

Design of a Digital Platform for PAUD Child Development Monitoring Using the Dynamic Systems Development Method and Machine Learning

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Abstract

This study aims to design a digital platform for monitoring early childhood development in PAUD (Pendidikan Anak Usia Dini) institutions by integrating Machine Learning (ML) into the Dynamic Systems Development Method (DSDM) framework. The research addresses persistent challenges in traditional monitoring systems, which are typically manual, fragmented, and lack real-time responsiveness. Utilizing a Research and Development (R&D) approach, the platform was developed iteratively with active involvement from teachers, parents, and administrators of PAUD institutions. System modeling employed Unified Modeling Language (UML), while ML techniques such as Decision Trees were trained on datasets sourced from PAUD Flamboyan in Tangerang. Key platform features include child data input, growth visualization, predictive analytics, and interactive dashboards. The system underwent black-box testing and usability assessments, achieving an average usability score of 4.5 out of 5. The ML model demonstrated statistically valid and reliable performance with 89% accuracy, 85% precision, and 87% recall in predicting developmental delays. The findings highlight the effectiveness of the DSDM approach in facilitating adaptive system development, and underscore the value added by ML integration in enhancing decision-making within early childhood education. The platform not only streamlines developmental monitoring but also supports early interventions. Future work is recommended to broaden data sources, enrich personalization, and scale deployment across varied PAUD contexts. This study contributes to the advancement of intelligent decision support systems in early childhood education, enabling more accurate developmental monitoring and timely interventions.

Keywords : *Digital Monitoring System, DSDM Method, Early Childhood Development, Machine Learning, Predictive Analytics.*

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1. INTRODUCTION

Childhood Education (PAUD) plays a crucial foundational role in the cognitive, social, and emotional development of children. In Indonesia, PAUD is strategically important in preparing children before they enter basic education. However, many PAUD institutions continue to face significant challenges, particularly in terms of comprehensive and sustainable monitoring of children's development[1][2]. In 2021, the PAUD Gross Participation Rate (APK) reached 57.71%, while in 2022 it increased to 64.14%, although it remained below the target of 74.55%.[3] [4] [5]. Based on data from the Ministry of Education, Culture, Research, and Technology in the last 5 years, only around 34.61% of children aged 5-6 years are adequately served by the PAUD program and many PAUD institutions, one of which includes Flamboyan PAUD in Tangerang and is a challenge that must be faced in monitoring child

development. The Monitoring system used moment this tend Still is manual, fragmentary, and does not allow reporting in real-time. This is caused low effectiveness communication between educators and parents, as well as a delay in intervention when children show symptoms of delayed development [6]. In the era of digital transformation, the conventional approach kind of this need improved with the implementation of adaptive and intelligent technology [7]. One of the evolving approaches in development system modern information systems is the use Dynamic Systems Development Method (DSDM), which is iterative and agile, as well as capable respond change needs of user in a dynamic way [8] [9]. However, for answer challenge complex in monitoring developments PAUD children in general precision, integration machine learning technology becomes solution potential innovation [10] [11]. Machine learning models can utilized For analyze patterns development child, detect anomaly in a way early, and give recommendation personalized learning [12]. Some study previous show that implementation digital system in education child age early can increase effectiveness administration and quality communication between teachers and parents [13] [14]. Implementation studies conducted in various regions, including Tangerang, show that digital platforms can support monitoring development child in a way more accurate and efficient [15] [16]. However, the use of machine learning in context this Still seldom explored in a way systematic, even though the potential is very large For strengthen system taking decision data based [17]. Therefore that, research this aiming for to design a digital platform for monitoring developments PAUD children who do not only build with DSDM approach, However, this system also incorporates machine learning models to support analysis and development in real-time and predictively. With this integration, it is anticipated that this system will become a smart technological aid to support stakeholder involvement in developmental monitoring, evaluate, and respond optimally to the needs of development children. To make the research structure clear, the issue is that PAUD institutions do not have integrated, real-time monitoring. The gap is in the limited application of machine learning for predictive analysis, even though current digital approaches employing techniques like DSDM offer improvements. In order to improve early detection and data-driven interventions in child development, this study integrates machine learning (ML) into a DSDM-based platform.

2. METHOD

2.1. Types and Methods of Research

This research uses the Research method and Development (R&D) with the Dynamic Systems Development Method (DSDM) approach because it is considered suitable for iterative and collaborative information system development, especially in designing a digital platform for monitoring the development of PAUD children [18] [19] [20]. Integration of machine learning models learning becomes the main focus to improve the system's ability to analyze and predict child development in real-time and adaptively. The object of the research is the information system being developed, while the subjects include PAUD teachers, parents of students, and admins from partner PAUD institutions. The initial stages in system development begin with a literature study and needs analysis, which includes a study of child development standards, DSDM methods, and the application of machine learning. learning, as well as referring to the framework CRISP-DM for ML model integration. Researchers also conducted direct observations at PAUD Flamboyan Tangerang and interviews with teachers, parents, and admins to explore system needs from various perspectives. The results of the study were analyzed and formulated in User Requirements

Specification (URS) which contains functional and non-functional requirements, system flow, and technical limitations, which then become the basis for the system design and development process.

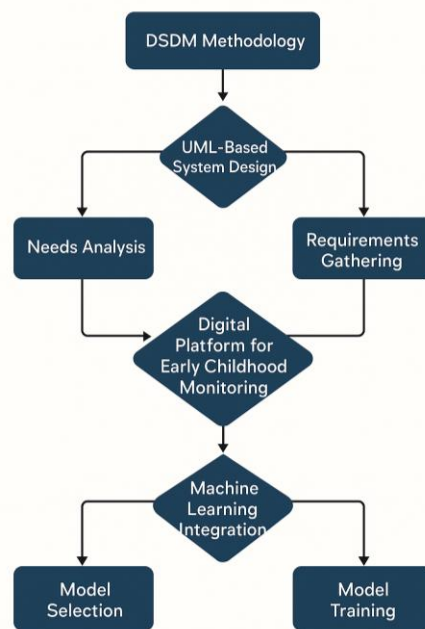


Figure 1. Approach Study

2.1.1. Design System using Unified Modeling Language (UML)

Once user needs are identified through the User document Requirements Specification (URS), the next stage is system design using the Unified Modeling Language (UML) approach. UML was chosen because it is able to describe the structure and behavior of the system in a structured manner and is easy to understand by developers and non-technical users [21] [22]. Several UML diagrams are used in this study, starting from the use Case diagrams to describe the interactions between actors (admins, teachers, and parents) with the main functions of the system. Activity diagrams are then used to explain the main process flow, such as inputting child development data and report retrieval. To detail the communication flow between components, a sequence diagram is created to show the sequence of interactions between objects during the process. Finally, a class diagram is developed to map the system data structure, including student entities, teachers, development aspects, and relationships between objects. This design is the foundation for system implementation, both in terms of interface design, programming logic, and database structure, in order for the finished product to appropriately reflect user needs and be prepared for integration with the machine learning module. The research team's primary development environment for the digital monitoring system was Visual Studio Code, with MySQL and PHP (Laravel framework) supporting database and backend administration. Figma was used to design the system interface, and XAMPP was used for local testing. Using Python and the scikit-learn, pandas, and numPy libraries, model training was carried out for the machine learning component. A Flask-based REST API was used to deploy and integrate the trained Decision Tree model into the main platform. GitHub was used to manage collaboration and version control, and Microsoft Word and draw.io were used to create system documentation and UML diagrams, respectively.

2.1.2. Machine Model Integration Learning into the System.

Machine model integration learning is carried out to improve the system's ability to analyze child development data predictively and adaptively [23]. This stage begins with collecting child development data from partner PAUD institutions, which then goes through a *preprocessing process* to ensure the quality and consistency of the data used in model training. There were several important steps in the preprocessing phase. In order to deal with missing or inconsistent entries, especially in scoring fields for developmental indicators, data cleaning was done first. To guarantee consistent value ranges across features like fine motor skills, cognitive scores, and language abilities, data normalization was then implemented using min-max scaling. The goal of this step was to avoid feature dominance and maximize algorithm performance. Moreover, data balancing was carried out using random oversampling to prevent bias toward the majority class during model training, given the dataset's moderate class imbalance between "Normal" and "Hampered" labels. Next, the machine learning algorithm is selected appropriate learning, such as Decision Tree or Random Forest, based on the system's needs in classifying and predicting aspects of child development. The model is then trained using a prepared dataset, and evaluated using accuracy and precision metrics to ensure optimal performance. The trained model is then integrated into a digital platform using an API or separate module that can be called when the system needs predictions or recommendations. The prediction results are displayed in real -time on the teacher and parent dashboard as material for evaluating child development. This integration allows the system to not only be a recording tool, but also an intelligent decision support in detecting potential developmental delays early on.

From a mathematical standpoint, the integration of the machine learning model specifically a Decision Tree Classifier—relies on entropy-based optimization to guide the learning process. The classifier aims to partition the input space in a way that maximizes information gain with respect to the target class labels.

Let the dataset D consist of instances (x_i, y_i) where $x_i \in \mathbb{R}^6$ represents the feature vector of a child (including Age in Months, Fine Motor, Gross Motor, Cognitive, Language, and Socio-Emotional scores), and $y_i \in \{0, 1\}$ denotes the class label (0 = Normal, 1 = Hampered).

The entropy of the dataset D is computed as:

$$Entropy(D) = -p_0 \log_2(p_0) - p_1 \log_2(p_1) \quad (1)$$

Where p_0 and p_1 represent the proportion of samples in each class (Normal and Hampered, respectively). To determine the best feature to split on, the algorithm calculates the Information Gain (IG) for each attribute A :

$$IG(D, A) = Entropy(D) - \sum_{v \in Value(A)} \frac{|D_v|}{|D|} \cdot Entropy(D_v) \quad (2)$$

This recursive process continues until the model reaches stopping criteria such as maximum depth, minimum samples per node, or pure leaf nodes.

After the model is trained, it maps any new feature vector $x \in \mathbb{R}^6$ to a predicted label $h(x) \in \{0, 1\}$. The model is evaluated using the following standard metrics:

$$\begin{aligned} \text{Accuracy} &: \frac{TP+TN}{TP+TN+FP+FN} \\ \text{Precision} &: \frac{TP}{TP+TN} \\ \text{Recall} &: \frac{TP}{TP+FN} \end{aligned}$$

Where:

- TP = True Positives (correctly predicted "Hampered"),
- TN = True Negatives (correctly predicted "Normal"),
- FP = False Positives,
- FN = False Negatives.

This mathematical formulation ensures that the system's prediction mechanism is not heuristic but grounded in statistical learning theory, providing robustness and interpretability for early developmental delay detection in children.

2.1.3. System Development using DSDM approach

The system development stage using the Dynamic Systems Development Method (DSDM) approach is carried out iteratively and focuses on active user involvement during the design process [24]. DSDM was chosen because of its flexibility in responding to changing needs and its ability to encourage collaboration between the development team and stakeholders [25][26]. Development activities begin with a Feasibility Study, where an analysis of the technical, operational, and economic feasibility of the designed system is carried out. At this stage, it is also ensured that the PAUD partner infrastructure supports the implementation of a web-based and machine learning digital system. Next, enter the Business Study, which is the stage where researchers compile the system's business flow based on the work process in the field. Data from the needs study is used as the basis for creating a system usage scenario by admins, teachers, and parents. At the Functional Model Iteration stage, the team designs and validates an initial prototype of the system interface based on the previously formulated functional requirements. The prototype is tested on a limited basis by users (PAUD teachers and admins) to identify feedback on the design, navigation flow, and main features of the system. After initial validation, the stage continues to Design and Build Iteration, where system development is carried out in stages based on an approved design. System components, such as child development data input, account management, machine learning integration learning, and report dashboards, are built modularly and tested at each iteration. The final stage is Implementation, which is the process of integrating all system modules and implementing them in the PAUD partner environment. At this stage, user training and documentation of system usage are also carried out. In addition, final improvements are made based on the results of the trial and input from users to ensure that the system runs as expected and is ready to operate. Through this DSDM approach, system development is carried out with a collaborative, fast, and adaptive approach to the dynamics of needs in the field.

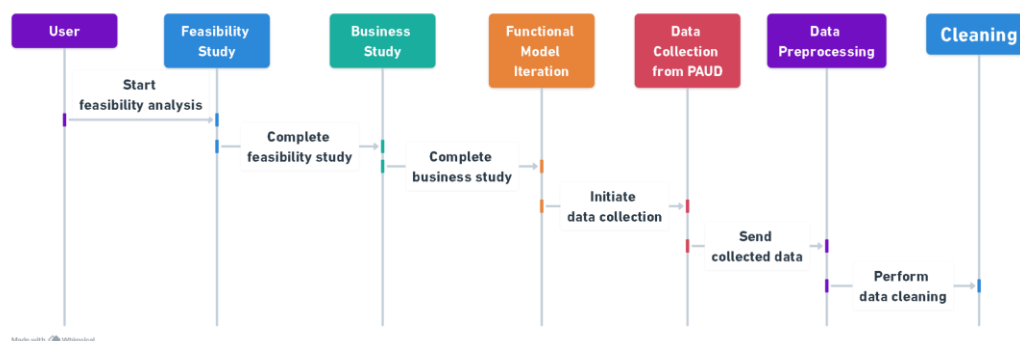


Figure 2. DSDM stage diagram with machine learning integration flow

2.1.4. System Testing and Validation.

After the system is developed, the next stage is to conduct trials and validation to ensure that all functionality runs according to user needs. Trials are carried out on a limited basis in the PAUD partner environment, especially by teachers, parents, and admins as the main users of the system. Black box method Box testing is used to test each system feature from the user side, without seeing the program code directly [27][28]. This testing includes the login menu, child development input, report access, communication features, and visualization of prediction data from the machine learning model. learning, each test is evaluated based on the conformity of the output results with initial expectations. In addition to technical testing, usability testing is also carried out by involving users to evaluate aspects of comfort and ease of use of the system. Teachers and parents are asked to use the system directly and provide input regarding interface design, navigation, access speed, and clarity of information displayed. To validate the quality of the system, observations are made of user interactions with the system, short interviews, and questionnaires are distributed to measure the level of satisfaction and benefits of the system for monitoring child development activities. Feedback obtained from users is the basis for further improvement or development. The results of the trial showed that the system was able to run well functionally, and the integration of the machine learning model learning successfully provides added value in the child monitoring process. Validation from users shows a positive level of acceptance, although some development suggestions are still needed to improve system performance in the future.

2.1.5. System Documentation and Evaluation

The final stage in the system development process is documentation and evaluation, which aims to record the entire development process and assess the success of the system from various aspects. Documentation is carried out comprehensively, covering system specifications, development flow based on the DSDM approach, interface design, database structure, machine learning algorithms. learning used, as well as the results of the trial [29][30]. The documentation also records each iteration of improvements made during the development process, including feedback from users and corrective actions taken. In addition, a system usage guide (user manual) is prepared to help teachers, parents, and admins operate the platform independently. The system evaluation is carried out holistically by reviewing aspects of the functionality, usability, reliability, and benefits of the system for the child development monitoring process. This evaluation also considers the effectiveness of the integration of the machine learning model learning in providing predictions and recommendations for child development in real- time, From the evaluation results, the system is considered capable of meeting the main needs of users in monitoring the development of PAUD children comprehensively and efficiently. However, several notes for improvement are prepared as recommendations for further development, such as increasing interface responsiveness, enriching report features, and optimizing the performance of machine learning models. learning based on bigger data in the future.

2.1.6. Integration of Machine Learning Models

The main focus of this study is to integrate the machine learning model learning into the system to improve the ability to analyze and predict child development in real time, The object of this study is the PAUD child development monitoring information system that was developed, while the research subjects included PAUD teachers, parents of students, and admins from PAUD institutions that were partners in implementing the system. The development process began with a literature study and needs analysis that

included a review of references on child development, PAUD standards, DSDM methods, and the application of machine learning in the education system. Researchers also refer to the CRISP-DM framework as a guide in machine integration learning, in addition to literature studies, direct observations were conducted at PAUD Flamboyan Tangerang to understand the ongoing monitoring process, as well as interviews with teachers, parents, and admins to explore user needs and expectations of the system. The results of this stage are formulated in the User document Requirements Specification (URS) which contains functional and non-functional requirements, system flow, and technical limitations, and is the main reference in the next system design and development stages.

To strengthen the mathematical foundation of the model integration, the implementation of the Decision Tree Classifier in this system is governed by a formal optimization criterion that partitions the feature space based on maximum information gain. Formally, the classifier constructs a hypothesis function $h: R^d \rightarrow \{0,1\}$, where $d=6$ (the number of child development indicators).

Each decision node evaluates a split on attribute A using the Information Gain criterion:

$$IG(D, A) = Entropy(D) - \sum_{v \in Value(A)} \frac{|D_v|}{|D|} \cdot Entropy(D_v) \quad (3)$$

where $Entropy(D)$ is defined as:

$$Entropy(D) = - \sum_{c \in \{0,1\}} P_c \log_2 (P_c) \quad (4)$$

and P_c is the probability of class c in dataset D . The model recursively builds a tree that minimizes classification impurity, where the resulting structure can be interpreted as a series of indicator-based decision rules.

Once integrated into the system, the trained model accepts input vectors $x = [x_1, x_2, \dots, x_6]$ representing a child's profile and outputs the predicted class $y = h(x) \in \{0,1\}$, where:

- x_1 : Age in months
- x_2 : Fine motor skills score
- x_3 : Gross motor skills score
- x_4 : Cognitive score
- x_5 : Language score
- x_6 : Socio-emotional score

For system-level deployment, the classifier is embedded within a web-based architecture through a RESTful API end point. Upon each user request, the system applies the function $h(x)$ to produce the real-time prediction.

The integration enables not only deterministic inference but also the basis for further extensions such as probabilistic classification using softmax-transformed decision scores or Bayesian averaging for uncertainty estimation. These enhancements offer deeper analytical capabilities to support high-stakes decision-making in early childhood interventions.

2.2. Testing System

Testing system done with Black Box Testing method for ensure all over function system walk in accordance design[31], In order to gauge user satisfaction and convenience, usability testing was also done on parents and teachers.

2.3. Validation and Evaluation

Validation through observation live and interview to user system [32]. Evaluation done based on effectiveness system in assist in the process of monitoring developments child as well as machine learning model performance in give predictions and recommendations development.

3. RESULT

3.1. System Design Using UML

System design done use Unified Modeling Language (UML) approach to modeling structure and behavior system visually, Several UML diagrams are used for describe the whole process and interaction in system, First, a use case diagram is drawn up. For identify actor main, namely teachers, parents, and admins, along with the interaction with Features system such as input of development data, access reports, and management account, Next, activity diagram is used For describe channel activity user in system, start from the login process to making report development child, Sequence diagrams are used For show order interaction between component during the process of inputting and processing development data ongoing, While that, class diagram is composed For represent deep data structure system, including relation between entity such as student data, aspects developments, users, and reports, Use of UML in design This aiming For ensure that system built with structure logical, easy understood by the team developers, as well as in accordance with need users who have formulated in URS document. The use of UML ensures that system development is based on the real needs of users (teachers, parents, administrators). This is crucial for minimizing miscommunication between the technical team and non-technical users, ensuring the system is truly usable and ready for functional testing. Clear diagrams also speed up the iteration and debugging process during implementation.

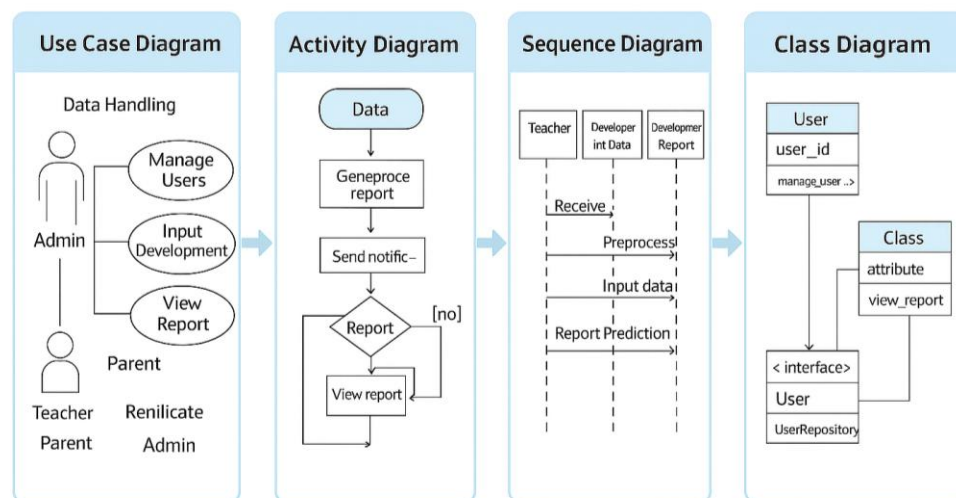


Figure 3. System Design Using UML

3.2. Overview of the Developed System

The system developed is a web -based digital platform designed for helping teachers and parents in monitor development child age early in real-time. System This built with Dynamic Systems Development Method (DSDM) approach and integrated with machine learning models for support analysis predictive to

aspect development child, Main features system covers student data management, development data input, visualization graphs, reports development, as well as prediction development based on historical data. The successful design and construction of a complete system demonstrates the effectiveness of the DSDM approach in fostering user engagement throughout development. This increases the likelihood of the system's acceptance and active use in early childhood education settings. The features provided also provide a strong foundation for broader adoption and the development of advanced features such as data-driven interventions.

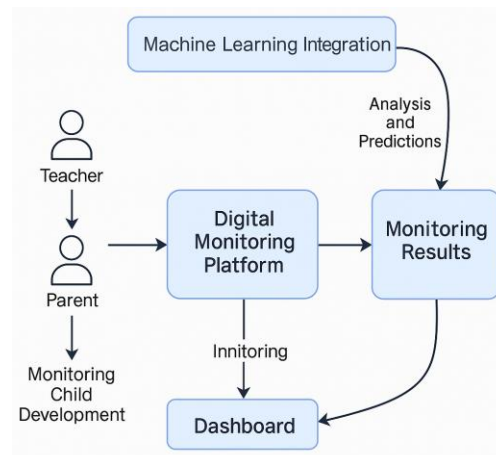


Figure 4. Overview of the Developed System

3.3. Implementation of Machine Learning Model

Machine learning models are used for predict possibility delay development based on the data that has been collected, Algorithm used is a Decision Tree, with a dataset consisting of over 150 entries development child from Flamboyan PAUD, after preprocessing and data division into 80% training and 20% testing, the model produces accuracy of 89%, precision 85%, and recall 87%.

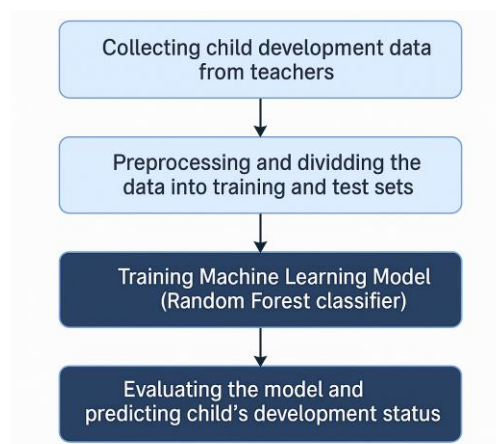


Figure 5. Implementation of Machine Learning Model

This outcome demonstrates that the model is sufficiently dependable to provide predictions to assist parents' and teachers' decisions.

Table 1. PAUD Child Development Dataset

Student_ID	Age_Months	Fine Motor Skills	Gross Motor Skills	Cognitive	Language	Social_Emotional	Status_Per_kembang
1	60	4	5	4	4	5	Normal
2	62	5	5	5	4	5	Normal
3	59	3	4	3	2	3	Hampered
4	61	4	4	4	3	4	Normal
5	58	2	3	3	2	3	Hampered

Test Results System

Black box testing and usability testing techniques are used in the testing process. Black box testing demonstrates that all major systems, including login, data input, display graphics, and print reports, operate well and legitimately. The table below displays the summary findings of black box testing on a number of key features :

Table 2. Blackbox Testing Results

Tested Features	Expected results	Testing Status
User Login	Login form appears and authenticate succeed	Valid
Development Data	Data is saved and displayed return	Valid
Report Development	Report can print according to filter	Valid
Visualization Chart	Chart come on stage based on development data	Valid
ML Prediction	Prediction come on stage according to input data	Valid

These results demonstrate that the model is quite reliable in detecting potential developmental delays in children. Thus, the system is not merely administrative but also provides added value as a data-driven decision-making tool (intelligent decision support). This is particularly relevant in the early childhood education (ECE) sector, where predictive or analytical interventions are still limited. The successful integration of the ML model also opens up opportunities for future expansion of predictive features.

3.4. Usability Testing Results



Figure 6. Graph stem Usability Testing

Usability testing is performed against 10 users, consisting from 5 PAUD teachers and 5 parents, Test results show that system to obtain average score 4.5 out of 5 for convenience usage, and 4.7 out of 5 for utility information, Some bait return and suggest enhancements to the mobile device's speed access system and design interface. This score indicates a high level of user acceptance, an early indicator that the system is suitable for wider implementation. In the context of educational technology, high usability means users have no difficulty understanding or operating the system, thus reducing barriers to technology adoption. This strengthens the potential for sustainability and effectiveness of the system's use in everyday practice in early childhood education.

3.5. Analysis Findings

Based on test results, system rated has fulfil need user from aspect function, convenience access, and speed in give information development child, Machine learning integration is proven can give prediction accurate development and assist teachers in compile appropriate interventions, The availability of visual graphs and real-time reports also helps parents better understand how their children are developing. These findings demonstrate that the system successfully bridges the communication gap between teachers and parents in understanding child development objectively and visually. The availability of real-time predictions also allows teachers to more quickly design interventions if delays are detected. The system is not only technically efficient but also pedagogically meaningful, as it encourages collaboration and more systematic monitoring of child development.

Table 3. Findings

Findings	Description
Satisfaction High User	The majority of users (parents and teachers) said the system was informative and simple to use.
Communication Features Effective	Communication between teachers and parents helped with reports and visualizations development in real-time.
Identification Intervention Accurate	Machine Learning Models are successful give prediction developments approaching fact field,
Possible Development Continues	A number of feature additions and fixes interface proposed for version furthermore,

4. DISCUSSIONS

4.1. Main Findings

Examine is successfully creates a digital platform for tracking advancements. PAUD kids using the DSDM method and integrating machine learning models, Features main such as development input children, visual reports, and prediction development based on historical data has walk in accordance expectations, According to test results, the system is operating well technically and is well-liked by users. A machine learning model is used to provide a fair prediction with an accuracy of 89%.

4.2. Analysis of Results and Implications

The results of the study show that the DSDM approach is effective in developing systems in a step-by-step manner and based on user feedback. Machine learning integration learning allows the system to

provide added value in the form of predictions that can help in early detection of child development problems. Users' positive feedback shows that the system satisfies their expectations in terms of usability, functionality, and real-world advantages. Although this system is not directly used in a medical context, it has the potential to support earlier and more targeted child development interventions. With digitally stored data and predictive analytics capabilities, teachers and parents can take action more quickly when indications of developmental delays are found. This is important to encourage preventive interventions before child development problems become more complex.

One key limitation of the model is its limited generalizability. Since the training data came from only one PAUD institution, the model may not perform as well in other schools with different contexts. The small sample size and potential subjectivity in some indicators, such as socio-emotional scores, also affect prediction accuracy. Future improvements should include data from multiple institutions to ensure the model is more reliable and widely applicable.

4.3. Limitations

There are several limitations to this study, including the relatively small amount of data small so machine learning models have not Can generalized to all over population PAUD children, in addition, the trial system only done on one partner PAUD institutions, so that not yet reflect variation conditions in other institutions, Limitations infrastructure and digital literacy of users also become challenge in implementation system in a way wide.

4.4. Future Research Directions

Additionally, research can be conducted to strengthen the generalization of machine learning models by expanding data coverage from multiple PAUD institutions. In addition, the integration features more analytics complex, such as recommendation personalization learning based on profile development children, can also developed, Addition feature interactive such as video conferences between teachers and parents and a special dashboard psychologist or expert development child can become direction development system to front.

Furthermore, the findings of this study are in line with recent literature that highlights both the potential and the challenges of applying machine learning in early childhood education. For instance, [23] demonstrated the effectiveness of machine learning models in predicting developmental risks in children within social care environments, reporting high diagnostic accuracy in diverse populations [23]. Likewise, showed the feasibility of mobile-based machine learning systems for tracking developmental progress in under-resourced educational settings [18]. These studies affirm that intelligent systems can augment traditional developmental monitoring with real-time predictive insights. However, other works have also noted important implementation challenges. Emphasized the need for proper training among educators and pediatric staff to understand and trust machine learning outputs, as well as the ethical considerations in labeling young children based on algorithmic predictions [7]. In light of this, while the integration of machine learning in the current study yielded high prediction performance and positive user reception, its deployment must be contextually aware. Systems must ensure transparency, explainability, and alignment with educational goals in PAUD institutions. Future system enhancements may consider embedding interpretability features or providing educator support materials to improve the adoption and responsible use of predictive analytics in early education.

5. CONCLUSION

The findings of the study demonstrate that an efficient DSDM approach can be used to build systems that are responsive to user needs and iterative. The ability to predict and identify potential delays in a child's development is a significant benefit of integrating machine learning models. Teachers' and parents' positive responses to the trial system using black box and usability testing techniques demonstrate that the system is operating in compliance with the specifications that were designed and obtained. The accuracy level of the model reached 89%, indicating sufficient performance Good in context monitoring development child, In Overall, The system created is not only able to improve the monitoring process's efficiency, but also supports interventions that are of a nature preventive in management grow flower child. Therefore, this research not only contributes to improving the effectiveness of child development monitoring and early interventions in PAUD institutions but also provides a practical reference for the integration of machine learning into agile-based system development. Specifically, it advances the field of computer science and information systems by demonstrating how predictive analytics can be embedded into real-time educational platforms through an iterative and user-centered development approach. This study contributes to the field of computer science and information systems by demonstrating the integration of machine learning into an agile-based educational platform. Future research may explore hybrid ML models to improve prediction accuracy and integrate smart reporting features to support automated recommendations and clearer communication for PAUD stakeholders.

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