efficient tool for identifying sports talent. TIDev simplifies and accelerates the talent identification process while providing accurate and reliable analyses, aiming to enhance athlete recruitment and coaching in East Kalimantan and produce future top athletes. The software has significant potential for further customization to meet the specific needs of different sports and age groups, broadening its impact on Indonesia's sports sector. However, the software's current limitation is its exclusion of psychological and cognitive tests, which are crucial for a comprehensive talent assessment. These omissions may lead to partial evaluations and overlook individuals with high potential in areas beyond physical abilities, particularly in sports requiring a combination of physical, mental, and intellectual skills. Future research should address these limitations by incorporating psychological and cognitive components, testing the software with larger samples, and employing advanced technologies like machine learning, big data analytics, wearable devices, and IoT for real-time data collection. Longitudinal studies tracking athlete development over several years and using qualitative and quantitative assessments are recommended to refine and validate the model further.

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**AUTHOR CONTRIBUTION STATEMENT**

In our manuscript, MRB, JJS, MIH, and SW made the following contributions: MRB conceptualized the study, drafted the manuscript, and revised it critically for intellectual content. JJS contributed to the collection of biomotor and anthropometric data. MIH performed data analysis, interpreted the results, and drafted the research report. SW designed the prototype and developed the talent identification software.

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