

# YOUTHIRON: Design and Evaluation of a Mobile Health–Based Adolescent Anemia Screening Information System Using Design Science Research

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**Abstract**—Adolescent anemia remains a significant public health problem in Indonesia due to limited early detection systems and low integration of digital health data management. This study aims to design and evaluate YOUTHIRON, a mobile-based anemia screening information system that integrates digital hematology parameters and a rule-based decision-support mechanism. The research applies the Design Science Research (DSR) approach, comprising problem identification, artifact design, development, and evaluation. System evaluation was conducted using black-box testing, the System Usability Scale (SUS) involving 30 adolescent respondents, and system performance testing. The results indicate that all functional modules achieved 100% validation, with a classification accuracy of 90% based on confusion matrix analysis, and a SUS score of 82.3 (SD = 4.5), categorized as excellent. The average system response time was 1.8 seconds. The findings demonstrate that YOUTHIRON improves screening efficiency by 66.7% and supports early detection and monitoring of adolescent anemia. However, this study is limited by a relatively small sample size and controlled testing conditions. This study contributes to the information systems field by providing a validated integration of mobile health architecture, rule-based clinical decision support, usability evaluation, and system performance measurement within a unified digital screening platform.

**Index Terms**—Anemia screening, decision support system, mobile health, system evaluation, youth health informatics.

## I. INTRODUCTION

The development of mobile health (mHealth) technology in

recent years has transformed digital healthcare services, particularly in preventive screening systems and community-based health monitoring [1]. The integration of mobile devices, cloud computing, and database systems enables real-time, centralized health data recording and analysis, thereby improving the effectiveness of early disease detection and data-driven decision-making [2]. The World Health Organization (WHO) also emphasizes that mHealth utilization plays an important role in expanding access to health screening among adolescents. This population group often faces limited access to formal healthcare services [3]. Recent studies have highlighted the growing role of mobile health technologies in supporting preventive healthcare monitoring and adolescent health services [4], [5].

In Indonesia, the prevalence of anemia among adolescents remains relatively high and has significant impacts on learning concentration, immune endurance, and long-term productivity [6]. However, anemia screening is still implemented in schools and primary healthcare facilities primarily manually, using paper-based forms or separate record-keeping systems that are not integrated with regional health information systems [7]. This condition has been reported to limit longitudinal monitoring, population-level analysis, and evidence-based reporting, all of which are required for effective health intervention planning [8]. Furthermore, screening results are still classified manually, which creates the potential for interpretation errors and data inconsistencies.

Previous studies have developed various digital health solutions, including web-based health information systems for maternal health monitoring [9] telemedicine platforms for remote consultations [10] and mobile-based diagnostic applications for disease symptom identification [11]. Furthermore, decision support systems using rule-based and machine-learning approaches have been widely applied to clinical risk classification [12]. However, these studies generally address these aspects in isolation. Some focus on mobile platforms without integrating clinical hematological data, while others implement decision support mechanisms

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without incorporating usability evaluation. As a result, few studies have integrated clinical data processing, decision support, and user-centered evaluation in a single platform. Therefore, there remains a clear research gap in the integration of (1) digital hematological parameters, (2) automated rule-based classification based on clinical standards, and (3) comprehensive evaluation including usability, accuracy, and system performance within a mobile-based adolescent anemia screening system [13].

From an Information Systems engineering perspective, therefore, three major challenges need to be addressed. First, the lack of integrated, digital, and centralized recording of anemia screening data makes population-level aggregation and analysis difficult [14]. Second, there is a lack of automated classification mechanisms based on clinical parameters that can systematically support decision-making [15]. Third, insufficient attention has been given to user-centered interface design, which contributes to low adoption rates of health applications among adolescents [16]. The increasing adoption of mobile health technology has also encouraged the development of digital healthcare services that are more accessible, efficient, and user-centered. In preventive healthcare contexts, mobile applications offer opportunities for faster data collection, real-time monitoring, and improved access to health information, particularly for adolescents who are highly familiar with smartphones. Therefore, integrating mobile health systems into adolescent anemia screening can improve early detection and support more effective health monitoring.

Although several studies have implemented mobile health applications and decision support systems in healthcare, many existing systems still focus on specific functionalities, such as symptom recording, health information delivery, or standalone clinical assessment. Limited studies have integrated hematological parameter processing, automated risk classification, usability evaluation, and system performance measurement within a single mobile-based platform for adolescent anemia screening. This limitation underscores the need for a more comprehensive, integrated approach to support early detection and preventive healthcare monitoring.

Based on these gaps and challenges, this study aims to: (1) design a mobile health-based adolescent anemia screening information system that integrates digital hematological data, (2) implement a rule-based decision support classification model based on WHO hemoglobin standards, and (3) evaluate system usability, classification accuracy, and performance using standardized methods including System Usability Scale (SUS), confusion matrix analysis, and response time measurement. The proposed system, YOUTHIRON, is developed using a three-tier architecture (presentation, application, and data layers) to ensure modularity, scalability, and data security [17].

In addition to supporting early screening activities, the proposed system also contributes to digital health transformation by demonstrating how mobile technology can be integrated with rule-based clinical assessment and real-time data processing. The integration of these components is

expected to improve the effectiveness of preventive healthcare services and provide a more practical screening mechanism for adolescent health monitoring.

The contribution of this study to the Information Systems discipline is threefold. First, it provides a validated integration of mobile health architecture and clinical data processing for adolescent anemia screening. Second, it demonstrates a rule-based decision support mechanism aligned with WHO clinical standards. Third, it offers an empirical evaluation framework combining usability ( $SUS = 82.3$ ), classification accuracy (90%), and system performance (1.8 seconds response time), which can serve as a reference model for developing data-driven preventive health information systems [18].

The development of YOUTHIRON also demonstrates how mobile health technology can be used to support more adaptive, data-driven healthcare services. By integrating digital screening processes with mobile-based information systems, the proposed approach may improve accessibility, efficiency, and user engagement in preventive healthcare practices, particularly among adolescents who are highly familiar with smartphones.

This paper is organized as follows. Section II presents the research methodology based on the Design Science Research approach. Section III presents the results and discussion, including system implementation and evaluation. Section IV concludes the study and provides recommendations for future research.

## II. RESEARCH METHOD

This study adopts the design science research (DSR) approach, which focuses on the development and evaluation of technological artifacts to address real-world problems within the context of health information systems. The DSR approach was selected because this research aims not only to analyze phenomena but also to produce a solution in the form of an empirically validated information system.

The research process begins with the problem identification stage, which involves analyzing the current state of adolescent anemia screening practices, which are still conducted manually and lack digital integration. The next stage is defining solution objectives, aimed at designing a mobile-based information system capable of recording screening data, performing automatic classification based on hemoglobin parameters, and generating structured screening reports.

The subsequent phase involves artifact design, including system architecture, database, and user interface design, as well as the development of an anemia classification algorithm. The system development stage is carried out using the Android platform for the user side and backend services for business logic processing and data management. After the system is fully developed, a demonstration phase is conducted through system implementation in an adolescent anemia screening scenario to ensure that system functionalities operate as required. The final stage is evaluation, which assesses functional quality, system performance, and the application's

usability.

#### A. System Architecture

The YOUTHIRON system is designed using a three-tier architecture to ensure system modularity, scalability, and ease of maintenance. The first layer is the presentation layer, implemented as an Android-based mobile application. This layer is responsible for user interaction, including identity data entry, hemoglobin value input, and the display of classification results and recommendations. The interface is designed using a user-centered design approach to align with adolescent user characteristics and usability needs.

The second layer is the application layer, which serves as the core of the system's business logic. This layer includes a rule engine module for anemia classification based on hemoglobin threshold values, an input validation module, and mechanisms for user authentication and authorization management.

The third layer is the data layer, which manages the storage and organization of user data and screening results. Data are stored in a structured format to support reporting processes, trend analysis, and potential integration with other health information systems.

#### B. Anemia Classification Model

The classification model implemented in the YOUTHIRON system adopts a rule-based decision support approach based on World Health Organization (WHO) hemoglobin standards. Unlike binary classification models, this study uses four classification levels to improve screening accuracy:

- Normal: Hb  $\geq 12$  g/dL
- Mild anemia: Hb 11–11.9 g/dL
- Moderate anemia: Hb 8–10.9 g/dL
- Severe anemia: Hb  $< 8$  g/dL

The classification model can be expressed as follows:

$$C(Hb) = \begin{cases} \text{Normal,} & Hb \geq 12 \\ \text{Mild Anemia,} & 11 \leq Hb < 12 \\ \text{Moderate Anemia,} & 8 \leq Hb < 11 \\ \text{Severe Anemia,} & Hb < 8 \end{cases} \quad (1)$$

This rule-based approach ensures transparency, clinical relevance, and consistency with international standards.

#### C. Symptom Instrument

In addition to hemoglobin values, the system incorporates a symptom-based screening component that includes fatigue, dizziness, pallor, shortness of breath, and difficulty concentrating. The symptom questionnaire was adapted from established clinical anemia indicators and validated through a literature review and expert consultation. This adaptation ensures that the instrument is clinically relevant and suitable for early-stage screening.

#### D. Evaluation Method

System evaluation was conducted through four main stages:

##### 1) Black-box testing

Conducted to validate that all system functionalities operated according to specifications, including input, processing, storage, and output modules. The evaluation process ensured that all system functionalities met the predefined requirements and could support real-time screening activities efficiently.

##### 2) Usability evaluation (SUS)

The usability evaluation involved 30 adolescent respondents aged 15–19 years, selected using purposive sampling. Inclusion criteria included active smartphone users and willingness to participate in the study, while exclusion criteria included incomplete questionnaire responses.

Based on gender distribution, 20 respondents (66.7%) were female, and 10 respondents (33.3%) were male. Based on screening results, 18 respondents (60%) were categorized as non-anemic, while 12 respondents (40%) showed indications of mild to moderate anemia. All respondents had previous experience using mobile applications and were familiar with smartphone-based health services.

To evaluate the reliability of the SUS instrument, Cronbach's alpha analysis was performed. The obtained Cronbach's alpha coefficient was 0.87, indicating excellent internal consistency and reliability of the usability instrument.

In addition, a descriptive comparison by gender was conducted to examine usability score trends across respondent groups. Female respondents had slightly higher average SUS scores than male respondents. However, inferential statistical testing, such as an independent t-test or ANOVA, was not performed due to the limited sample size. Future studies are recommended to involve larger respondent groups to enable more comprehensive statistical analysis.

SUS scores were calculated according to standard procedures, and the analysis included both the mean and standard deviation to ensure statistical reliability. Previous studies also emphasized that usability evaluation plays an important role in determining user acceptance of mobile healthcare applications [19].

##### 3) Accuracy evaluation

Accuracy was measured using a confusion matrix, comparing system classifications with validation by health practitioners.

##### 4) Response time testing

System performance was measured based on the time interval between data input submission and the display of classification results.

### E. Testing Environment

System testing was conducted on Android devices running Android 10-13 under stable network conditions (WiFi and 4G). This setup ensures consistent performance evaluation across different device specifications.

### F. System Architecture Diagram

Figure 1 illustrates the three-tier architecture implemented in the YOUTHIRON system. Conceptually, the system architecture consists of the following components.

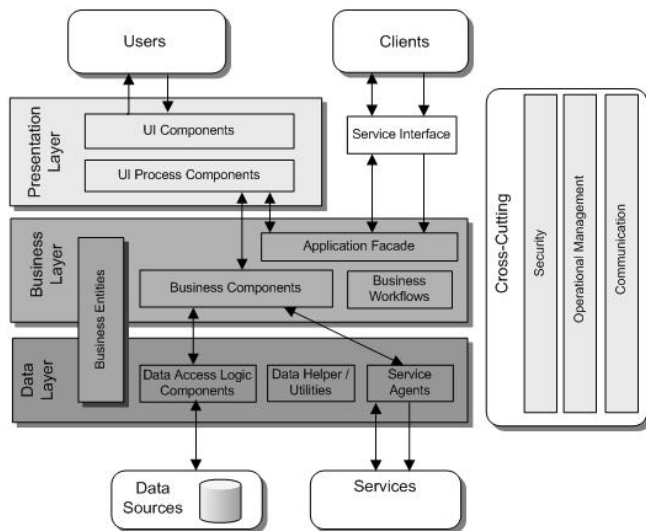


Fig. 1. YOUTHIRON system architecture.

- 1) *Presentation layer (client side – Android application)*
- 2) This layer is responsible for handling user interactions, including:
  - Adolescent identity data input
  - Hemoglobin (Hb) value input
  - Displaying anemia classification results
  - Displaying screening history
- 3) *Application layer (business logic & rule engine)*
- 4) This layer manages:
  - Input data validation
  - Rule-based anemia classification processes
  - User authentication management
  - Report processing and data recapitulation
- 5) *Data layer (database management system)*
- 6) This layer functions to:
  - Store user data
  - Store Hb screening results
  - Store system activity logs
  - Support queries for analysis and reporting purposes

The separation of these layers aims to improve system maintainability, data security, and scalability, enabling future expansion into a broader health platform.

### G. Anemia Classification Process

The anemia classification workflow in the YOUTHIRON system (Fig. 2) is described as follows:

- The user inputs the hemoglobin (Hb) value.
- The system validates that the input is numeric and within a

clinically acceptable range.

- The system compares the Hb value with WHO classification thresholds.
- $\text{Hb} \geq 12 \text{ g/dL} \rightarrow \text{Normal}$
- $\text{Hb } 11\text{--}11.9 \text{ g/dL} \rightarrow \text{Mild anemia}$
- $\text{Hb } 8\text{--}10.9 \text{ g/dL} \rightarrow \text{Moderate anemia}$
- $\text{Hb} < 8 \text{ g/dL} \rightarrow \text{Severe anemia}$
- The classification result is displayed and stored in the database.

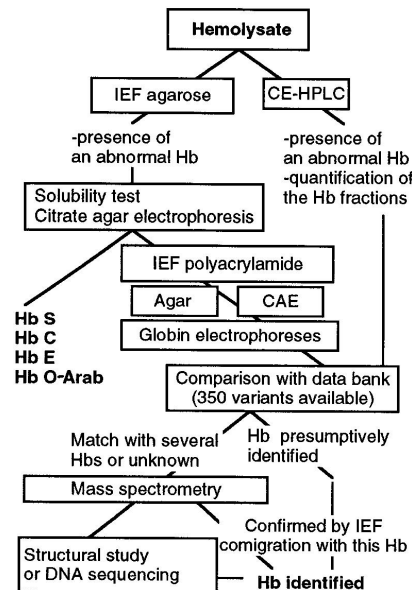


Fig. 2. YOUTHIRON system workflow.

The rule-based approach was selected because it is deterministic, transparent, and appropriate for early-stage screening in line with clinical standards. Furthermore, this structure allows future development toward multivariate classification models if additional variables, such as age, body mass index (BMI), or iron intake patterns, are incorporated.

### H. Black-Box Testing Scenarios

To ensure that all system functionalities operate in accordance with the specified requirements, black-box testing was conducted using predefined testing scenarios presented in Table 1.

Table 1.  
Functional Testing Scenario

| No | Test Scenario                           | Input             | Expected Output                    | Status |
|----|-----------------------------------------|-------------------|------------------------------------|--------|
| 1  | Valid identity data input               | Name, age, gender | Data stored in the database        | Valid  |
| 2  | Hb input $\geq 12 \text{ g/dL}$         | 13.2              | System displays "Normal."          | Valid  |
| 3  | Hb input $11\text{--}11.9 \text{ g/dL}$ | 11.5              | System displays "Mild Anemia."     | Valid  |
| 4  | Hb input $8\text{--}10.9 \text{ g/dL}$  | 9.2               | System displays "Moderate Anemia." | Valid  |

|   |                          |                        |                                      |       |
|---|--------------------------|------------------------|--------------------------------------|-------|
| 5 | Hb input < 8 g/dL        | 7.5                    | System displays "Severe Anemia."     | Valid |
| 6 | Non-numeric Hb input     | "abc"                  | Validation error message appears     | Valid |
| 7 | Access screening history | Click the history menu | Complete screening history displayed | Valid |

Testing was conducted across multiple Android devices with varying specifications to ensure consistent system performance. All core functionalities were evaluated without examining the internal code structure, in accordance with the principles of black-box testing.

### III. RESULT & DISCUSSION

This study resulted in the development of a mobile health (mHealth)-based adolescent anemia screening information system, YOUTHIRON, designed to support early detection of anemia risk by integrating clinical symptom data and digital hematological parameters. The system was developed using a prototype approach, enabling iterative interaction and refinement during early development stages.

The system involves two primary actors: (1) adolescents as users who input identity data and symptom information, and (2) administrators or healthcare personnel who validate data and input laboratory examination results. The main system features include user registration and login, symptom-based screening input, entry of hemoglobin (Hb) values, automatic anemia classification, a monitoring dashboard, and examination history. The system was implemented as a mobile web-based application, allowing access via smartphones without requiring installation, thereby supporting accessibility in mHealth services.

#### A. System Implementation

Figure 3 presents the application interface, including the landing page and main dashboard. The landing page serves as the initial interaction point, providing basic information and intuitive navigation. The dashboard displays hematological parameters such as Hb, RBC, MCV, and RDW, which are processed in real time to generate indicators such as BMI, Mentzer Index, and RDWI. The results are presented using visual indicators (e.g., ideal and at risk), making it easy for non-medical users to interpret the output. In addition, the system provides educational content, iron supplementation reminders, and records of screening history.

The mobile-based interface in Figure 3 was designed to support user-friendly interaction and efficient screening activities among adolescents. The system dashboard enables users to monitor hematological indicators and screening outcomes in real time through simplified visual representations.

In addition, the application integrates educational modules, personalized monitoring support, and screening history

management to enhance user participation in digital health services. The interface also uses simplified visual indicators to help adolescent users understand screening outcomes more intuitively and to support early awareness of anemia prevention.

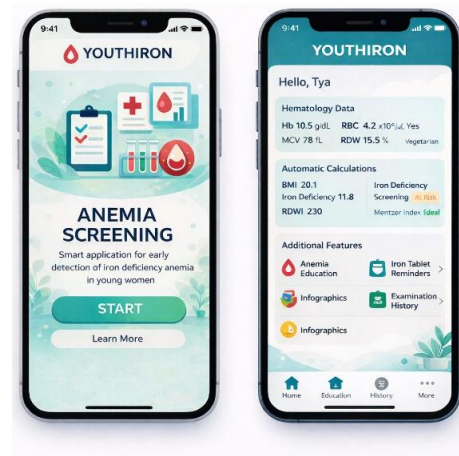


Fig. 3. YOUTHIRON mHealth application.

#### B. Anemia Classification Results

The system applies classification according to World Health Organization standards, as shown in Table 2.

Table 2.  
Anemia Categories Based on WHO Standards

| Hemoglobin (Hb) Value | Category        |
|-----------------------|-----------------|
| $\geq 12$ g/dL        | Normal          |
| 11–11.9 g/dL          | Mild Anemia     |
| 8–10.9 g/dL           | Moderate Anemia |
| $< 8$ g/dL            | Severe Anemia   |

This integration demonstrates a practical implementation of the digital hematology concept, combining laboratory data with an information system to support data-driven health decisions.

#### C. Symptom-Based Risk Assessment

Table 3 presents the symptom scoring used for anemia risk assessment.

Table 3.  
Anemia Risk Assessment Scoring

| Symptom                  | Weight |
|--------------------------|--------|
| Fatigue                  | 2      |
| Dizziness                | 2      |
| Pallor                   | 3      |
| Shortness of breath      | 2      |
| Difficulty concentrating | 1      |

The total score is calculated using the following equation:

$$Score = \sum_{i=1}^n (w_i \times s_i) \quad (2)$$

where  $w_i$  represents the symptom weight and  $s_i$  represents the symptom condition, where 1 indicates the presence of a symptom, and 0 indicates the absence of a symptom. Table 4

shows the anemia risk classification categories.

Table 4.  
Risk Classification

| Score    | Risk Level |
|----------|------------|
| 0–3      | Low        |
| 4–6      | Moderate   |
| $\geq 7$ | High       |

Example calculation: A user experiences the following symptoms:

- Fatigue (1)
- Dizziness (1)
- Pallor (1)
- Shortness of breath (0)
- Difficulty concentrating (1)

$$\text{Score} = (2 \times 1) + (2 \times 1) + (3 \times 1) + (2 \times 0) + (1 \times 1) = 8$$

The result indicates a high risk of anemia; therefore, the system recommends a further medical examination.

#### D. System Performance and Accuracy

The system's classification accuracy was evaluated using a confusion matrix by comparing its outputs with expert validation results. Table 5 presents the confusion matrix used to evaluate the classification performance of the YOUTHIRON system.

Table 5.  
Confusion Matrix of Anemia Classification

| Predicted Class | Actual Positive | Actual Negative |
|-----------------|-----------------|-----------------|
| Normal          | 12              | 1               |
| Anemia          | 2               | 15              |

Based on the confusion matrix results, the system achieved an accuracy of 90%, sensitivity of 88.2%, specificity of 93.7%, and an F1-score of 90.0%. These results indicate that the system provides reliable classification performance for early-stage adolescent anemia screening. The accuracy is calculated as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

where TP represents true positive, TN represents true negative, FP represents false positive, and FN represents false negative.

#### E. Response Time Evaluation

System performance testing shows that the average response time from data input to classification output is 1.8 seconds, indicating the system provides fast, efficient processing under normal operating conditions.

#### F. Usability Evaluation

Usability testing was conducted using the System Usability Scale (SUS) involving 30 respondents. A SUS score of 82.3 indicates excellent usability and high user acceptance.

Table 6.  
Evaluation Results

| Parameter             | Value |
|-----------------------|-------|
| Number of respondents | 30    |

|                    |           |
|--------------------|-----------|
| Average SUS score  | 82.3      |
| Standard deviation | 5.6       |
| Grade              | A         |
| Acceptability      | Excellent |

#### G. Implementation Impact Analysis and Limitation

The implementation of the YOUTHIRON system delivers several significant improvements over the conventional manual screening method. In terms of screening time efficiency, the manual process typically takes 10–15 minutes per user, whereas the YOUTHIRON system reduces this to 3–5 minutes. The efficiency improvement is calculated using the following formula:

$$\text{Efficiency}(\%) = \frac{T_{\text{manual}} - T_{\text{system}}}{T_{\text{manual}}} \times 100 \quad (4)$$

where  $T_{\text{manual}}$  represents the processing time using the manual method and  $T_{\text{system}}$  represents the processing time using the YOUTHIRON system. Based on the measurement results, the system achieved an efficiency improvement of 66.7%, indicating a substantial acceleration in the screening process. The comparison between manual screening and the YOUTHIRON system was conducted descriptively because detailed paired measurement data were unavailable. Future studies are recommended to perform paired t-tests to evaluate statistical significance between screening methods. In terms of classification performance, the system achieved an accuracy rate of 90%, calculated using the standard accuracy formula:

$$\text{Accuracy} = \frac{TP + TN}{\text{Total Data}} \quad (5)$$

This result is based on a comparison between system-generated results and validation by healthcare professionals, indicating that the system can provide a reliable anemia risk classification. From the perspective of user acceptance, the evaluation results show that 86% of respondents found the system easy to use, 90% expressed willingness to use it again, and 83% stated that the system helped them better understand anemia risk. These findings indicate that implementing the mHealth approach positively affects usability and improves adolescent health literacy.

Overall, these results confirm that the YOUTHIRON system effectively enhances screening efficiency, supports decision-making, and improves user engagement in preventive healthcare. However, this study has several limitations. The system evaluation was conducted using a limited number of respondents under controlled testing conditions and stable network environments. Therefore, the findings may not fully represent system performance and user behavior in large-scale or real-world deployment contexts. Future studies are recommended to involve a larger, more diverse population and to evaluate system performance under varying network conditions and in real clinical environments.

#### H. Discussion

The results of this study demonstrate that integrating a mobile health (mHealth)-based information system can

significantly improve the effectiveness of adolescent anemia screening. The YOUTHIRON system not only facilitates digital data recording but also provides automated risk classification based on hematological parameters and symptom-based assessment, thereby addressing the research gap, as previous studies often implemented these components separately.

Compared to prior studies that focused either on mobile health applications [9], [10], [11] or decision support systems [10], this study offers a more comprehensive approach by integrating rule-based classification aligned with World Health Organization (WHO) standards, usability evaluation, and system performance measurement within a single platform. The findings also indicate that integrating mobile health technology with rule-based clinical screening can support more efficient preventive healthcare services, particularly in adolescent health monitoring and early detection programs. In addition, the proposed system demonstrates the potential of mobile health applications to improve accessibility, screening efficiency, and user engagement in preventive healthcare practices. The system achieved a System Usability Scale (SUS) score of 82.3, indicating excellent usability, and a classification accuracy of 90%, confirming its reliability for early screening purposes. These findings are consistent with previous studies showing that mobile health systems and clinical decision support technologies can improve healthcare accessibility and screening efficiency [20], [21].

The high usability score obtained in this study indicates that users were able to interact with the system intuitively with minimal difficulty. This indication suggests that the interface design and navigation structure were sufficiently optimized for adolescent users, supporting effective user interaction during the screening process. In addition, the positive usability results indicate the potential for broader adoption of the system in preventive healthcare activities.

The implementation also resulted in a 66.7% improvement in time efficiency, reducing screening duration from 10–15 minutes to 3–5 minutes. In addition, the average response time of 1.8 seconds indicates that the system delivers fast, responsive performance, which is essential for mobile applications. High user acceptance levels further demonstrate that the system is easy to use and contributes to improving adolescent health literacy. In practice, the proposed system can assist healthcare personnel and educational institutions in conducting more structured and efficient anemia screening among adolescents. The integration of mobile health technology also supports digital health transformation by enabling faster access to screening information and improving user participation in preventive healthcare programs.

The integration of mobile health technology with rule-based screening mechanisms also demonstrates the potential of information systems to support data-driven preventive healthcare services. By enabling faster screening processes and

more structured clinical data management, the proposed system may help healthcare providers and educational institutions improve adolescent health monitoring. Furthermore, implementing digital screening systems can increase healthcare accessibility and promote early awareness of anemia prevention among adolescents.

The study also highlights the role of mobile-based information systems in supporting preventive healthcare programs by enabling more efficient and accessible screening. The integration of digital hematological data processing, automated classification, and user-centered mobile interfaces demonstrates how information systems can facilitate healthcare delivery beyond conventional manual approaches. In addition, the system's positive usability and performance outcomes indicate that mobile health applications have considerable potential to support broader health monitoring initiatives among adolescents in educational and community healthcare environments.

The implementation of YOUTHIRON also underscores the broader role of mobile health information systems in supporting adaptive, technology-driven preventive healthcare services. By integrating automated screening, real-time data processing, and mobile accessibility, the system can enable more adaptive, efficient healthcare monitoring. Furthermore, the use of mobile-based screening systems may help improve health awareness, increase user participation in preventive healthcare programs, and facilitate more structured health data management in adolescent healthcare environments.

The findings of this study further indicate that integrating mobile health systems into preventive healthcare services may yield long-term benefits for health data management and monitoring. Digital screening systems can support more systematic data collection processes, reduce manual recording errors, and improve the efficiency of health information delivery. In addition, the availability of real-time screening results on mobile devices may encourage adolescents to become more actively involved in monitoring their own health and increase awareness of anemia prevention and early detection practices.

Despite the promising findings, a broader evaluation involving larger populations and more diverse clinical environments is still needed further to validate the robustness and scalability of the proposed system.

#### IV. CONCLUSION

This study developed a mobile health (mHealth)-based adolescent anemia screening information system called YOUTHIRON, integrating digital hematological data processing, a rule-based anemia classification model aligned with WHO standards, and an interactive mobile interface within a unified platform. Implementing a three-tier architecture enables real-time data processing, enabling users to obtain screening results and health indicators efficiently in an

easily interpretable format.

The evaluation results demonstrate that the system performs effectively across functionality, usability, and performance. The SUS usability evaluation yielded a score of 82.3, indicating excellent user acceptance. In addition, the system achieved 90% classification accuracy and improved screening efficiency by reducing processing time compared to conventional manual methods. The average response time of 1.8 seconds further indicates that the proposed system delivers responsive performance suitable for mobile-based healthcare applications.

These findings indicate that YOUTHIRON is feasible as a mobile-based health information system to support early detection and monitoring of adolescent anemia. The integration of mobile health technology with rule-based clinical screening also demonstrates the potential to improve accessibility, efficiency, and user engagement in preventive healthcare services, particularly among adolescents. Moreover, the system can support healthcare personnel and educational institutions in conducting faster and more structured screening activities.

From an Information Systems perspective, this study contributes by demonstrating how to integrate mobile health architecture, clinical data processing, and empirical system evaluation within a preventive healthcare context. The findings also provide practical insights into implementing mobile health systems for public health screening and digital health monitoring.

The proposed system may also serve as a reference model for future mobile health system development, particularly in preventive healthcare services that require efficient screening, real-time data processing, and user-centered interaction. The results of this study also indicate that mobile health-based information systems can support more efficient and accessible preventive healthcare services, particularly in adolescent health monitoring activities. The integration of automated screening and real-time mobile access demonstrates the potential of digital health technologies to improve healthcare delivery and encourage early health awareness among users.

However, this study has several limitations, including the relatively small number of respondents and testing conducted under controlled conditions. Therefore, future research should involve larger, more diverse populations, evaluate system performance in real-world healthcare environments, and explore more advanced predictive models to improve classification performance, scalability, and long-term system effectiveness.

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