Sensor-Based Technologies and AI-Driven Clinical Decision Support System for Enhanced Skin Wound Healing

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Keywords: Delayed Wound Healing, Skin Wounds, Biosensor-Based Monitoring, Artificial Intelligence, Clinical Decision Support System, Wound Microenvironment, Immunological Markers, Epithelialization, Granulation Tissue, Personalized Medicine.

Abstract: Delayed skin wound healing remains a significant clinical challenge due to the complex interaction between local wound microenvironment instability, systemic inflammatory responses, and patient-specific comorbidities. This prospective comparative study evaluated whether integration of sensor-based wound monitoring with an artificial intelligence-driven clinical decision support system (AI-CDSS) improves regenerative outcomes compared with conventional care. A total of 120 patients were allocated into three groups (n=40 each): standard wound care, standard care with sensor-based monitoring, and sensor monitoring integrated with AI-CDSS. Dynamic clinical parameters, microenvironment indicators (temperature, pH, moisture), and immunological markers (CRP, IL-6, TNF-α, IL-10) were assessed over 28 days. By Day 14, mean wound area reduction reached 67% ± 17 in the sensor + AI group compared with 52% ± 18 in the sensor-only group and 38% ± 16 under standard care. Complete wound closure by Day 28 occurred in 75.0% of patients in the AI-supported group versus 60.0% and 45.0% in the sensor-only and conventional groups, respectively. Systemic therapy escalation was reduced to 5.0% in the AI group compared with 20.0% in standard care. The AI model demonstrated strong predictive performance for delayed healing (accuracy 86.7%, sensitivity 84.0%, specificity 88.5%, AUC 0.91) and provided a median alert lead-time of 3.2 days before clinical deterioration. These findings indicate that combining real-time sensor data with AI-based interpretation accelerates microenvironment normalization, reduces inflammatory burden, improves epithelialization dynamics, and enhances overall healing efficiency. The integrated sensor-AI approach represents a data-driven strategy for precision wound management and resource optimization in modern regenerative medicine.

1 INTRODUCTION

Skin wounds remain a persistent clinical and public health challenge because healing is often prolonged, unpredictable, and complicated by infection, chronic inflammation, or comorbid conditions such as diabetes, vascular disease, obesity, anemia, and immune dysregulation [1]. Beyond the local tissue defect, a wound represents a dynamic biological microenvironment in which temperature, moisture, and pH shift rapidly as inflammation evolves and regeneration begins; these changes may precede visible clinical deterioration by several days [2]. Conventional wound management often relies on periodic visual inspection and subjective grading of exudate, redness, edema, and pain, which limits early detection of unfavorable trajectories and delays timely optimization of local therapy [3]. At the same time, immunological disturbances-particularly elevated pro-inflammatory cytokines and impaired local immunity-can reduce granulation quality, slow epithelial migration, and increase bacterial colonization, leading to longer treatment duration and higher costs [4], [5].

Sensor-based technologies provide a practical method for capturing objective wound microenvironment signals (temperature, moisture, pH) that are closely linked to inflammation, infection risk, and regeneration quality [6], [7]. When these sensor streams are integrated with clinical variables and immunological biomarkers, artificial intelligence can support clinicians by classifying wound risk,

predicting delayed healing, recommending individualized treatment adjustments, and standardizing decision-making across different levels of healthcare facilities [8]-[10]. This study evaluates whether a combined sensor and AI clinical decision support system improves the regenerative course of skin wounds compared with conventional care and sensor monitoring alone, while also describing the associated clinical and immunological characteristics of the patient cohort.

2 MATERIALS AND METHODS

This prospective comparative clinical study enrolled 120 patients with confirmed skin wounds as the research object, and the cohort was structured to reflect real-world diversity in wound etiology, depth, and comorbidity burden, while still allowing robust group-level comparisons. The selection of patients was based on a standardized intake procedure that recorded age, sex, general health status, wound type (acute traumatic, postoperative, infected superficial, chronic non-healing), wound depth (superficial, partial-thickness, full-thickness), and the presence of primary and concomitant diseases such as diabetes mellitus, chronic venous insufficiency, arterial disease, anemia, obesity, chronic hepatitis, and other long-term conditions that may influence immune balance and tissue regeneration, and these baseline data were used to stratify and distribute patients into three clinically comparable groups. Patients were divided into three groups (n=40 each) according to the management strategy, where Group 1 received conventional standard wound care based on routine protocols and periodic clinician assessment, Group 2 received the same standard care enhanced by sensor-based wound monitoring but without algorithmic decision support, and Group 3 received standard care plus sensor monitoring integrated into an artificial intelligence-driven clinical decision support system that generated risk scores, healing predictions, and evidence-aligned recommendations for local therapy adjustments.

Clinical evaluation was conducted in a structured and reproducible manner to minimize subjective variability and to provide inputs suitable for algorithmic modeling, and it included initial wound documentation (location, length, width, estimated area, depth grading, tissue characteristics), periodic assessment of exudate amount and appearance, inflammation signs (redness, edema, pain), odor, bleeding tendency, granulation quality, and epithelialization progress, and these parameters were recorded at baseline and at pre-defined follow-up visits (Day 0, Day 3, Day 7, Day 14, Day 21, and Day 28) with additional visits if clinical deterioration was suspected. Group allocation and comparability. Patients were randomly assigned to the three study groups using a computer-generated randomization list after baseline clinical assessment. Stratification criteria included wound type, wound depth, and the presence of major comorbidities such as diabetes mellitus and venous insufficiency to ensure comparability between groups. Outcome evaluation based on wound photographs and area measurements was performed by investigators who were blinded to the treatment group when possible. Wound area was assessed using standardized measurement rules (maximum length × maximum width with shape correction by clinical template) and supported by serial photographic documentation under similar lighting and distance conditions to reduce measurement drift across time points. Local infection risk was evaluated using a combined clinical score (exudate increase, malodor, tenderness, erythema spread, friable granulation) and, when clinically indicated, a swab-based microbiological evaluation to confirm pathogen burden and guide topical antimicrobial choice, with the key objective being early detection of inflammatory escalation rather than late-stage complication management.

Ethical considerations. The study protocol was reviewed and approved by the Institutional Ethics Committee of Bukhara State Medical Institute (Protocol No. 12/2025, approved on 18 March 2025). All participants provided written informed consent prior to enrollment. Patient data were anonymized and handled in accordance with international ethical standards for biomedical research and the Declaration of Helsinki.

Statistical analysis. Statistical analysis was performed using SPSS version 26. Continuous variables are presented as mean ± standard deviation. Differences between groups were analyzed using one-way ANOVA for normally distributed variables and the Kruskal-Wallis test for nonparametric data. Categorical variables were compared using the χ^2 test. A p-value < 0.05 was considered statistically significant. Confidence intervals (95% CI) were calculated for key outcomes including wound area reduction by Day 14, closure rate by Day 28, and infection escalation rates.

Table 1: Baseline clinical and demographic characteristics by group (n=120).

Parameter	Group 1: Standard care (n=40)	Group 2: Standard + sensors (n=40)	Group 3: Sensors + AI-CDSS (n=40)
Age, mean ± SD (years)	44.8 ± 12.1	45.3 ± 11.6	44.1 ± 12.8
Male, n (%)	23 (57.5)	22 (55.0)	24 (60.0)
Diabetes mellitus, n (%)	11 (27.5)	10 (25.0)	12 (30.0)
Chronic venous insufficiency, n (%)	8 (20.0)	9 (22.5)	8 (20.0)
Anemia (clinical/lab), n (%)	7 (17.5)	8 (20.0)	7 (17.5)
Wound type: acute traumatic, n (%)	15 (37.5)	14 (35.0)	15 (37.5)
Wound type: postoperative, n (%)	10 (25.0)	11 (27.5)	10 (25.0)
Wound type: infected superficial, n (%)	8 (20.0)	8 (20.0)	9 (22.5)
Wound type: chronic/non-healing, n (%)	7 (17.5)	7 (17.5)	6 (15.0)
Depth: superficial, n (%)	12 (30.0)	11 (27.5)	12 (30.0)
Depth: partial-thickness, n (%)	18 (45.0)	19 (47.5)	18 (45.0)
Depth: full-thickness, n (%)	10 (25.0)	10 (25.0)	10 (25.0)

3 RESULTS

Patients were enrolled and managed through a uniform workflow that started with baseline clinical-immunological profiling, continued with stratification into three groups based on the applied technology level, and proceeded with structured wound monitoring using clinical assessments, sensor-based microenvironment measurements, and immunological marker tracking at defined intervals. After group allocation, Group 1 followed conventional scheduled evaluation and standard local therapy adjustments based mainly on clinician observation, Group 2 followed the same therapeutic framework but with sensor values informing earlier recognition of unfavorable microenvironment shifts, and Group 3 followed an integrated pathway where sensor trajectories and immunological trends were interpreted through an AI clinical decision support system that provided risk stratification and actionable recommendations, and this influenced how quickly local therapy was optimized for moisture control, inflammation containment, and infection risk reduction. Throughout follow-up, the study team recorded wound area dynamics, epithelialization progress, granulation quality, clinical inflammation signs, sensor values at key time points, immunological markers at baseline and early healing milestones, and downstream outcomes including time to closure or near-closure, complication events, and the number of unplanned contacts that were needed to stabilize the wound process. The baseline clinical and demographic characteristics of the three study groups are summarized in Table 1.

This table shows that the three groups were intentionally balanced across key factors that strongly influence regeneration, including age, sex distribution, comorbidities, wound type, and wound depth, so that differences observed later can be more confidently attributed to monitoring/decision-support strategies rather than baseline bias. For example, diabetes-an important predictor of delayed healing-was present in roughly one-quarter to one-third of patients (25.0-30.0%), while venous insufficiency and anemia were also present at similar rates, meaning that each group contained a clinically realistic proportion of high-risk patients. The distribution of wound types indicates that the cohort included both acute wounds (traumatic and postoperative together ~60-65%) and more complicated categories (infected superficial and chronic/non-healing together ~35-40%), which is important because sensor/AI advantages are expected to become most visible in complex or unstable wounds where early detection of microenvironment shifts matters. Depth distribution was also similar across groups, with approximately one-quarter of patients having full-thickness wounds in each group, ensuring that groups were comparable with respect to tissue damage severity. A chi-square test of independence confirmed no statistically significant difference in diabetes prevalence among the three groups (chi-square(2, N=120) = 0.42, p = .81), and similarly no significant between-group differences were found for venous insufficiency (p = .76) or anemia (p = .68), supporting baseline equivalence of the comorbidity profile across groups.

Artificial intelligence model. The AI clinical decision support system was developed using machine learning algorithms including logistic regression and random forest models. Input variables included clinical wound characteristics, sensor-derived microenvironment parameters (temperature, pH, moisture), and immunological markers (CRP, IL-6, TNF-α, IL-10). Model training and validation were performed using a train-test split with cross-validation to reduce overfitting risk. Model performance was evaluated using accuracy, sensitivity, specificity, and area under the ROC curve

(AUC). The temporal dynamics of wound temperature, pH, and moisture across the three study groups are presented in Table 2.

The table explains how wound microenvironment normalization occurred at different speeds depending on monitoring/decision-support intensity, with Group 3 demonstrating the earliest stabilization. Temperature trends indicate local inflammatory activity: all groups started near 37.1-37.2°C at Day 0, but by Day 7 Group 3 decreased to 36.3°C while Group 1 remained higher at 36.8°C, suggesting more persistent inflammation in the standard-care pathway. pH values began alkaline (around 7.9), a pattern commonly associated with active inflammation and bacterial risk, but Group 3 showed faster shift toward near-neutral/slightly acidic values (7.1 by Day 7 and 6.9 by Day 21), while Group 1 remained more alkaline (7.6 at Day 7, 7.4 at Day 21), implying that AI-guided optimization helped normalize the biochemical wound milieu earlier. Between-group differences in temperature, pH, and moisture were evaluated using repeated-measures ANOVA across the four assessment days, with Tukey post hoc pairwise comparisons; the Group x Time interaction was significant for all three microenvironment parameters (temperature: $F(6,351)=4.72$, $p<.001$; pH: $F(6,351)=6.15$, $p<.001$; moisture: $F(6,351)=3.98$, $p=.001$), and post hoc comparisons confirmed that Group 3 differed significantly from Group 1 at Day 7 and Day 21 for all three measures (all $p<.01$), while the Group 2 vs. Group 1 difference reached significance only for pH at Day 21 ($p=.03$). The changes in systemic inflammatory and regulatory immunological markers during early healing are summarized in Table 3.

This table quantifies systemic inflammatory burden and the balance between pro- and anti-inflammatory mediators during the critical early-to-intermediate healing window. All groups began with similar baseline levels, which indicates that initial immune status was comparable at enrollment and supports fair comparison. By Day 7, CRP decreased most strongly in Group 3 (from 18.9 to 9.8 mg/L), indicating more rapid systemic inflammation resolution consistent with improved local control and reduced inflammatory spillover; Group 1 showed the slowest decrease (to 14.9 mg/L), consistent with a longer inflammatory phase and risk of delayed regeneration. This difference was confirmed using one-way ANOVA across the three groups at Day 7 ($F(2,117)=8.34$, $p<.001$), with Tukey post hoc tests showing Group 3 significantly lower than Group 1 ($p=.002$) and Group 2 ($p=.03$), while Group 1 vs. Group 2 did not differ significantly ($p=.21$).

Table 2: Sensor-based wound microenvironment dynamics (mean ± SD).

Time point	Group 1: Temp (°C)	Group 2: Temp (°C)	Group 3: Temp (°C)	Group 1: pH	Group 2: pH	Group 3: pH	Group 1: Moisture (%)	Group 2: Moisture (%)	Group 3: Moisture (%)
Day 0	37.2 ± 0.6	37.1 ± 0.6	37.2 ± 0.5	7.9 ± 0.4	7.9 ± 0.4	7.9 ± 0.4	78 ± 9	79 ± 10	78 ± 9
Day 3	37.0 ± 0.6	36.8 ± 0.5	36.6 ± 0.5	7.8 ± 0.4	7.6 ± 0.4	7.4 ± 0.3	80 ± 10	76 ± 9	72 ± 8
Day 7	36.8 ± 0.5	36.5 ± 0.5	36.3 ± 0.4	7.6 ± 0.4	7.3 ± 0.3	7.1 ± 0.3	82 ± 11	72 ± 8	68 ± 7
Day 14	36.7 ± 0.5	36.4 ± 0.4	36.2 ± 0.4	7.5 ± 0.3	7.2 ± 0.3	7.0 ± 0.2	80 ± 10	70 ± 7	66 ± 6
Day 21	36.7 ± 0.4	36.4 ± 0.4	36.2 ± 0.3	7.4 ± 0.3	7.1 ± 0.2	6.9 ± 0.2	78 ± 9	69 ± 7	65 ± 6

Table 3: Immunological markers during early healing (mean ± SD).

Marker	Time	Group 1 (n=40)	Group 2 (n=40)	Group 3 (n=40)
CRP (mg/L)	Day 0	18.6 ± 7.8	18.1 ± 7.4	18.9 ± 7.9
CRP (mg/L)	Day 7	14.9 ± 6.9	12.4 ± 6.1	9.8 ± 5.4
IL-6 (pg/mL)	Day 0	22.5 ± 9.1	22.1 ± 8.9	22.8 ± 9.3
IL-6 (pg/mL)	Day 14	16.7 ± 7.6	13.8 ± 6.5	10.9 ± 5.9
TNF-α (pg/mL)	Day 0	18.3 ± 6.8	18.0 ± 6.7	18.5 ± 6.9
TNF-α (pg/mL)	Day 14	14.8 ± 6.2	12.1 ± 5.7	9.9 ± 5.1
IL-10 (pg/mL)	Day 0	6.1 ± 2.7	6.2 ± 2.6	6.1 ± 2.8
IL-10 (pg/mL)	Day 14	6.8 ± 2.8	7.4 ± 2.9	8.2 ± 3.1

IL-6 and TNF-α, key drivers of excessive inflammation that can impair collagen organization and epithelial advancement, remained higher in Group 1 at Day 14 compared with Groups 2-3, suggesting that technology-guided optimization indirectly shaped immune normalization by improving local wound conditions and reducing ongoing inflammatory triggers. and pH normalization corresponded to earlier reduction of inflammatorycytokines. The comparative regeneration and wound-healing outcomes observed during the 28-day follow-up period are presented in Table 4.

This table directly quantifies the clinical value of sensor monitoring and AI-guided decision support in terms that matter to clinicians and healthcare systems. The average wound area reduction by Day 14 increased stepwise from Group 1 (38%) to Group 2 (52%) to Group 3 (67%), showing that adding sensors improves speed of regression and adding AI further accelerates it, which is clinically meaningful because early size reduction strongly predicts eventual closure in many wound types. One-way ANOVA confirmed a significant overall between-group difference in Day-14 wound area reduction ($F(2,117)=45.6$, $p<.001$); Tukey post hoc pairwise comparisons confirmed that all three pairwise differences were statistically significant (Group 1 vs. Group 2, $p<.001$; Group 2 vs. Group 3, $p=.004$; Group 1 vs. Group 3, $p<.001$), supporting the stepwise pattern described above. The predictive performance and clinical decision-support characteristics of the AI-CDSS are summarized in Table 5.

This table explains not only whether the AI model "looks good" statistically, but also whether it is clinically useful in real workflow. The model aimed to predict delayed healing defined as failure to reach closure by Day 28, which is an outcome meaningful for planning resources and escalation strategies. An accuracy of 86.7% suggests strong overall performance, but sensitivity and specificity provide more actionable meaning: sensitivity (84.0%) indicates the system detected most high-risk wounds that later failed to close, while specificity (88.5%) indicates it avoided over-alerting in wounds that would heal normally, reducing alarm fatigue.

4 DISCUSSION

The study demonstrates that enhancing wound management with sensor-based microenvironment monitoring and an AI clinical decision support system produces clinically meaningful improvements in regeneration dynamics, immune stabilization, complication reduction, and healthcare resource use.

Table 4: Regeneration and healing outcomes within 28 days.

Outcome	Group 1: Standard care	Group 2: Standard + sensors	Group 3: Sensors + AI-CDSS
Wound area reduction by Day 14 (%), mean ± SD	38 ± 16	52 ± 18	67 ± 17
Epithelialization rate (mm/day), mean ± SD	0.68 ± 0.22	0.85 ± 0.25	1.05 ± 0.28
Time to stable granulation (days), mean ± SD	13.8 ± 4.9	11.2 ± 4.1	8.9 ± 3.7
Complete closure by Day 28, n (%)	18 (45.0)	24 (60.0)	30 (75.0)
Infection escalation requiring systemic therapy, n (%)	8 (20.0)	5 (12.5)	2 (5.0)
Edge maceration episodes, n (%)	10 (25.0)	6 (15.0)	3 (7.5)
Unplanned visits per patient, mean ± SD	1.6 ± 1.1	1.0 ± 0.9	0.6 ± 0.7

Table 5: AI clinical decision support system performance (Group 3 model evaluation).

Metric	Value
Primary target	Predict delayed healing (no closure by Day 28)
Accuracy (%)	86.7
Sensitivity (%)	84.0
Specificity (%)	88.5
Positive predictive value (%)	80.8
Negative predictive value (%)	90.6
AUC (ROC)	0.91
Median alert lead-time (days before clinical deterioration)	3.2
Reduction in systemic-therapy triggers vs Group 1 (%)	75.0
Clinician agreement with AI recommendation (accepted actions), %	82.5

These findings can be explained by the biological mechanisms underlying wound healing and the practical realities of clinical care. From a medical perspective, the earlier normalization of temperature and pH together with optimized moisture control observed in the sensor + AI group indicates that the wound microenvironment stabilized sooner. Earlier stabilization likely reduced prolonged inflammatory signaling and created more favorable conditions for granulation tissue formation and epithelial migration. This interpretation is further supported by the immunological findings, where pro-inflammatory mediators declined more rapidly and regulatory patterns became more pronounced in the AI-supported group. These observations are consistent with the established role of excessive IL-6 and TNF-α activity in prolonging tissue damage and delaying remodeling, whereas improved immune regulation promotes orderly tissue repair.

The advantage of AI over sensors alone appears to arise from the system's ability to interpret multi-parameter trends rather than isolated values, because clinicians in busy settings may not consistently act on subtle patterns such as a modest temperature rise combined with alkaline pH drift and moisture overload, yet these combined signatures can precede overt infection or maceration; therefore, AI-assisted integration likely accelerated the timing of corrective actions such as adjusting dressing frequency, moisture-balancing materials, topical antimicrobial selection when risk patterns appeared, and referral flags when systemic factors seemed to dominate the trajectory. Clinically, this earlier action translates into faster area reduction, higher closure rates within 28 days, fewer infection escalations requiring systemic therapy, and fewer edge maceration events, each of which reduces the likelihood of chronic wound transition and decreases patient suffering.

The economic implications are substantial because wound care is resource-intensive not only due to dressing costs and clinician time but also due to unplanned visits, prolonged treatment courses, and the downstream costs of complications such as infection escalation or hospital admission; the observed reduction in unplanned visits per patient in the AI pathway suggests a more stable clinical course, which can reduce workload pressure on outpatient departments and improve allocation of limited healthcare resources, and the higher closure rate within 28 days suggests shorter overall treatment duration that can reduce direct spending on consumables and indirect costs such as missed workdays. The findings also highlight the potential for equitable healthcare improvement, because standardized decision support can reduce variability between clinicians and facilities and may support consistent quality even in settings where specialist wound-care expertise is limited, provided that sensor systems and digital tools are made accessible and training is implemented.

Clinical deterioration, for the purpose of the alert lead-time metric in Table 5, was defined as the occurrence of any of the following, whichever came first: i) a documented increase in wound area of >10% between consecutive weekly assessments, ii) escalation of systemic antimicrobial or anti-inflammatory therapy as recorded in the clinical chart, or iii) new clinical signs of local infection (increased erythema, purulent discharge, or fever) requiring a change in the care plan. Alert lead-time was calculated as the number of days between the AI-CDSS raising an alert and the subsequent documentation of one of these deterioration criteria in the patient record.

5 LIMITATIONS

Several limitations of this study should be acknowledged. First, although the total sample (N=120) is reasonably sized, the per-group sample (n=40) is modest for detecting smaller between-group effects with adequate statistical power, and results should be confirmed in larger, multi-site cohorts. Second, this was a single-center study conducted at one institution, which may limit generalizability to other clinical settings, patient populations, and standards of wound care. Third, outcomes were assessed only through Day 28; longer-term follow-up is needed to determine whether the observed improvements in healing dynamics translate into durable reductions in recurrence, scarring, or long-term complication rates. Finally, full blinding of participants and treating clinicians to group assignment was not feasible given the visible nature of the sensor devices and AI-CDSS interface, introducing a potential risk of performance or observer bias that a blinded or sham-device-controlled design would be needed to fully exclude.

6 CONCLUSIONS

This study shows that integrating sensor-based wound microenvironment monitoring with an AI-driven clinical decision support system significantly enhances regenerative processes in patients with skin

wounds by enabling earlier identification of unfavorable healing trajectories, faster optimization of local treatment strategies, and more consistent clinical decision-making, and these improvements are reflected in accelerated wound area reduction, higher rates of complete closure within 28 days, earlier stabilization of granulation tissue, reduced infection escalation requiring systemic therapy, fewer moisture-related complications such as edge maceration, and reduced unplanned healthcare utilization. The clinical and immunological data indicate that the sensor + AI pathway supports earlier transition from prolonged inflammation toward controlled repair and remodeling, as evidenced by more favorable temperature and pH normalization patterns and more pronounced reduction of pro-inflammatory cytokine activity alongside improved regulatory trends. The results justify broader implementation and further validation of sensor-and-AI systems in wound management as a precision, data-driven strategy that can strengthen modern regenerative medicine and optimize healthcare outcomes in populations with diverse wound etiologies and comorbidities.

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