International Journal of Information Technology and Computer Science Applications (IJITCSA)
p-ISSN: 2964-3139 e-ISSN: 2985-5330
Vol. 03, No. 03, page 132 - 142
Submitted 13/11/2025; Accepted 24/12/2025; Published 25/12/2025

NeoCare: Telehealth System with Intelligent Notification for Neonatal Care

[1]Tb Ai Munandar, [2]Tyastuti Sri Lestari, dan [3]Achmad Noe'man
[1,2,3]Informatics, Universitas Bhayangkara Jakarta Raya, INDONESIA
e-mail : [1]tbaimunandar@gmail.com, [2]tyas@ubharajara.ac.id,
[3]achmad.noeman@dsn.ubharajaya.ac.id

Corresponding Autor: Tb Ai Munandar

Abstract

Neonatal mortality in low- and middle-income countries remains high, partly because early physiological deterioration is detected late and continuous monitoring is limited outside specialized units. To address this gap, this study presents NeoCare: Telehealth System with Intelligent Notification for Neonatal Care, a multi-actor platform that integrates neonatal data management, vital-sign monitoring, and machine-learning–based alerts. The research followed a software engineering approach comprising stakeholder and context analysis, requirements engineering, clinical data acquisition, system and database design, intelligent notification model design, and prototype implementation. Retrospective neonatal records from two Indonesian referral hospitals were used to characterize heterogeneous and homogeneous clinical populations and to inform the design of classification features for vital-sign–based risk assessment. NeoCare is realized as a layered architecture with sensor, device, communication, processing-intelligence, and application layers. The prototype includes web and mobile interfaces tailored to four actor groups: hospital administrators, doctors, midwives, and parents. Administrators manage users, hospitals, vital-sign data, and machine-learning models while supervising alert output. Doctors and midwives access dashboards that display neonatal lists, detailed histories, trend graphs, and consultation management, supporting triage and longitudinal follow-up. Parents use a simplified mobile interface to view their baby's status, monitor vital-sign trends, receive alerts, and schedule consultations. The system embeds an intelligent notification mechanism that flags abnormal patterns and presents them through color-coded indicators and concise messages. The results demonstrate the technical feasibility and coherence of a role-based, data-driven telehealth platform for neonatal care, providing a solid foundation for future work on clinical validation, device integration, and large-scale deployment.

Keywords—telehealth, neonatal care, intelligent notification, machine learning, vital signs monitoring.

1 Introduction

Neonatal mortality remains a pressing global health challenge despite decades of progress. In 2022–2023, an estimated 2.3 million newborns died in the first 28 days of life—around 6,300 deaths every day—while the decline in neonatal mortality has been slower than that of post-neonatal under-five deaths and has begun to plateau in many regions [1], [2]. Low- and middle-income countries (LMICs) carry a disproportionate share of this burden; in Indonesia, recent estimates suggest a neonatal mortality rate of roughly 11–15 deaths per 1,000 live births, corresponding to tens of thousands of newborn deaths annually despite notable gains since the 1990s [3]. These preventable deaths are closely linked to delayed recognition of deterioration, limited access to specialized neonatal services, and fragmented continuity of care between hospital and home.

In resource-constrained settings, neonatal intensive care units (NICUs) often face shortages of specialized staff, limited bed capacity, and unequal geographic distribution of referral centers. After early discharge, many newborns—especially those who are premature or clinically unstable—are followed only through intermittent outpatient visits or paper-based home records, with vital signs and anthropometric data rarely captured systematically. Bedside observation in smaller facilities frequently relies on manual vital-sign measurement and informal clinical judgement, which can lead to missed early warning signs and delayed escalation of care. These structural constraints point to the need for models of neonatal care that extend surveillance beyond the NICU and enable timely, data-driven responses closer to families.

Telehealth and telemedicine have emerged as promising approaches to bridge gaps in neonatal expertise and monitoring by enabling remote consultations, virtual rounds, and shared decision-making across levels of care. Recent teleneonatology pilots have shown that real-time audiovisual communication between peripheral hospitals and higher-level NICUs can improve access to specialist input, optimize bed utilization, and support safer decisions around transport and discharge [4]. Complementing these implementation studies, a 2025 bibliometric analysis documented a substantial increase in research on telemedicine for newborns and NICUs over the past two decades, with a clear shift toward integrated, networked models of neonatal care [5]. However, most existing deployments still focus on synchronous video consultations and image sharing rather than continuous physiologic data streams combined with automated early warning and role-specific clinical interfaces.

Parallel advances in neonatal informatics and artificial intelligence (AI) have demonstrated how large-scale electronic health records, high-frequency monitoring data, and predictive models can transform neonatal care from reactive to proactive. Barrett et al. summarize how neonatal informatics—combining data standards, EHRs, and AI—has driven progress in areas such as sepsis detection, necrotizing enterocolitis prediction, imaging analysis, and mortality risk stratification, while highlighting the importance of workflow integration and clinician trust [6]. A complementary systematic review by Tudor et al. shows that AI models in NICUs can predict clinical outcomes and length of stay with promising accuracy, yet most remain at early development stages with limited external validation and sparse embedding in real-world systems [7]. Rallis et al. similarly note that AI applications in NICUs span neurocritical care, respiratory support, sepsis, and retinopathy of prematurity, but emphasize the need for robust evaluation and ethically sound deployment [8].

Machine-learning-based early warning systems are particularly relevant to neonatal safety, as clinical deterioration is often subtle and develops over hours rather than minutes. In a recent modeling competition using data from more than 6,000 NICU admissions, Sullivan et al. compared logistic regression, gradient-boosting trees, neural networks, and other techniques for neonatal mortality prediction; dynamic models that incorporated temporal patterns of heart rate and oxygen saturation provided earlier and more informative risk signals than static baselines [9]. Subsequent work by the same group and others has shown that machine-learning models can serve as early warning systems for neonatal infection, synthesizing vital signs and laboratory markers to flag sepsis risk before overt clinical deterioration [10]. Beyond neonatology, Thiele et al. demonstrated that real-time models trained on high-frequency vital signs can detect impending deterioration up to 10 hours before onset in general hospital populations, illustrating the potential of continuous data streams for intelligent notification [11].

At the same time, rapid innovation in neonatal monitoring hardware is expanding the range of physiologic data that can be captured both inside and outside the NICU. Emerging wearable and non-contact sensor technologies enable continuous measurement of heart rate, respiratory rate, oxygen saturation, and movement with fewer wires and less skin irritation, while novel camera-based systems can derive respiratory and hemodynamic parameters from RGB-D signals [12], [13]. Although most of these technologies are still evaluated in controlled NICU environments with relatively small samples, they point toward near-future telehealth scenarios in which vital-sign data from incubators, bassinets, or home devices can be streamed securely to cloud-based platforms for real-time analysis and visualized for different user groups.

Despite these advances, significant gaps remain in translating AI and telemedicine into holistic, family-centered neonatal care supported by concrete software tools. Many AI models are developed on single-center datasets, lack interoperability with existing hospital systems, and are rarely packaged into user-friendly applications that fit clinicians' daily routines [6], [7]. Telehealth initiatives, in turn, often operate as stand-alone services with limited integration of structured data, decision support, or parent-facing dashboards [4], [5]. For LMICs, additional barriers include uneven digital infrastructure, heterogeneous documentation practices, and the need to design solutions that function reliably with modest bandwidth and ubiquitous, low-cost devices such as Android smartphones.

Indonesia exemplifies this tension between opportunity and constraint. The country has achieved a marked reduction in neonatal mortality since 1990, yet thousands of newborns still die each year from preventable causes, and access to specialized neonatal care remains uneven across districts [3]. At the same time, national commitments to universal health coverage, rapid expansion of mobile connectivity, and growing investments in digital health create fertile ground for telehealth-enabled models of neonatal care. However, existing digital initiatives have primarily targeted adult or general primary care; integrated telehealth platforms specifically tailored to the needs of neonates, their parents, and multidisciplinary hospital teams—complete with monitoring dashboards, appointment management, and alert supervision—are still rare.

Within this landscape, there is a compelling rationale for telehealth systems that do more than transmit images or support episodic consultations. For high-risk newborns, what is needed is continuous or high-frequency collection of vital signs and anthropometric data, automated risk assessment based on established clinical thresholds and machine-learning models, and intelligent notification that directs the right information to the right provider or caregiver at the right time. Such systems must accommodate multiple actors—administrators, neonatologists, midwives, and parents—while maintaining data security, privacy, and clarity of clinical responsibility. They should also be transparent and interpretable, favoring models whose decisions can be understood by clinicians and explained to families, and they must be realized as concrete, usable applications that can fit into everyday neonatal workflows.

The present work introduces NeoCare: Telehealth System with Intelligent Notification for Neonatal Care, a telehealth platform designed to address these gaps. NeoCare integrates structured neonatal data from two Indonesian referral centers, routine vital-sign measurements, and multi-actor dashboards with an intelligent notification module that classifies neonatal status and triggers alerts based on patterns in vital signs and clinical features. The system is implemented as a layered architecture and realized in a set of web and mobile prototypes: an administrative console for managing users, vital-sign data, and machine-learning models; a parent application for monitoring the baby's condition and managing consultation appointments; and dedicated dashboards for doctors and midwives to monitor neonates, review vital-sign trends, and handle scheduled consultations. To support adoption in resource-constrained settings, NeoCare focuses on classical, interpretable machine-learning algorithms and a modular design that can be deployed alongside existing hospital information systems or as a stand-alone solution.

This paper focuses on the conceptualization, design, and prototype implementation of NeoCare as a telehealth system with intelligent notification rather than on exhaustive model benchmarking. We describe the system requirements and stakeholder analysis, the data resources and their complementary clinical profiles, the overall architecture and database design, the realized multi-actor interfaces, and the intelligent notification pipeline that translates neonatal vital-sign data into actionable alerts. By situating NeoCare within contemporary developments in neonatal telehealth, AI, and monitoring technologies, we aim to demonstrate how an integrated, context-aware telehealth platform can contribute to earlier detection of deterioration, better coordination of care, and more confident participation of parents in the care of their newborns. In doing so, this work seeks to provide a methodological, architectural, and prototypical reference for future AI-enabled telehealth systems dedicated to neonatal care in Indonesia and similar settings.

2 Research methods

This study employed a multi-stage, software engineering–oriented research method that combined context and stakeholder analysis, requirements engineering, multi-center data collection, system architecture and database design, and multi-actor prototype development. The overarching goal was to design and implement NeoCare: Telehealth System with Intelligent Notification for Neonatal Care as a concrete, usable platform for hospital administrators, doctors, midwives, and parents, rather than solely as an abstract model.

Although the design was informed by contemporary literature on neonatal telehealth, AI-enabled monitoring, and IoT-based health systems, the emphasis of the research method was on translating these concepts into a working prototype that supports real-world workflows: managing neonatal data, monitoring vital signs, handling consultation appointments, and supervising alerts generated by an intelligent notification mechanism.

2.1. Context and Stakeholder Analysis

The first stage focused on understanding the clinical context and the actors involved in neonatal care at the participating hospitals. The analysis mapped how newborns move through the care pathway—from admission, treatment, and monitoring to discharge and follow-up—and identified where information gaps and handover problems most often occur.

Four primary stakeholder groups were identified:

1) Hospital administrators are responsible for governance, data management, and oversight of system usage.
2) Doctors are responsible for diagnosis, clinical decisions, and managing high-risk neonates.
3) Midwives, who perform day-to-day monitoring and provide frontline care.
4) Parents, who care for the baby at home, need clear information and guidance.

In addition, the NeoCare system itself was treated as an operational actor that continuously monitors incoming data and produces intelligent notifications. For each stakeholder, roles, information needs, and access privileges were documented. This provided the basis for designing role-specific interfaces and defining how each actor would use NeoCare in practice—for example, administrators managing master data and alerts, parents viewing the baby's status and appointments, midwives monitoring multiple neonates, and doctors combining monitoring with consultation management.

2.2. Requirements Analysis

The second stage involved formalizing these needs into functional and non-functional requirements. Functional requirements were expressed as services that NeoCare must provide, such as

1) The system provides user authentication and role-based access control.
2) The task involves the registration and management of neonatal profiles.
3) Recording, storage, and visualization of vital signs and anthropometric data.
4) Management of consultation appointments and associated clinical notes.
5) The system generates, displays, and manages intelligent notifications related to abnormal vital signs.

Each function was described using structured specifications (goal, actor, preconditions, main flow, alternative flows, and error handling) and organized into NEO-CARE use cases. Non-functional requirements covered security and privacy of neonatal data, reliability under intermittent connectivity, usability for non-technical users (especially parents), and scalability for future integration with hospital information systems.

To ensure a shared understanding between technical and clinical stakeholders, system behavior and interactions were modeled using UML artifacts. Use case diagrams showed which actors interact with which services; activity diagrams described workflows such as managing neonatal data, updating vital signs, responding to alerts, and managing appointments; and sequence and collaboration diagrams captured how interface components, controllers, and database entities interact when key tasks (e.g., creating an alert) are executed. These models served as blueprints for subsequent implementation.

2.3. Data Collection and Characterization

The third stage consisted of collecting and characterizing neonatal clinical data to ground the system in real practice and to inform the design of the intelligent notification logic. Retrospective medical records were obtained, through formal collaboration with hospital medical-records units, from two referral hospitals in Indonesia:

1) RS Bhayangkara Banten (Banten Province) provides a relatively homogeneous, lower-risk neonatal population.
2) RSUD dr. Soedono Madiun (East Java), providing a more heterogeneous population that includes premature and clinically complex cases.

The extracted variables included patient identity (anonymized), payer status, medical and nursing diagnoses, admission and discharge dates, anthropometric measures (birth weight, length, head and chest circumferences), physiological parameters (heart rate, respiratory rate, temperature, and, where available, oxygen saturation), and gestational age.

Descriptive statistics and graphical summaries were used to compare distributions of key variables between the two hospitals and to understand the range and heterogeneity of vital-sign values that NeoCare would need to handle. The more heterogeneous dataset was designated as the primary reference for designing classification features and alert thresholds, whereas the more homogeneous dataset was considered a representative low-risk profile to test whether the system's notification logic could accommodate stable cases without producing unnecessary alerts.

2.4. System Architecture and Design

The fourth stage translated the requirements and data characteristics into a modular system architecture suited for telehealth deployment. NeoCare adopts a five-layer architecture (see Figure 1) :

1) Sensor Layer (Data Acquisition)—represents the sources of neonatal vital signs and anthropometric measurements, such as temperature and heart rate sensors, incubator devices, or manual entry at the bedside.
2) Device Layer (Client Applications)—comprises Android and web clients used by parents, doctors, midwives, and administrators to view data, input measurements, and receive notifications.
3) Communication Layer—provides secure communication between clients and the back-end through RESTful APIs and encrypted channels, ensuring reliable data transfer under varying network conditions.
4) Processing & Intelligence Layer—hosts the relational database, business logic for managing records and appointments, user and role management, and the intelligent notification component that classifies neonatal status and generates alerts.
5) Application & Service Layer—exposes role-specific dashboards and services, including administrator consoles, clinical monitoring pages, and parent-facing views.

The database schema was designed to reflect this architecture and to support traceability of clinical events. Core tables include patients, vital signs, alerts, consultation notes, users, doctors, midwives, parents, and hospital information. Primary and foreign keys link vital signs and alerts to specific neonates and to the users who record or respond to them, enabling complete audit trails and longitudinal analysis of care.

2.5. Multi-Actor Prototype Development

The fifth stage involved building a working prototype of NeoCare that operationalizes the architecture for each actor group. For administrators, a web-based interface was developed to manage master data (neonates, parents, midwives, and doctors), configure hospital information, and supervise alerts and model configurations. The administrator dashboard includes patient lists, detailed patient views with identity and clinical information, tables of historical vital signs, and pages dedicated to viewing and filtering alerts by status, type, and time.

For parents, an Android-based interface was implemented to focus on individual baby monitoring and interaction with healthcare providers. The parent dashboard displays basic identity information and the latest vital signs using intuitive cards and color-coded indicators to highlight abnormal values. It also provides graphs of vital-sign trends over time and a consultation-appointment module that allows parents to request and review appointments with doctors directly within the system.

For midwives, the prototype offers a monitoring dashboard oriented toward operational workload. The interface summarizes the number of neonates under their care and lists active and discharged infants, with quick access to vital-sign histories and graphical visualizations. This design supports real-time and near–real-time monitoring of multiple babies and helps midwives identify which neonates require closer observation.

For doctors, a dedicated mobile interface combines monitoring, triage, and consultation management. The home screen shows the number of assigned patients, the count of upcoming consultations, and quick triage cues such as labels for potential hypothermia or other risk patterns based on vital signs. Doctors can drill down into detailed patient histories, review graphs of vital-sign trajectories, and manage appointments and consultation notes.

Backend services implement the logic needed to support these interfaces: user authentication and authorization, CRUD operations for neonatal and user data, storage and retrieval of vital signs, management of consultation requests and schedules, and logging of all alerts generated by the system. This stage demonstrates that the abstract architecture can be realized as a coherent, role-based telehealth platform.

2.6. Design of the Intelligent Notification Mechanism

The final methodological stage focused on designing the intelligent notification mechanism that underpins NeoCare's alerting behavior. Rather than aiming for exhaustive model benchmarking, the emphasis was on defining a practical and interpretable approach that could be embedded into the prototype and demonstrated in the user interfaces. The notification logic is framed as a classification task that assigns each new or updated set of vital signs to a status category such as normal, attention, or critical. Feature selection is guided by clinical relevance and the available datasets, incorporating anthropometric measures (e.g., birth weight and length) and physiological parameters (heart rate, respiratory rate, temperature, and, where applicable, oxygen saturation), together with contextual information such as gestational age.

Classical, interpretable machine-learning methods—such as k-Nearest Neighbors and decision trees—are prioritized conceptually because they can be implemented within the processing layer, and their behavior can be explained in terms familiar to clinicians. In the current prototype, this logic is combined with clinically informed thresholds so that:

1) Incoming vital-sign data are evaluated against predefined ranges and, where appropriate, model-based decision rules.
2) Status labels are produced and stored alongside each record.
3) New alerts are created in the alerts table when values or patterns fall into attention or critical categories.

These alerts are then propagated to the relevant interfaces: administrators see them in a consolidated alert-management page, doctors and midwives see them in patient lists and detail views, and parents receive simplified notifications and visual cues highlighting abnormal readings. In this way, the research method ensures that the intelligent notification concept is not only defined at the algorithmic level but is also realized end-to-end—from data acquisition to visual display and user action—within the NeoCare prototype.

3 Results

The main tangible result of this study is a working telehealth prototype, NeoCare, that operationalizes the previously designed architecture and high-level system model into concrete software for four actor groups: hospital administrators, parents of neonates, midwives, and doctors. The development work began by translating the use-case diagram of the "Telehealth System with Intelligent Notification for Neonatal Care" into implementable modules (see Figure 1). Each ellipse in the use-case model—such as managing neonatal data, recording vital signs, configuring machine-learning models, monitoring neonatal conditions, and scheduling consultations—was mapped to one or more interface screens and back-end services. The implemented prototype therefore embodies the logical structure outlined in the requirements engineering phase and demonstrates that the architecture is technically feasible.

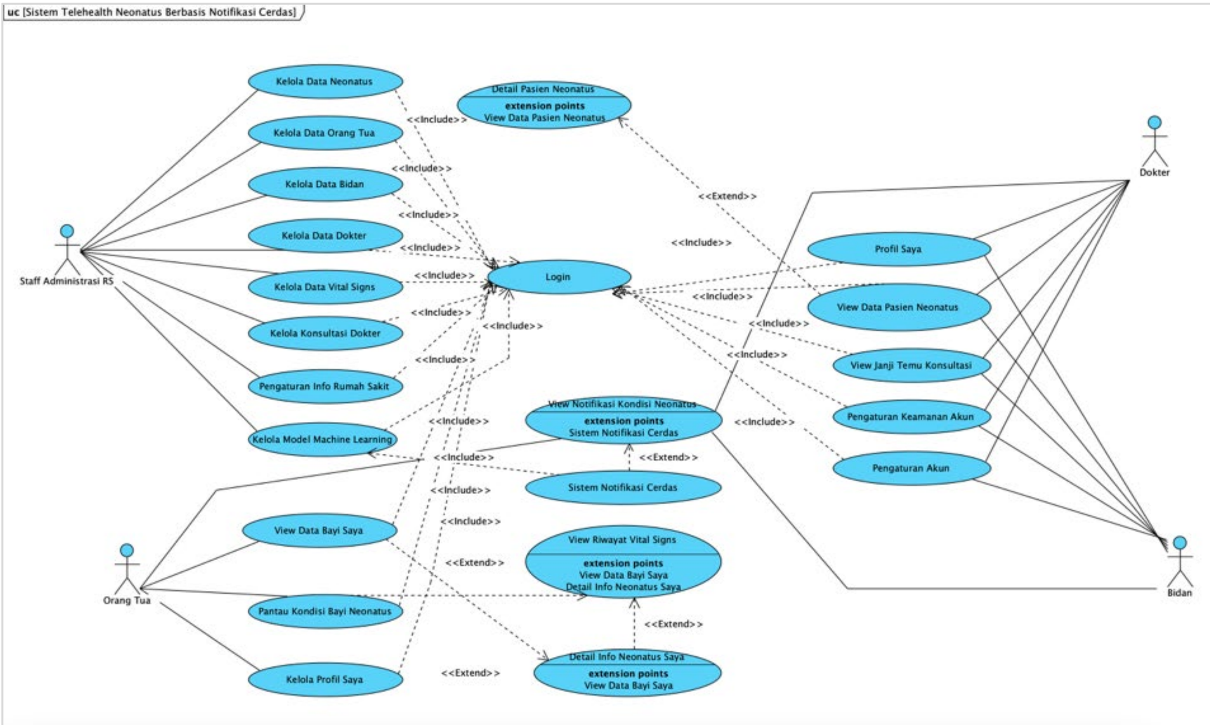

Figure 1. NeoCare Use Case Diagram

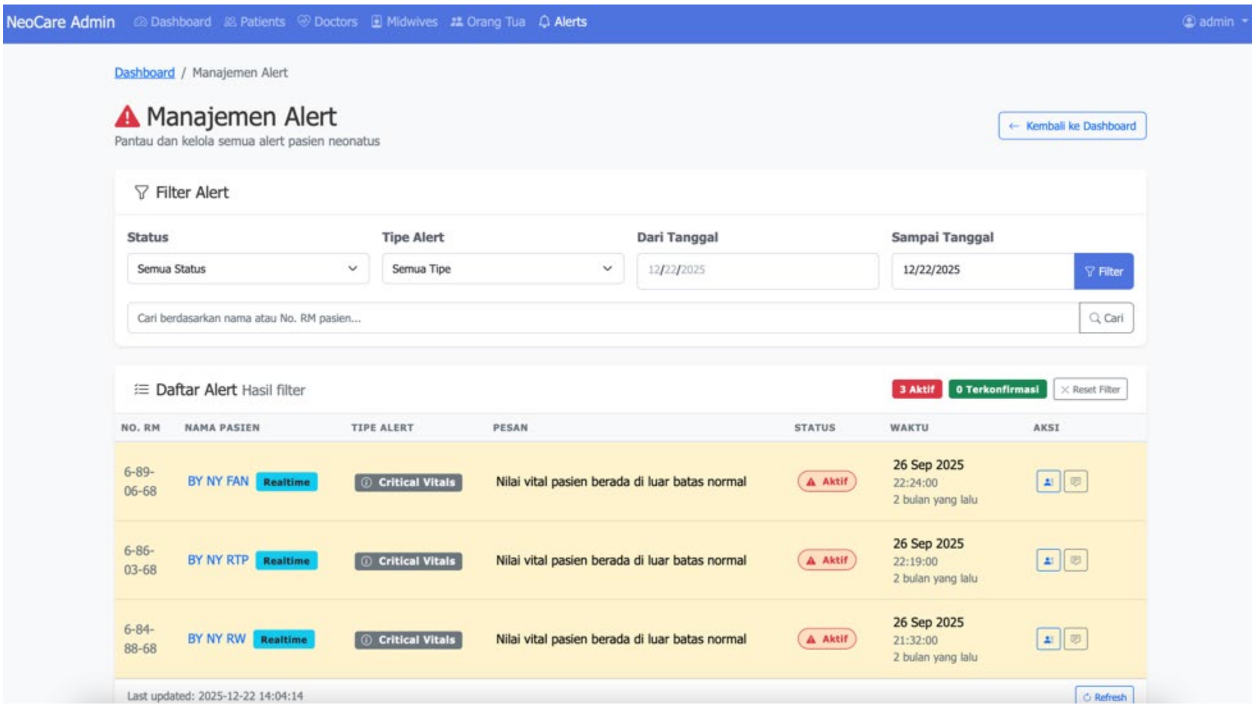

Figure 2. Alert Management of NeoCare

For hospital administrators, NeoCare provides a comprehensive web-based interface to manage all core data entities and to oversee the intelligent notification engine. In the prototype, administrators can register and update profiles for neonates, parents, midwives, and doctors; configure hospital information; and manage the catalogue of machine-learning models used by the notification subsystem. The patient-detail page aggregates individual identity, address, and parental data together with current medical information, responsible clinicians, and latest health status. At the bottom of this view, the system lists the full history of health examinations, including weight, length, heart rate, respiratory rate, temperature, and head and chest circumference, in a structured table. A visual summary of recent health status is presented through colored cards that highlight key vital signs—for example, showing a normal heart rate in green and a body temperature flagged as “Attention” in red. This combination allows administrators and senior staff to quickly assess whether the system is capturing data correctly and whether alerts are aligned with clinical expectations.

A dedicated alert-management page operationalizes the intelligent notification concept for administrators (see Figure 2). This interface shows a filter panel for narrowing alerts by status, type, and date range, followed by a paginated list of alerts generated by the system. Each row displays the medical record number, patient name, alert type (for instance, “Critical Vitals” and “Realtime”), a concise alert message indicating that vital signs are outside normal limits, the current alert status (active or acknowledged), and the time of occurrence. From this view, users can acknowledge alerts and trace them back to the underlying patient records. In practice, this screen demonstrates how NeoCare centralizes the output of the machine-learning models and rule-based checks into a single operational dashboard, which is crucial for patient safety governance and audit.

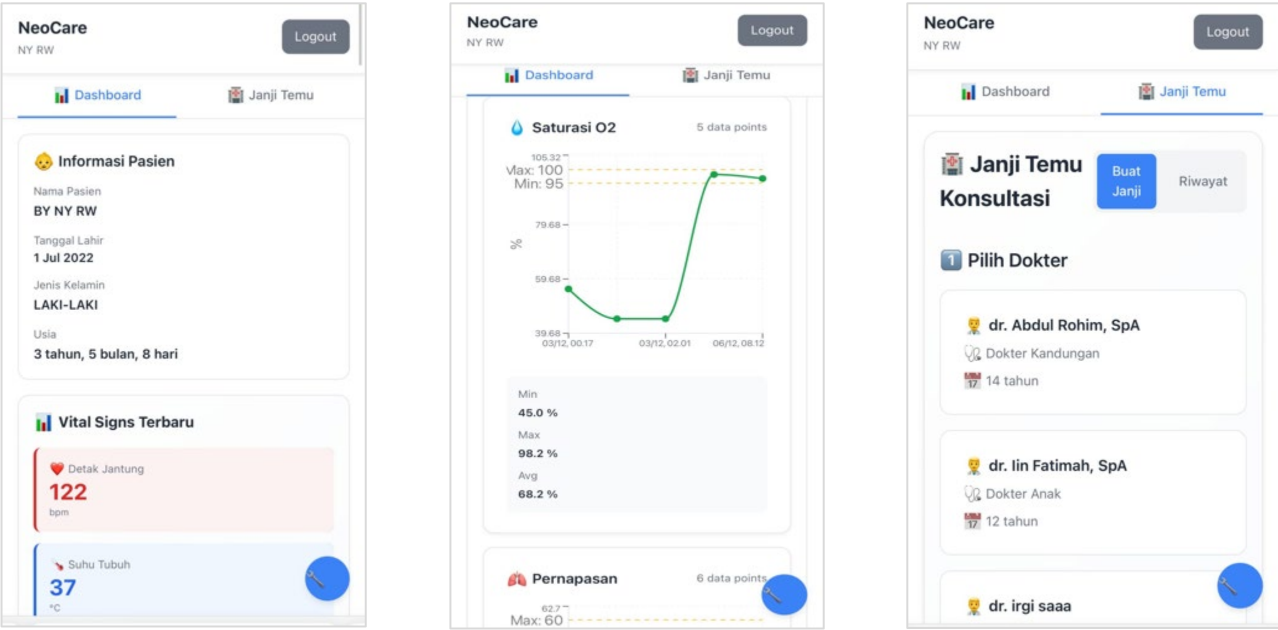

Figure 3. NeoCare Mobile for Parents Actor

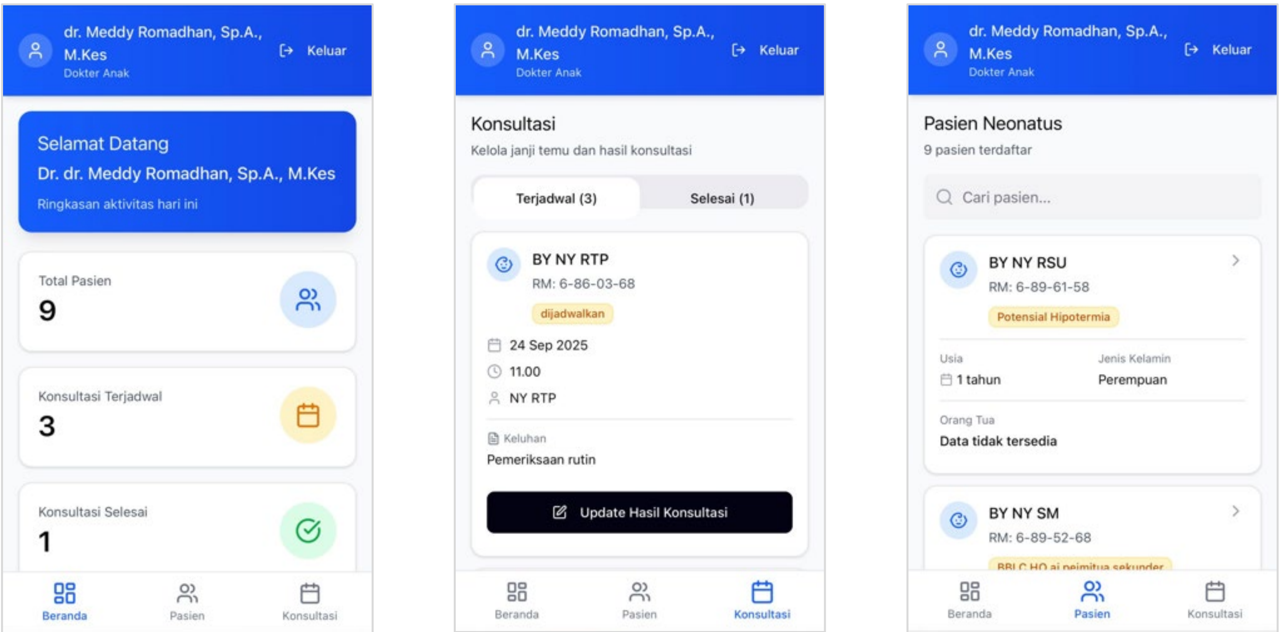

Figure 4. Neocare Mobile Application for Midwives

For parents, NeoCare offers a simplified mobile interface focused on their baby (see Figure 3). The dashboard presents key information such as the infant’s name, date of birth, sex, and age, followed by the latest vital signs.

When a parameter exceeds its safe range—such as an elevated heart rate or temperature—the corresponding card is highlighted, making it immediately obvious that the value is abnormal. Parents can scroll down to see trend graphs, for example, a time series of oxygen saturation with visible minimum, maximum, and average values, along with plotted points that show whether recent measurements are approaching or crossing alarm thresholds. This design translates complex physiological information into an intuitive visual language that nonclinical users can understand, thereby enabling them to participate more actively in monitoring their infant's condition.

The parent application also incorporates an appointment-management feature that connects families with doctors through the same platform. In the "Consultation Appointment" section, parents can browse a list of available doctors, see their specialty and years of experience, and create new appointments. The system presents tabs for creating new bookings and viewing past appointments, making it possible for parents to align follow-up visits with episodes of abnormal monitoring. This functionality demonstrates how telehealth monitoring and traditional outpatient care can be coordinated through a single digital entry point, rather than existing as separate systems. For midwives, NeoCare provides a monitoring-oriented dashboard that reflects their operational role in day-to-day neonatal care (see Figure 4). The midwife interface shows summary indicators at the top (total neonates under supervision, those currently active, and those recently discharged), followed by a list of neonatal patients segmented into tabs such as "All," "Active," and "Discharged." Each patient card displays the medical record number, name, birth date, sex, and the responsible doctor. Status labels (for example, indicating that a neonate is active) help midwives quickly identify which infants require ongoing attention. From each card, midwives can navigate to more detailed information and examine recent vital signs, which are visualized as tables and graphs similar to those in the administrator and doctor views.

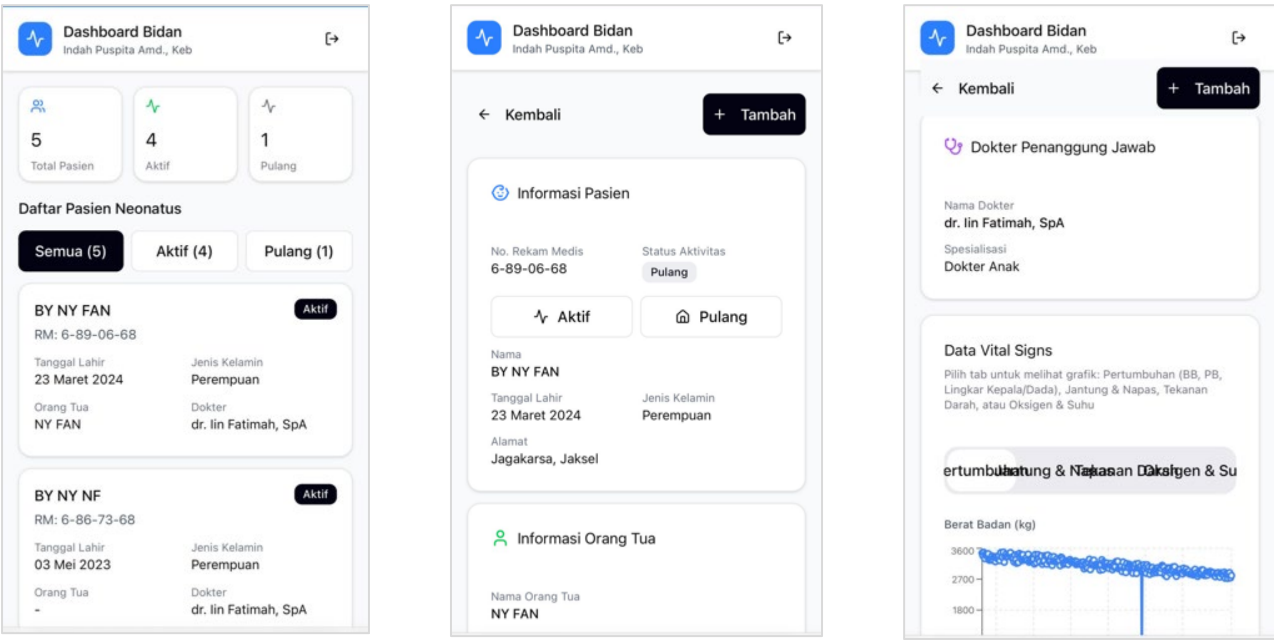

Figure 5. Neocare Mobile Application for Doctor

Doctors access NeoCare through a dedicated mobile interface tailored to clinical decision-making. The doctor's home screen greets the user with an overview of their workload, including the total number of patients under their care, the number of scheduled consultations, and the number of completed visits. A separate "Patients" section lists all assigned neonates, with risk-oriented labels such as "Potential Hypothermia" displayed prominently on the cards of infants whose vital signs indicate possible danger. This acts as a triage mechanism, allowing clinicians to prioritize which baby should be assessed first. By tapping on a patient, doctors can review detailed histories, inspect vital-sign trends, and cross-reference alerts generated by the system.

The consultation module in the doctor interface links telemonitoring data with clinical encounters. In the "Consultations" tab, doctors can see upcoming and completed appointments, each card showing the patient name, medical record number, scheduled date and time, and chief complaint. During or after a consultation, the doctor can update the consultation outcome directly through the app, ensuring that follow-up plans and clinical impressions are stored in a structured form. This feature connects monitoring, alerts, and clinical decision-making, showing that NeoCare is not just a tool for collecting data but an active system for managing neonatal care.

4 Discussion

The results indicate that NeoCare successfully translates a high-level telehealth architecture into a coherent multi-actor system that reflects the real workflows of neonatal care. The implementation of separate yet interconnected interfaces for administrators, parents, midwives, and doctors demonstrates the practicality of the role-based design articulated in the requirements phase. Each actor sees a tailored view of the same underlying clinical reality: administrators oversee data governance and the performance of the intelligent notification engine, clinicians focus on triage, monitoring, and consultation, and parents are supported in understanding their baby's condition and acting on alerts. This alignment between actor roles and system functions is a critical prerequisite for sustainable telehealth deployment in complex clinical environments.

From a telehealth perspective, NeoCare contributes by moving beyond traditional video-centric telemedicine toward integrated, data-driven neonatal monitoring. The administrator and clinical dashboards show that continuous or frequent vital-sign measurements can be aggregated into intuitive visual summaries, while the alert management interface demonstrates how abnormal patterns can be surfaced proactively. The presence of risk labels and colored indicators within the doctor and parent views suggests that the system can act as an early warning layer that complements, rather than replaces, professional judgment. In practical terms, this means that subtle but persistent deviations in heart rate, respiratory rate, temperature, or oxygen saturation are less likely to be overlooked, particularly when families live far from hospitals and may delay seeking care.

The multi-platform nature of the prototype also has important implications for equity and accessibility. By offering rich web interfaces for hospital staff and mobile-optimized applications for parents and clinicians, NeoCare acknowledges the heterogeneous digital infrastructure typical of many Indonesian and other low- and middle-income settings. Parents may primarily access the system via affordable Android smartphones, whereas hospitals may rely on desktop browsers within their internal networks. The fact that the same underlying data and alert logic are exposed through different front-ends suggests that the architecture is flexible enough to support expansion to other devices and integration with existing hospital information systems in the future.

The prototype emphasizes the prospects for transparent and understandable intelligent notification for end users. Even though the current version primarily showcases rule-based and classical machine-learning logic rather than advanced black-box models, the interface design already emphasizes clarity: alerts are accompanied by plain-language messages stating that vital signs are outside normal ranges, summary cards display both numerical values and qualitative labels (normal, attention, critical), and risk tags such as "Potential Hypothermia" make explicit the clinical concern behind a flagged pattern. This transparency is likely to be essential for clinician trust and for helping parents understand why the system suggests particular actions.

At the same time, the results highlight several limitations. First, the current evaluation is mainly functional and descriptive. The prototype confirms that data can be stored, visualized, and used to trigger alerts as designed, but it does not yet provide rigorous evidence that NeoCare improves clinical outcomes, reduces response time to deterioration, or changes provider and parent behavior. Controlled clinical studies, usability testing with real users, and long-term monitoring of alert performance will be required to establish such impacts. Second, while the architecture accommodates machine-learning models, the paper does not yet report detailed performance metrics such as sensitivity, specificity, or false-alert rates for particular algorithms. Without these metrics, it is difficult to quantify how reliably the intelligent notification component distinguishes between normal variation and clinically significant deterioration.

A further limitation concerns data coverage and generalizability. The training and validation data used to design NeoCare's intelligent notification features originate from two hospitals with specific case-mix profiles. Although the deliberate combination of heterogeneous and homogeneous datasets is methodologically sound, there is no guarantee that the same models or alert thresholds will perform equally well in other hospitals with different equipment, documentation practices, or patient populations. In addition, while the prototype supports real-time or near-real-time data capture conceptually, the current demonstration is based on simulated or manually entered vital signs rather than direct integration with bedside or wearable sensors. Future work should therefore prioritize connecting NeoCare to real monitoring devices and assessing how well it performs under routine operational load.

Despite these limitations, the study indicates that an integrated telehealth platform with intelligent notification for neonatal care is technically achievable and can be expressed in user interfaces that are intelligible to both clinicians and parents. The coherent set of screens for each actor—administrators managing alerts and user roles, doctors and midwives triaging neonates and documenting consultations, and parents following vital-sign trends and booking appointments—provides a concrete foundation for future iterations. In subsequent phases, the same architecture can support more advanced analytics, such as personalized risk scores, adaptive thresholds based on gestational age, or automatic prioritization of alerts across a hospital's entire neonatal cohort.

5 Conclusion

This study has presented the design and prototype implementation of NeoCare: Telehealth System with Intelligent Notification for Neonatal Care. Starting from a structured software engineering approach, the research translated real clinical needs in neonatal care into a multi-layer architecture, a relational data model, and a set of role-based interfaces for hospital administrators, doctors, midwives, and parents. The resulting system demonstrates that it is technically feasible to integrate neonatal vital-sign monitoring, clinical documentation, and intelligent notification within a single telehealth platform that spans hospital and home settings.

The implemented prototype shows how key functions envisioned at the architectural level can be realized in practice. Administrators can govern users, hospitals, and machine-learning models while overseeing alerts generated by the system. Doctors and midwives gain dashboards that support triage, longitudinal monitoring of vital signs, and structured documentation of consultations. Parents receive a simplified yet informative view of their baby's status, including trends in vital signs and appointment scheduling with specialists. Across these interfaces, NeoCare embeds an intelligent notification mechanism that flags deviations from normal ranges and surfaces clinically important patterns in a way that is understandable to both clinicians and families.

Beyond the technical realization, the work contributes conceptually by demonstrating the value of a multi-actor, data-driven telehealth design tailored specifically to neonates. The combination of heterogeneous and homogeneous hospital datasets provides a pragmatic foundation for developing and validating machine-learning models that can underpin the notification logic. The prototype also illustrates how explainability can be preserved—through clear messages, color-coded indicators, and risk labels—even when automated classification and rule-based checks are involved. These characteristics are essential for building trust and encouraging adoption in safety-critical domains such as neonatal care.

At the same time, the study has limitations that point to directions for future work. The current evaluation focuses on functional correctness and usability at the prototype level; it does not yet measure impacts on clinical outcomes, timeliness of response, or user behavior in real-world deployments. Model performance metrics for specific algorithms and alert configurations also require more rigorous assessment using larger and more diverse datasets. Furthermore, the present version relies on simulated or manually entered vital signs rather than full integration with bedside or wearable sensors and has not yet been interoperable with existing hospital information systems.

Future research will therefore need to extend NeoCare along several dimensions: integrating real-time data from medical devices, refining and benchmarking machine-learning models, conducting usability studies with clinicians and parents, and evaluating the system in prospective clinical pilots. Despite these open challenges, the work reported here establishes a solid methodological and technical foundation for telehealth solutions that provide continuous, intelligent support for neonatal care. In conclusion, NeoCare demonstrates a viable pathway toward safer, more connected, and more family-centered neonatal services in Indonesia and other resource-constrained settings.

BIBLIOGRAPHY

[1] World Health Organization, *"Newborn mortality,"* Fact sheet, 14 Mar. 2024. [Online]. Available : https://www.who.int/news-room/fact-sheets/detail/newborn-mortality

[2] United Nations Inter-agency Group for Child Mortality Estimation (UN IGME), *Levels & Trends in Child Mortality: Report 2024* – Estimates Developed by the United Nations Inter-agency Group for Child Mortality Estimation. New York, NY, USA: UNICEF, 2025.

[3] UNICEF Indonesia, *"A leap forward in neonatal care,"* UNICEF Indonesia, 26 Apr. 2024. [Online]. Available: https://www.unicef.org/indonesia/health/stories/leap-forward-neonatal-care

[4] J. H. L. Wagenaar et al., "Implementation and effectiveness of Teleneonatology for neonatal intensive care unit consultations in the Netherlands: A hybrid type III implementation pilot," *BMC Pediatrics*, vol. 25, no. 1, art. 574, 2025, doi: 10.1186/s12887-025-05923-y.

[5] L. Luo et al., "Worldwide research performance on telemedicine for newborns and neonatal intensive care units: A bibliometric and visualization study," *Digital Health*, vol. 11, 2025, doi: 10.1177/20552076251336283.

[6] R. Barrett et al., "Transforming neonatal care through informatics: A review of artificial intelligence, data, and implementation considerations," *Semin. Perinatol*., 2025, doi: 10.1016/j.semperi.2025.152144.

[7] S. Tudor et al., “Artificial intelligence in predicting clinical outcomes and length of stay in neonatal intensive care units: Systematic review of opportunities and challenges,” *J. Med. Internet Res*., vol. 27, 2025, Art. no. e63175.

[8] D. Rallis, M. Baltogianni, K. Kapetaniou, and V. Giapros, “Current applications of artificial intelligence in the neonatal intensive care unit,” *BioMedInformatics*, vol. 4, no. 2, pp. 1225–1248, 2024, doi: 10.3390/biomedinformatics4020067.

[9] B. A. Sullivan et al., “Comparing machine learning techniques for neonatal mortality prediction: Insights from a modeling competition,” *Pediatr. Res.*, vol. 98, no. 2, pp. 405–411, 2025, doi: 10.1038/s41390-024-03773-5.

[10] B. A. Sullivan and R. W. Grundmeier, “Machine learning models as early warning systems for neonatal infection,” *Clin. Perinatol.,* vol. 52, no. 1, pp. 167–183, 2025, doi: 10.1016/j.clp.2024.10.011.

[11] D. Thiele et al., “Machine learning models for the early real-time prediction of deterioration in intensive care units: A novel approach to the early identification of high-risk patients,” *J. Clin. Med.,* vol. 14, no. 2, art. 350, 2025, doi: 10.3390/jcm14020350.

[12] B. A. Krbec et al., “Emerging innovations in neonatal monitoring: A comprehensive review of progress and potential for non-contact technologies,” *Front. Pediatr.,* vol. 12, art. 1442753, 2024, doi: 10.3389/fped.2024.1442753.

[13] E. Senechal et al., “Next generation of non-contact and wireless vital sign monitoring technology in the neonatal intensive care unit: A systematic review,” *Pediatr. Res*., 2025, doi: 10.1038/s41390-025-04469-0.