

AI-based Mobile Application for Pressure Injury Healing: Real-World Evidence from a Retrospective Study

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Abstract

Background: Pressure injuries (PIs) are a major concern in hospital care, contributing to prolonged hospital stays, reduced quality of life, and increased healthcare costs. Accurate and timely staging is critical for effective management, highlighting the need for practical and clinically validated tools that can support precise PI assessment and improve patient outcomes.

Objective: This study aimed to evaluate both the technical performance and the real-world clinical effectiveness of an artificial intelligence (AI)-based application for PI staging and dressing selection in a tertiary care hospital setting.

Methods: We developed a convolutional neural network-based mobile application using 9,083 wound images and conducted external validation with 448 independent images. The application was embedded into barcode point-of-care (BPOC) devices for bedside use and real-time electronic medical record (EMR) integration. To assess clinical effectiveness, we conducted a retrospective analysis of 610 matched cases using propensity score matching, comparing changes in Pressure Ulcer Scale for Healing (PUSH) scores over 7 days between the app-use group and the non-app-use group. Subgroup analyses were performed according to the timing of app usage and PI stage.

Results: The model achieved high diagnostic accuracy across PI stages, with a weighted area under the receiver operating characteristic curve (AUROC) of 0.969 in internal testing and 0.971 in external validation. In the clinical evaluation, the use of the application was associated with significantly greater improvement in PUSH scores for Stage 2 and above PIs (48.80% vs. 35.58%, OR=1.825, 95% CI=1.152–2.891, P=.010). Subgroup analysis revealed that early app usage led to higher odds of healing improvement (51.69% vs. 36.08%, adjusted OR=1.862, 95% CI=1.004–3.454, P=.048), while delayed usage showed a positive trend without statistical significance.

Conclusions: This study demonstrates that an AI-based application can be effectively deployed at the bedside to improve clinical

decision-making and enhance pressure injury healing, particularly when implemented during the initial phase of pressure injury management. To our knowledge, this is the first real-world study to demonstrate both technical validity and clinical benefits of AI -powered PI staging and dressing recommendations.

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Original Manuscript

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the first real-world study to demonstrate both technical validity and clinical benefits of AI-powered PI staging and dressing recommendations.

Keywords: pressure injury, wound healing, deep learning, mobile application, clinical decision support, real-world evidence.



Introduction

Pressure injuries (PIs) are characterized by localized damage to the skin and/or underlying tissue caused by pressure or a combination of pressure and shear [1]. Although they usually appear over bony prominences, PIs can develop anywhere on the body [2]. PIs significantly contribute to extended hospital stays, decreased quality of life, and increased mortality [2,3]. Globally, the prevalence of PIs among adult hospitalized patients is estimated to be 12.8% [4], with hospital-acquired pressure injuries costing the U.S. healthcare system approximately \$26.8 billion annually [5]. Despite advancements in prevention and treatment approaches, the burden of PIs remains substantial.

A formal classification of PIs was first introduced in the 1950s [6], and the system primarily used today is based on the criteria established by the National Pressure Ulcer Advisory Panel (NPUAP): stages 1 to 4, unstageable full-thickness pressure injury, and deep tissue pressure injury, which are defined according to the deepest parts of the ulcer and the type of tissue affected [1]. Accurate staging is essential as it directly impacts treatment planning, resource allocation, and quality-of-care evaluations [7]. Accordingly, timely assessment of skin condition and early detection of PIs are critical tasks for nurses [1]. However, clinical evidence suggests that nurses often experience difficulties in accurately staging PIs and selecting appropriate dressing materials [8]. A previous study reported that nurses in both tertiary and small- to medium-sized hospitals had difficulty in accurately classifying PI stages. In Korea, the inter-rater agreement rate among nurses working in hospitals with 100 to 300 beds was relatively low at 69% [9]. Similarly, in a 663-bed tertiary hospital in Australia, the inter-rater agreement rate was 67.3%, with particularly low staging accuracy for more severe PIs such as Stage 3, Stage 4, and unstageable [8]. Even after staging correctly, choosing the appropriate dressing material based on complex and lengthy guidelines can still be time-consuming and cognitively demanding in busy clinical settings. As nursing workloads continue to increase, and digital healthcare becomes more prominent, automated point-of-care tools are

increasingly needed to support accurate wound assessment and timely intervention. Clinical decision support systems (CDSS) can play a key role in addressing these challenges and narrowing the knowledge gap in PI staging and dressing selection.

In recent years, several studies have developed artificial intelligence (AI)-based deep learning models using PI images to support clinical decision-making in wound assessment and management [10-14]. While these studies demonstrate potential utility in the nursing field, most have notable limitations. Many studies were based on small datasets of approximately 100 images [10]. Others, despite using larger datasets of around 2,000 images, failed to include Stage 1 injuries [11] or conducted external validation without demonstrating the clinical impact of their models [12]. Furthermore, existing solutions often require specialized hardware, such as high-performance cameras or scanners, which limit their practicality in everyday clinical settings [13,14]. To overcome these limitations, this study aims to develop a practical application that operates without the need for complex equipment and to evaluate its potential benefits for wound healing. We developed a deep learning-based application capable of classifying all PI stages—including Stage 1 to 4, unstageable, and suspected deep tissue injuries (DTIs)—while also recommending appropriate dressing materials based on clinical guidelines. All nurses at Samsung Medical Center already use Barcode Point-of-Care (BPOC) devices, which are equipped with built-in cameras and fully integrated with the electronic medical record (EMR) system. This infrastructure allows for real-time wound scanning and documentation at the bedside, making BPOC devices ideal for clinical AI applications. Unlike previous commercial products that require high-end imaging equipment or are limited to retrospective validation, our system was designed for real-time, bedside use with BPOC devices. This enhances its practical applicability in routine nursing care without additional devices and infrastructure for EMR integration.

In addition to evaluating the classification performance of our application model, this study also aimed to assess whether this system contributes to wound healing. Wound healing progress was

monitored over time using the Pressure Ulcer Scale for Healing (PUSH), a validated wound assessment tool developed by the NPUAP [15,16]. To gain meaningful insights into the effectiveness of an AI application for pressure injury management, we integrated the application into the EMR system and assessed both algorithmic performance and clinical outcomes.

Methods

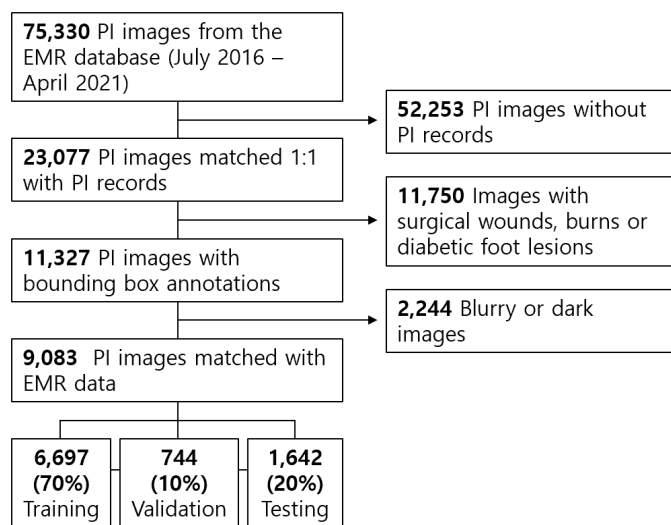
Development

Dataset and Preprocessing

This retrospective study was conducted on inpatients at Samsung Medical Center, a tertiary academic hospital in Seoul, Korea, between July 2016 and April 2021. The study was reviewed and approved by the Institutional Review Board (IRB) of Samsung Medical Center (IRB No. SMC 2022-08-163), with the requirement for informed consent waived because of the retrospective design.

A total of 75,330 images and associated clinical records were extracted from the EMR system. Images lacking corresponding clinical records were excluded. From these, 23,077 images that exactly matched pressure injury staging were initially identified. Images related to surgical wounds, diabetic foot ulcers, burns, or other unrelated skin conditions were excluded. After this preprocessing, a total of 9,083 images were retained for analysis (Figure 1).

The distribution of images by PI stage was as follows: 998 Stage 1, 3,777 Stage 2, 397 Stage 3, 513 Stage 4, 920 unstageable, and 2,478 for DTIs. The dataset was randomly split into 70% for training (n=6,697), 10% for validation (n=744), and 20% for testing (n=1,642), resulting in a total of 9,083 cases. All images were labeled according to the NPUAP criteria [1]. Three wound care nurses, each with more than 10 years of clinical experience, independently annotated the images. Any annotation disagreements were resolved through consensus among the annotators. Inter-rater reliability was assessed using Fleiss' Kappa, yielding an agreement coefficient of 0.861.

Figure 1. Flowchart of Modeling Process.

Modeling and Training

The proposed pressure injury classification model is based on the Big Transfer (BiT) architecture, utilizing a ResNet-152x2 backbone pretrained on the ImageNet-21K dataset [17]. This architecture leverages the strong generalization capabilities of BiT, making it well suited for transfer learning tasks in the medical domain, where labeled data are often limited [18,19].

To enhance the model's ability to focus on diagnostically relevant features, a Bottleneck Attention Module (BAM) [20] was integrated into the model. Instead of increasing network depth, BAM is inserted after the main convolutional blocks to enhance feature refinement while maintaining computational efficiency. The BAM consists of two main components: a Channel Gate, which captures inter-channel dependencies through global average pooling followed by a multi-layer perceptron (MLP), and a Spatial Gate, which captures spatial dependencies using convolutional operations. This structure enables the model to emphasize clinically meaningful regions and suppress irrelevant features, which is especially beneficial in wound images that may contain various visual artifacts. During training, all input images were resized to a fixed resolution of 512×512 pixels. To improve generalization and reduce overfitting, standard data augmentation techniques were applied, including random cropping and random horizontal flipping. Additionally, pixel values were

normalized to zero mean and unit variance. Model performance was evaluated on the internal test set using sensitivity, specificity, accuracy, precision, F1-score, and the area under the receiver operating characteristic curve (AUROC).

External Validation

The external dataset was collected from a separate cohort of patients at the same institution. A total of 448 images (Stage 1: 77, Stage 2: 87, Stage 3: 78, Stage 4: 36, unstageable: 82, DTIs: 88) were obtained between December 2021 and April 2022, excluding data used for model development and training. All images were labeled according to the NPUAP criteria. Three wound care nurses, each with over 10 years of clinical experience, annotated the entire dataset. Any annotation disagreements were resolved through consensus among the annotators. The model's performance on this external validation set was assessed using the same evaluation metrics as for the internal test set.

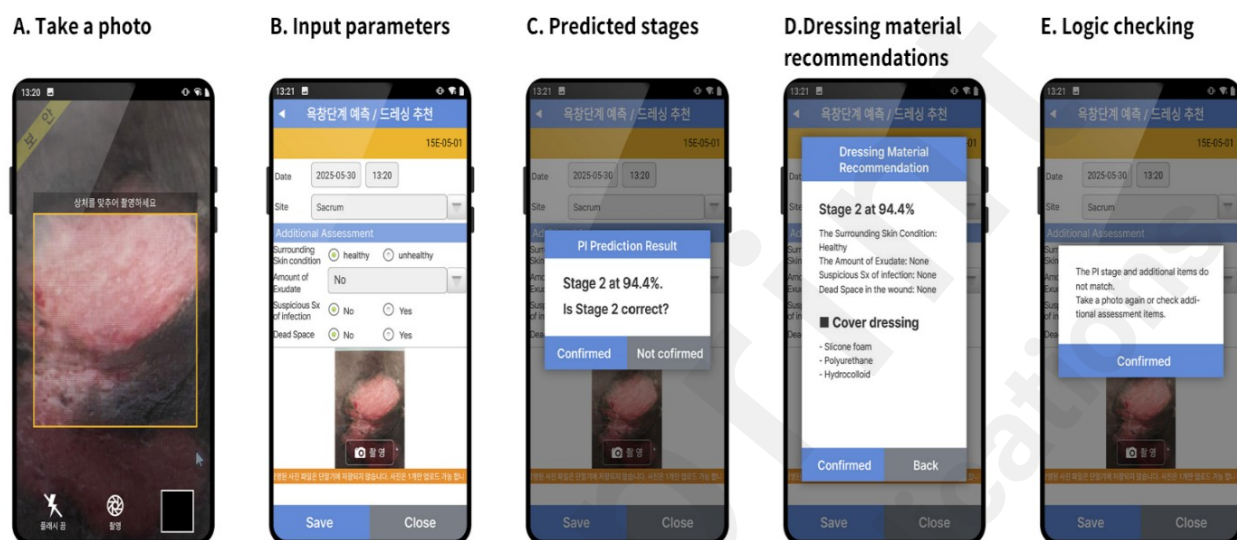
Application Development and EMR Integration

To develop an algorithm for recommending dressing materials based on individual PI conditions, we incorporated factors such as the condition of the surrounding skin, the amount of exudate, suspected symptoms of infection, and the presence of dead space in the wound, based on the NPUAP and the Korean Nursing Practice Guideline for Pressure Injury [1,21].

All nurses at Samsung Medical Center already use mobile BPOC devices for tasks such as administering medications and measuring vital signs. These devices have built-in cameras, making them ideal for wound scanning. Therefore, the installation of new applications and their integration into clinical workflows were considered highly feasible. We developed a deep learning-based application for pressure injury management specifically designed for BPOC devices. The application programming interface was developed to integrate with camera-equipped BPOC devices. At the bedside, nurses use the BPOC device to capture wound images, which are transmitted to an AI server

through the application. The AI analyzes the images, determines the pressure injury stage, and based on skin attributes recommends appropriate dressing materials (Figure 2). All results are automatically documented in the EMR, facilitating real-time clinical decision-making.

Figure 2. Example of the Application.



Effect of Application Use on Pressure Injury Healing

The PUSH tool, developed by the NPUAP [15], is a validated wound assessment instrument designed to monitor PI progress over time [16]. The PUSH score comprises three components: wound size (0–10, based on length $\times$ width), exudate amount (0–3), and tissue type (0–4), yielding a maximum total score of 17. A decreasing PUSH score indicates improvement, whereas an increasing score suggests deterioration.

According to the hospital's nursing practice guidelines, all parameters are required to be entered during the initial assessment of a pressure injury. For pressure injury assessment, nurses document parameters such as wound size, amount of exudate, tissue type, and PI stage. Nurses were allowed to freely choose between the manual EMR input method and the app-based input method.

The app-use group was defined as patients whose nurses used the application to photograph PIs,

input skin condition parameters, and receive dressing material recommendations generated by the app's algorithm. In contrast, the non-app-use group consisted of patients whose skin condition was recorded directly into EMR without using the app; in these cases, nurses selected dressing materials based on clinical guidelines. The choice to use the app or rely solely on the EMR was left to the nurse's discretion. Between January 2022 and May 2024, changes in PUSH scores were analyzed for adult patients aged 40 years or older who used the application. Patients with hospital stays exceeding 180 days were excluded. Ultimately, 305 cases were included in the app-use group (Figure 3).

To ensure comparability, propensity score matching (PSM) was applied at a 1:1 ratio using nearest-neighbor matching based on calculated propensity scores. Covariates included age, sex, baseline PI stage, history of diabetes mellitus, baseline PUSH score, and hospital units, which were identified in previous studies as factors influencing pressure injury healing. Matching on hospital unit adjusted for differences in patient populations across departments. After matching, 305 cases each were included in the app-use and non-app-use groups (610 in total). A subgroup analysis was also conducted. Patients who used the app from the onset of PI were classified as the early app-use group, whereas those who initiated app use later were classified as the delayed app-use group.

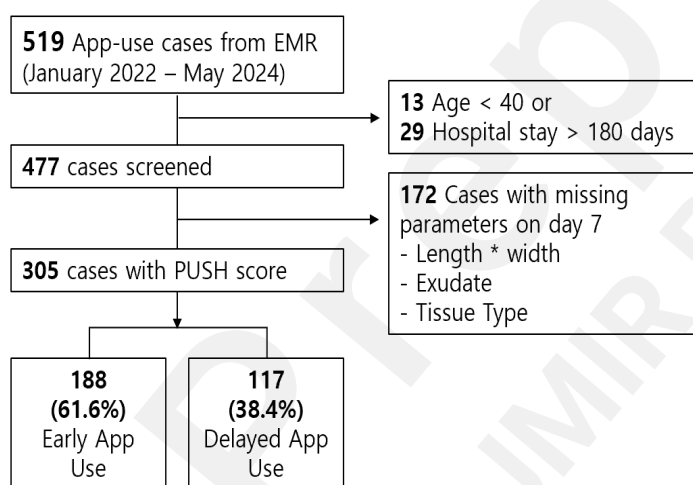
The effect of application use on PI healing was evaluated by comparing changes in PUSH scores measured on the day of initial PI occurrence (day 0) and seven days later (day 7). To account for differences in healing tendencies by severity, cases were further stratified into Stage 1, which typically heals well with wound protection alone, and all other stages (stage 2 and above). A 7-day interval was chosen to provide a clinically meaningful window for evaluating healing. Shorter intervals may not adequately reflect healing progress, whereas longer intervals could introduce confounding influences.

After 1:1 PSM, covariate balance between groups was evaluated using absolute standardized mean differences (ASMD). For variables with $ASMD > 0.1$, generalized estimating equations (GEE) with a logit link were applied to calculate crude and adjusted odds ratios with 95% confidence

intervals (CIs), adjusting for the remaining imbalanced covariates.

All statistical analyses were performed using R version 4.4.0. Descriptive statistics were reported as absolute numbers with percentages for categorical variables, and as mean with standard deviation (SD) or as median with interquartile range (IQR) for continuous variables. Categorical variables were compared between groups using the Pearson's chi-squared (χ^2) test or Fisher's exact test, as appropriate. Continuous variables were assessed using Student's t-test or the Wilcoxon rank-sum test, depending on the normality assumption.

Figure 3. Flowchart of Study Cohort for Assessing the Effect of Application Use on PI Healing.



Results

Model Performance

Table 1 presents the performance of the convolutional neural network across both the internal test set and the external validation set. Model performance was evaluated for each PI stage using sensitivity, specificity, accuracy, precision, F1-score, and AUROC, with 95% confidence intervals.

Overall, the model demonstrated strong classification performance across PI stages, with a

weighted AUROC of 0.969 (95% CI, 0.961–0.976). Specificity was consistently high across all stages (≥ 0.877), while sensitivity ranged from 0.493 in Stage 3 to 0.922 in Stage 4. Stage 3 had the lowest sensitivity (0.493) and F1-score (0.638), reflecting the clinical difficulty of distinguishing these lesions. Nevertheless, precision remained high (0.902). Performance remained robust in the external dataset, with a weighted AUROC of 0.971 (95% CI, 0.962–0.979). For Stage 1, sensitivity remained essentially stable between the internal and external datasets (0.885 vs. 0.883), while precision (0.584 vs. 0.944) and F1-score (0.704 vs. 0.913) improved markedly. Specificity for Stage 1 also increased (0.930 vs. 0.989), indicating fewer false positives and more reliable identification. For Stage 2 and Stage 3, sensitivity improved (Stage 2: 0.750 vs. 0.885; Stage 3: 0.493 vs. 0.667), while specificity and precision declined moderately (Stage 2 specificity: 0.949 vs. 0.914; Stage 3 specificity: 0.997 vs. 0.946; Stage 3 precision: 0.902 vs. 0.722). AUROC showed a slight increase for Stage 2 (0.965 vs. 0.971) and a decrease for Stage 3 (0.983 vs. 0.939). Nonetheless, AUROC values for both stages remained high, supporting the overall discriminative ability of the model.

For advanced-stage lesions (Stage 4, DTI, and unstageable), AUROC values of external testing set ranged from 0.965 to 0.991, indicating excellent classification. Stage 4 maintained high sensitivity in the internal and external datasets (0.922 vs. 0.917), specificity (0.999 vs. 0.985), and AUROC (0.999 vs. 0.991). DTI showed strong overall performance with high precision (0.738 vs. 0.868) and specificity (0.877 vs. 0.975), although sensitivity decreased (0.918 vs. 0.720). Unstageable lesions also showed consistent performance, with AUROC improving (0.968 vs. 0.982). The largest performance gap was noted for Stage 3. Although sensitivity improved (0.493 vs. 0.667), both precision (0.902 vs. 0.722) and specificity (0.997 vs. 0.946) decreased. This is clinically important, as Stage 3 injuries are visually ambiguous and often difficult to distinguish from other stages, even for experienced clinicians. Despite these declines in performance, the model maintained high specificity, indicating that misclassification of other stages as Stage 3 remained infrequent. Weighted average metrics confirmed stable performance between the internal and external datasets:

sensitivity (0.800 vs. 0.821), specificity (0.935 vs. 0.961) and AUROC (0.969 vs. 0.971). These results suggest that the model's predictive performance generalized well from the internal to the external dataset, thereby confirming its reliability.

Table 1. Model performance.

	Sensitivity (95% CI)	Specificity (95% CI)	Accuracy (95% CI)	Precision (95% CI)	F1-score (95% CI)	AUROC ^a (95% CI)
Internal Testing set						
Stage 1	0.885 (0.851-0.919)	0.930 (0.902-0.957)	0.925 (0.897-0.953)	0.584 (0.536-0.632)	0.704 (0.657-0.750)	0.975 (0.958-0.992)
Stage 2	0.750 (0.726-0.775)	0.949 (0.938-0.961)	0.863 (0.844-0.882)	0.919 (0.905-0.934)	0.826 (0.805-0.847)	0.965 (0.955-0.975)
Stage 3	0.493 (0.427-0.560)	0.997 (0.989-1.000)	0.974 (0.949-1.000)	0.902 (0.856-0.949)	0.638 (0.569-0.707)	0.983 (0.962-1.000)
Stage 4	0.922 (0.884-0.961)	0.999 (0.993-1.000)	0.995 (0.984-1.000)	0.976 (0.954-0.999)	0.949 (0.917-0.981)	0.999 (0.996-1.000)
DTI	0.918 (0.900-0.936)	0.877 (0.855-0.898)	0.888 (0.867-0.909)	0.738 (0.709-0.767)	0.818 (0.793-0.844)	0.964 (0.952-0.976)
Unstageable	0.669 (0.619-0.718)	0.984 (0.970-0.998)	0.956 (0.932-0.979)	0.805 (0.761-0.848)	0.731 (0.683-0.778)	0.968 (0.947-0.988)
Weighted Average	0.800 (0.777-0.823)	0.935 (0.924-0.947)	0.897 (0.882-0.912)	0.828 (0.807-0.849)	0.801 (0.778-0.824)	0.969 (0.961-0.976)
External Testing set						
Stage 1	0.883 (0.810-0.946)	0.989 (0.978-0.997)	0.971 (0.954-0.984)	0.944 (0.885-0.988)	0.913 (0.860-0.953)	0.988 (0.975-0.997)
Stage 2	0.885 (0.818-0.949)	0.914 (0.884-0.940)	0.908 (0.882-0.932)	0.713 (0.622-0.790)	0.790 (0.721-0.844)	0.971 (0.956-0.983)
Stage 3	0.667 (0.574-0.762)	0.946 (0.923-0.965)	0.897 (0.871-0.921)	0.722 (0.621-0.817)	0.693 (0.613-0.770)	0.939 (0.911-0.960)
Stage 4	0.917 (0.824-1.000)	0.985 (0.974-0.995)	0.980 (0.967-0.992)	0.846 (0.726-0.951)	0.880 (0.797-0.952)	0.991 (0.984-0.998)
DTI^b	0.720 (0.625-0.808)	0.975 (0.960-0.989)	0.929 (0.906-0.949)	0.868 (0.785-0.938)	0.787 (0.710-0.849)	0.965 (0.944-0.982)
Unstageable	0.898 (0.833-0.955)	0.972 (0.953-0.988)	0.958 (0.938-0.975)	0.888 (0.820-0.950)	0.893 (0.840-0.938)	0.982 (0.965-0.994)
Weighted Average	0.821 (0.786-0.853)	0.961 (0.952-0.968)	0.936 (0.922-0.947)	0.828 (0.795-0.858)	0.821 (0.785-0.852)	0.971 (0.962-0.979)

^aAUROC: area under the receiver operating characteristic.

^bDTI: Deep Tissue Injury.

Effect of Application Use on Pressure Injury Healing

Comparability Between the App-use Group and the Non-app-use Group

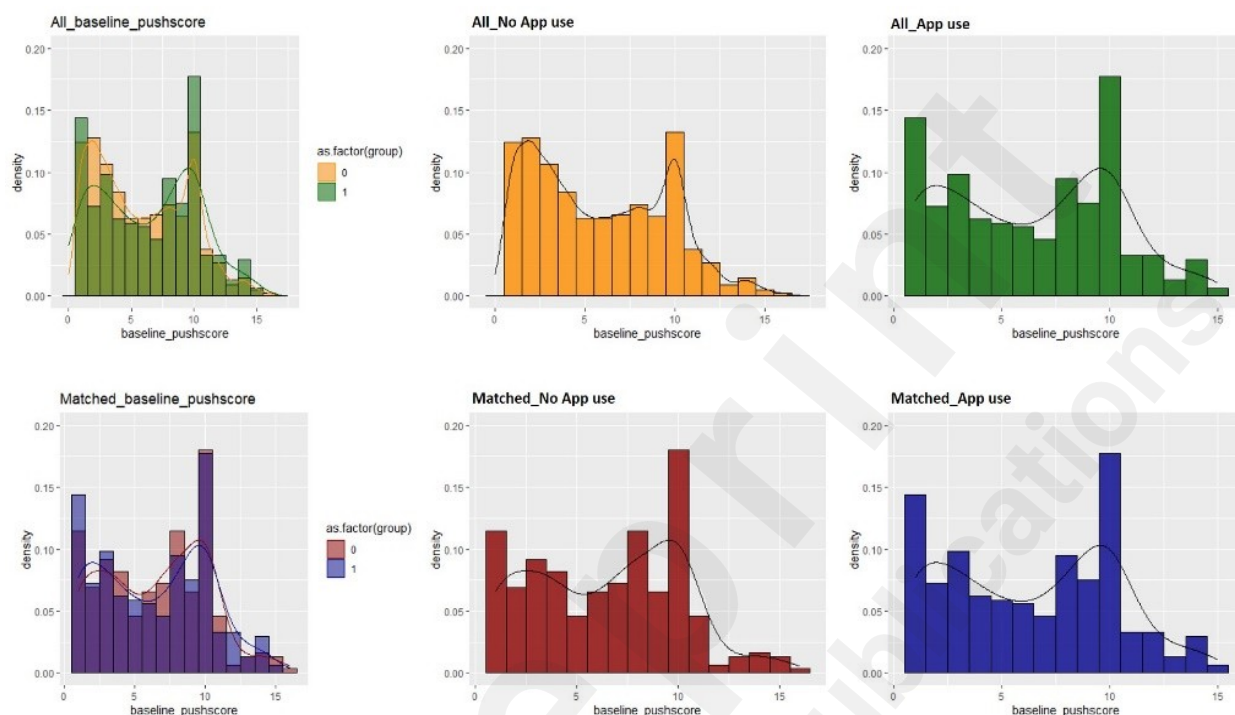
To ensure comparability between the app-use group and the non-app-use group, propensity score matching (PSM) was performed. A total of 610 cases were included in the matched dataset, with 305 in the app-use group and 305 in the non-app-use group, as summarized in Table 2. Covariates such as age, sex, PIs stages, history of diabetes mellitus, baseline PUSH score and hospital units were included in the matching process to account for potential differences in PIs characteristics, healing status, and nursing care quality across units. After matching, the characteristics of the two cohorts were well balanced, with ASMDs less than 0.1 except for the hospital units, indicating good covariate balance. The ASMD value for hospital units over 0.2 was considered adequate for the purpose of our analysis to include a broad range of patients admitted to various hospital units and ensure representative coverage of diverse disease spectra. Therefore, the covariate balance was considered generally adequate for the purpose of our analysis and hospital unit was not used for variable adjustment (Multimedia Appendix 1). Many patients were in their 60s or 70s, accounting for approximately 59% of each group. The sex distribution was similar between groups (Non-app-use: 63.28% male vs. App-use: 62.62% male, ASMD = 0.01). The most common baseline PI stage was Stage 1 (Non-app-use: 46.56% vs. App-use: 45.57%), followed by Stage 2 (Non-app-use: 24.59% vs. App-use: 24.92%). The proportion of patients with a history of diabetes was slightly higher in the app-use group (44.26%) compared to the non-app-use group (39.34%), but this difference was not statistically significant ($P=.2182$). The baseline PUSH score also showed no significant difference between groups (mean $\pm$ SD: 6.60 ± 3.67 vs. 6.43 ± 3.85 , $P=.5975$). The distribution of baseline PUSH scores before and after propensity score matching is illustrated in Figure 3. As shown, the matching procedure substantially improved the comparability between the app-use and non-app-use groups, particularly with respect to baseline wound severity. This visual confirmation further supports the adequacy of the covariate balance achieved by PSM.

Table 2. Baseline characteristics (N=610).

Characteristics		Non-app-use (n=305) n (%) or Mean (SD)	App-use (n=305) n (%) or Mean (SD)	ASMD ^a	P value
Age	40s	11 (3.61%)	10 (3.28%)	0.06	.9712
	50s	39 (12.79%)	44 (14.43%)		
	60s	77 (25.25%)	72 (23.61%)		
	70s	102 (33.44%)	102 (33.44%)		
	over 80s	76 (24.92%)	77 (25.25%)		
Sex	F	112 (36.72%)	114 (37.38%)	0.01	.8668
	M	193 (63.28%)	191 (62.62%)		
Baseline Pressure Injury stages	Stage 1	142 (46.56%)	139 (45.57%)	0.06	.9918
	Stage 2	75 (24.59%)	76 (24.92%)		
	Stage 3	15 (4.92%)	14 (4.59%)		
	Stage 4	3 (0.98%)	5 (1.64%)		
	Unstageable	28 (9.18%)	29 (9.51%)		
	DTI ^b	42 (13.77%)	42 (13.77%)		
Baseline PUSH ^c score		6.60 (3.67)	6.43(3.85)	0.04	.5975
History of DM ^d	No	185 (60.66%)	170 (55.74%)	0.10	.2182
	Yes	120 (39.34%)	135 (44.26%)		

^aASMD: Absolute value of Standardized Mean Difference.^bDTI: Deep Tissue Injury.^cPUSH: Pressure Ulcer Scale for Healing.^dDM: Diabetes Mellitus.

Figure 4. Illustration of the distribution of PUSH scores in the app-use and non-app-use groups before and after propensity score matching (PSM).



PUSH Scores Changes: The App-Use Group vs. The Non-App-Use Group

Table 3 summarizes changes in PUSH scores between the app-use and non-app-use groups. Across all stages, the app-use group showed a higher rate of PUSH score improvement than the non-app-use group (30.49% vs. 26.23%), although this difference did not reach statistical significance (OR=1.314, 95% CI=0.899–1.922, $P=.158$). For Stage 1 PIs, the improvement rate was slightly lower in the app-use group compared with the non-app-use group (8.63% vs. 15.49%), and the difference was not statistically significant (OR=0.537, 95% CI=0.247–1.184, $P=.123$). In contrast, for Stage 2 and above PIs, the app-use group demonstrated a significantly greater improvement rate compared with the non-app-use group (48.80% vs. 35.58%). This corresponded to an odds ratio of 1.825 (95% CI=1.152–2.891, $P=.010$), indicating that app-use was associated with nearly 1.8-fold

higher odds of healing improvement in more advanced PI stages.

Table 3. PUSH scores change: the app-use group vs. the non-app-use group (N=610).

Stages	Non-app-use n / N (%)	App-use n / N (%)	OR	P value
			95% CI	
All Stages	80 / 305 (26.23%)	93 / 305 (30.49%)	1.315 (0.899-1.922)	.158
Stage 1	22 / 142 (15.49%)	12 / 139 (8.63%)	0.537 (0.244-1.184)	.123
Stage 2 and above	58 / 163 (35.58%)	81 / 166 (48.8%)	1.825 (1.152-2.892)	.010

Subgroup Analysis of PUSH Score Based on the Timing of Application Usage

Multimedia Appendix 2 displays the covariate balance across the non-app-use, the early app-use, and the delayed app-use. In comparison between the non-app-use and the early app-use, sex and baseline PUSH score demonstrated negligible imbalance (ASMD<0.1) but age and baseline PIs stages showed imbalance. In comparison between the non-app-use and the delayed app-use, all the variables of age, sex, baseline PIs stages and baseline PUSH score demonstrated imbalance. Imbalanced variables were adjusted for group comparisons.

Table 4 summarizes subgroup Analysis of the PUSH score changes based on the timing of application usage. Across all stages combined, no significant differences were observed between the early app-use and non-app-use groups (adjusted OR=1.277, 95% CI=0.752–2.168, $P=.365$) or between the delayed app-use and non-app-use groups (adjusted OR=1.332, 95% CI=0.713–2.487, $P=.369$). For Stage 1 PIs, the improvement rate was lower in both the early and delayed app-use groups compared with the non-app-use group (early: 7.07% vs. 13.19%; delayed: 12.50% vs. 19.61%), but these differences were not statistically significant (early: adjusted OR = 0.476, 95% CI=0.177–1.281, $P=.142$; delayed: adjusted OR = 0.523, 95% CI=0.132–2.067, $P=.356$). In contrast, for Stage 2 and above, patients in the early app-use group demonstrated significantly higher odds of PUSH score improvement compared with the non-app-use group (51.69% vs. 36.08%; adjusted OR=1.862, 95% CI= 1.004–3.454, $P=.048$). The delayed app-use group also showed a higher rate of improvement compared with the non-app-use group (45.45% vs. 34.85%), corresponding to an

adjusted OR of 1.847 (95% CI=0.891–3.830, $P=.099$), although this difference did not reach statistical significance.

Table 4. Subgroup analysis of PUSH score based on the timing of application usage.

(A) Non-app-use vs. Early app-use (N=376)						
Stage	Non-app-use n/N (%)	Early app-use n/N (%)	Crude OR		Adjusted OR	
			95% CI	<i>P</i> value	95% CI	<i>P</i> value
All Stages	47/188 (25.00%)	53/188 (28.19%)	1.236 (0.762-2.005)	.391	1.277 ^a (0.752-2.168)	.365
- Stage 1	12/91 (13.19%)	7/99 (7.07%)	0.510 (0.189-1.374)	.183	0.476 ^b (0.177-1.281)	.142
- Stage 2 and above	35/97 (36.08%)	46/89 (51.69%)	1.889 (1.040-3.431)	.037	1.862 ^a (1.004-3.454)	.048
(B) Non-app-use vs. Delayed app-use (N=234)						
Stage	Non-app-use n/N (%)	Delayed app-use n/N (%)	Crude OR		Adjusted OR	
			95% CI	<i>P</i> value	95% CI	<i>P</i> value
All Stages	33/117 (28.21%)	40/117 (34.19%)	1.373 (0.767-2.456)	.286	1.332 ^c (0.713-2.487)	.369
- Stage 1	10/51 (19.61%)	5/40 (12.50%)	0.552 (0.157-1.942)	.355	0.523 ^d (0.132-2.067)	.356
- Stage 2 and above	23/66 (34.85%)	35/77 (45.45%)	1.633 (0.818-3.258)	.164	1.847 ^c (0.891-3.830)	.099

Group comparison was conducted using Generalized Estimating Equation (GEE), with adjustment for imbalanced variables.

^aage (numeric), baseline Stage.

^bage (numeric).

^cage (numeric), sex, baseline Stage, baseline PUSH score.

^dage (numeric), sex, baseline PUSH score.

Discussion

While many AI models for wound management have shown promising results in internal or external validations, their impact on actual patient healing at the bedside has rarely been examined. Most

existing studies have prioritized diagnostic accuracy or inter-institutional validity, providing limited evidence on real-world clinical outcomes. This study addressed that gap by developing a user-friendly mobile application and evaluating both its classification performance and its effect on wound healing in clinical practice. To our knowledge, this is the first study to provide real-world evidence that an AI-based tool for PI management, directly embedded into routine nursing workflows and linked with EMR documentation, can generate measurable improvements in patient outcomes. This integration highlights the practical feasibility of translating algorithmic accuracy into bedside benefit, as further acknowledged by the Healthcare Information and Management Systems Society (HIMSS) DAVIES Award recognition [22].

Our results are consistent with prior studies showing that, despite high overall classification performance in PI staging, deep learning models continue to face challenges in accurately identifying Stage 3 lesions. For example, one study using EfficientNet-B4 reported high performance but noted difficulty in distinguishing Stage 2 from Stage 3 due to visual similarity and boundary ambiguity [11]. Similarly, others showed that AI-assisted classification improved overall accuracy and interrater agreement, yet performance for Stage 3 remained suboptimal [12]. In line with these findings, our study also observed relatively low sensitivity for Stage 3 in both internal and external validation, reflecting the inherent complexity of intermediate-stage wounds.

To minimize bias, we applied PSM based on well-established factors influencing wound healing, including age, sex, baseline PI stage, diabetes history, initial PUSH score, and hospital unit. After PSM, the app-use group exhibited significantly greater healing improvement than the non-app-use group among patients with Stage 2 and above PIs, suggesting that the application provides effective decision support for more advanced lesions. Our findings further indicate that early app-use was particularly beneficial, as patients in the early app-use group demonstrated greater PUSH score improvements compared with the non-app-use group. Although delayed app-use showed a trend toward improved healing (adjusted OR=1.847), this was not statistically significant. By contrast,

Stage 1 wounds showed no significant difference, which is expected since superficial injuries typically heal well with standard protective care, limiting the added value of AI-based recommendations.

Overall, these findings underscore the importance of early intervention in PI management and highlight the potential of AI-powered decision support integrated into nursing workflows. While this study was conducted in a large tertiary hospital, further research is needed to evaluate scalability in other care environments, such as long-term care facilities, community hospitals, and home-care settings, where staffing models and resource availability differ. The increasing uptake of the application in practice also suggests growing trust and usability among nurses, further supporting its potential for broader adoption.

However, strengthening causal inference requires prospective study designs. Prospective research could also provide insights into longitudinal adherence, sustainability of use, and nurse-reported experiences, thereby enriching understanding of the human–AI interface in wound care. Moreover, while our study demonstrated short-term improvements over a 7-day period, this timeframe may not fully capture the long-term healing trajectory. Longitudinal studies with extended follow-up are warranted to determine whether early AI-guided interventions translate into sustained benefits and complete wound closure.

Finally, the inclusion of wound-related features documented through the application—such as surrounding skin condition, exudate amount, signs of infection, and wound depth—may provide additional insights into the determinants of healing outcomes [1,21]. Incorporating user feedback from clinical practice can also guide refinements to improve usability, such as enabling documentation of multiple PI sites. Continued iteration and evaluation across diverse contexts will be critical to ensuring the sustained utility of AI-based wound care tools. While the current version does not yet leverage real-time learning from accumulated user data, future iterations may benefit from adaptive AI models that refine recommendations based on user feedback and clinical outcomes.

Limitations

This study has several limitations that should be acknowledged. First, it was conducted retrospectively at a single tertiary care institution, which may limit the generalizability of the findings to other clinical settings, such as long-term care facilities or hospitals with different staffing models or patient populations. Future multicenter studies would help to verify the external validity of the findings across diverse healthcare environments.

Second, although PSM was applied to minimize bias between the app-use and non-app-use groups, residual confounding due to unmeasured variables such as nutritional status, medications, and severity of comorbidities cannot be entirely ruled out. Our matching process incorporated key factors including age, sex, PI stage, hospital unit, diabetes history, and baseline PUSH score; however, further refinement using additional clinical variables could strengthen the validity of causal inference.

Third, Nurses' knowledge and practice environments (e.g., years of clinical experience, workload, training, knowledge and technological proficiency) may influence the healing trajectory of pressure injuries. However, it was not feasible to isolate the impact of individual nurse characteristics on patient outcomes or to attribute outcomes to specific nurses, because each patient was cared for by multiple nurses across different shifts. In addition, the retrospective design of this study precluded the collection of objectively measured data on these factors. Previous studies have investigated nursing-related determinants of pressure injury healing using validated instruments such as the Nursing Work Index-Revised (NWI-R-PT) [23] and the Pieper-Zulkowski Pressure Ulcer Knowledge Test (PZ-PUKT) [24]. Future prospective studies should therefore incorporate such validated tools to examine whether, and in what ways, nurse-level characteristics shape both the adoption and the clinical effectiveness of the application.

Fourth, the healing outcome was assessed over a relatively short period of 7 days. Although this

window is reasonable for detecting early trends in healing, it may not fully capture the long-term effects of intervention or the complete healing trajectory. Moreover, the PUSH score, while widely validated, still relies on subjective interpretation of parameters such as exudate and tissue type, which may introduce interrater variability. Incorporating objective measurements or image-based automated scoring could enhance accuracy in future work.

Lastly, the study did not examine nurses' adherence to the app's dressing material recommendations or their satisfaction and perceived usability. Since clinical decision support systems can only be effective when they are accepted and properly utilized by end-users, future research should include qualitative assessments of nurse engagement and user experience to guide iterative development and successful implementation. In addition, prospective or randomized controlled studies should explicitly evaluate whether the dressing recommendations generated by the application are implemented in practice and how adherence influences clinical outcomes.

Conclusion

This study demonstrates that an AI-based application can be effectively deployed at the bedside to improve clinical decision-making and enhance pressure injury healing, particularly when implemented during the initial phase of PI management. To our knowledge, this is the first real-world study to demonstrate both technical validity and clinical benefits of AI-powered PI staging and dressing recommendations in a hospital setting. Future research should move beyond algorithmic optimization to include prospective, multi-center designs, integration of nurse-level characteristics, and assessment of long-term adherence and outcomes, thereby establishing AI-supported PI care as a sustainable and clinically effective tool.

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Competing interests

None declared.

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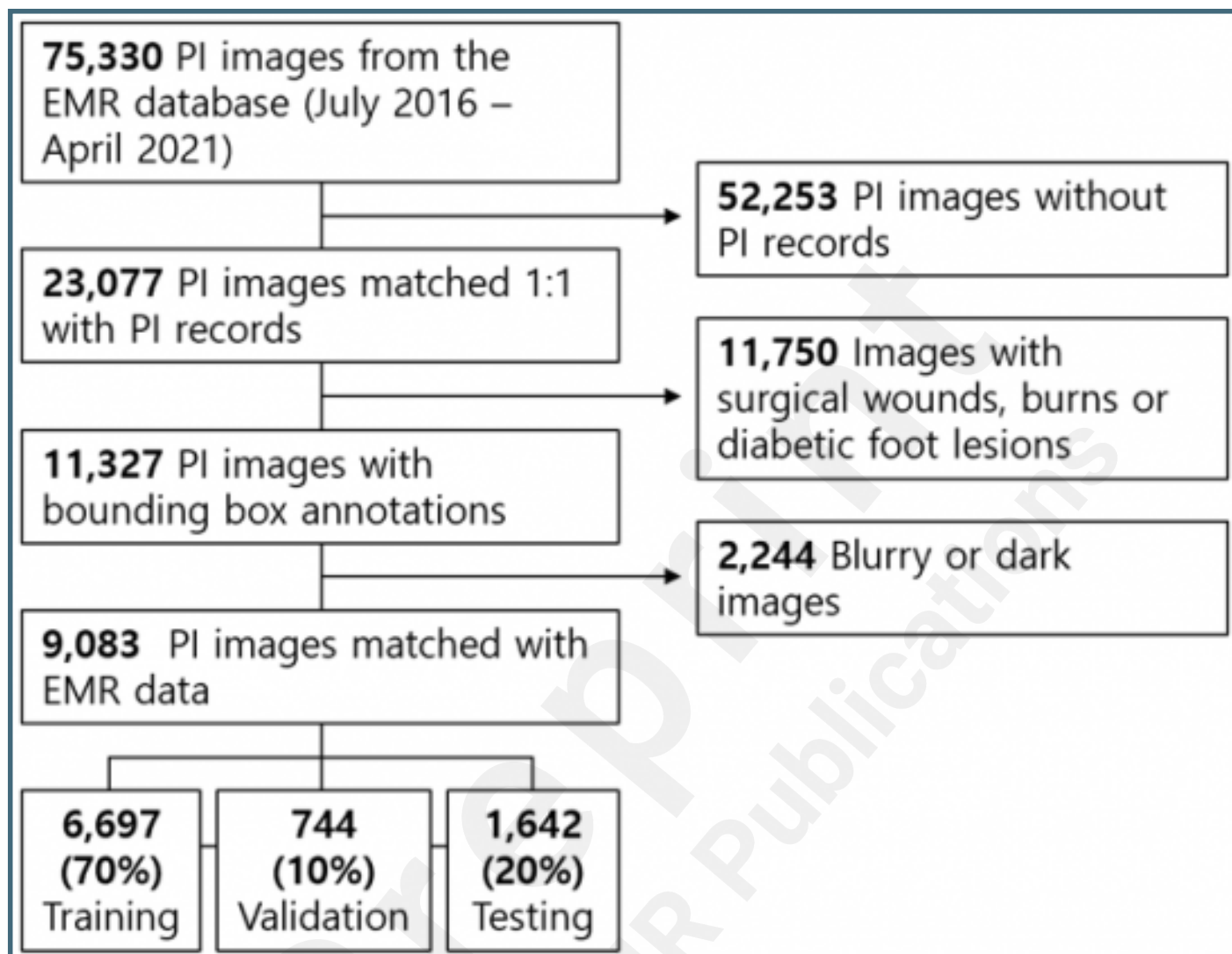
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Supplementary Files

Figures

Flowchart of the Study.



Example of the Application.



Flowchart of Study Cohort for Assessing the Effect of Application Use on PI Healing.

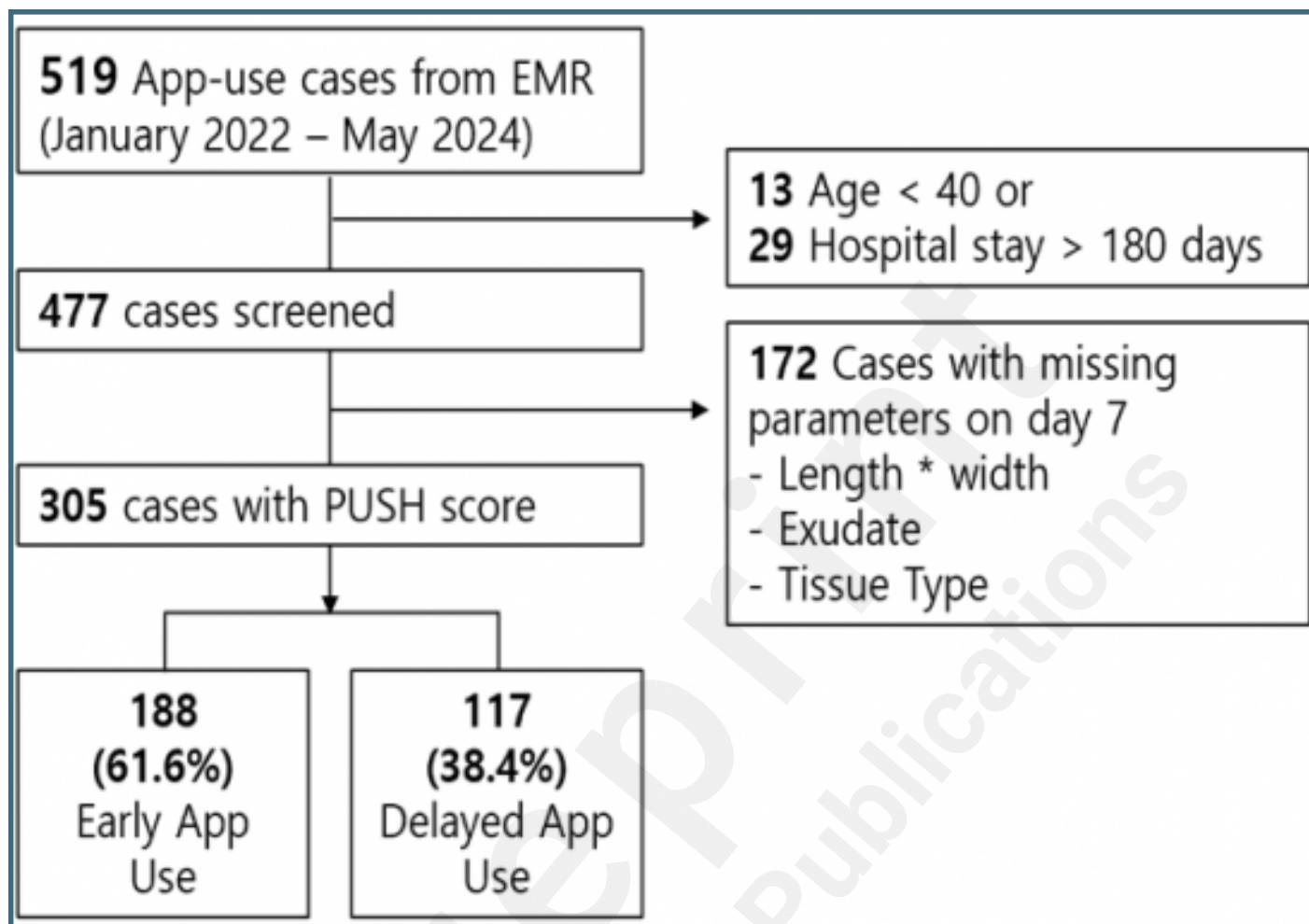
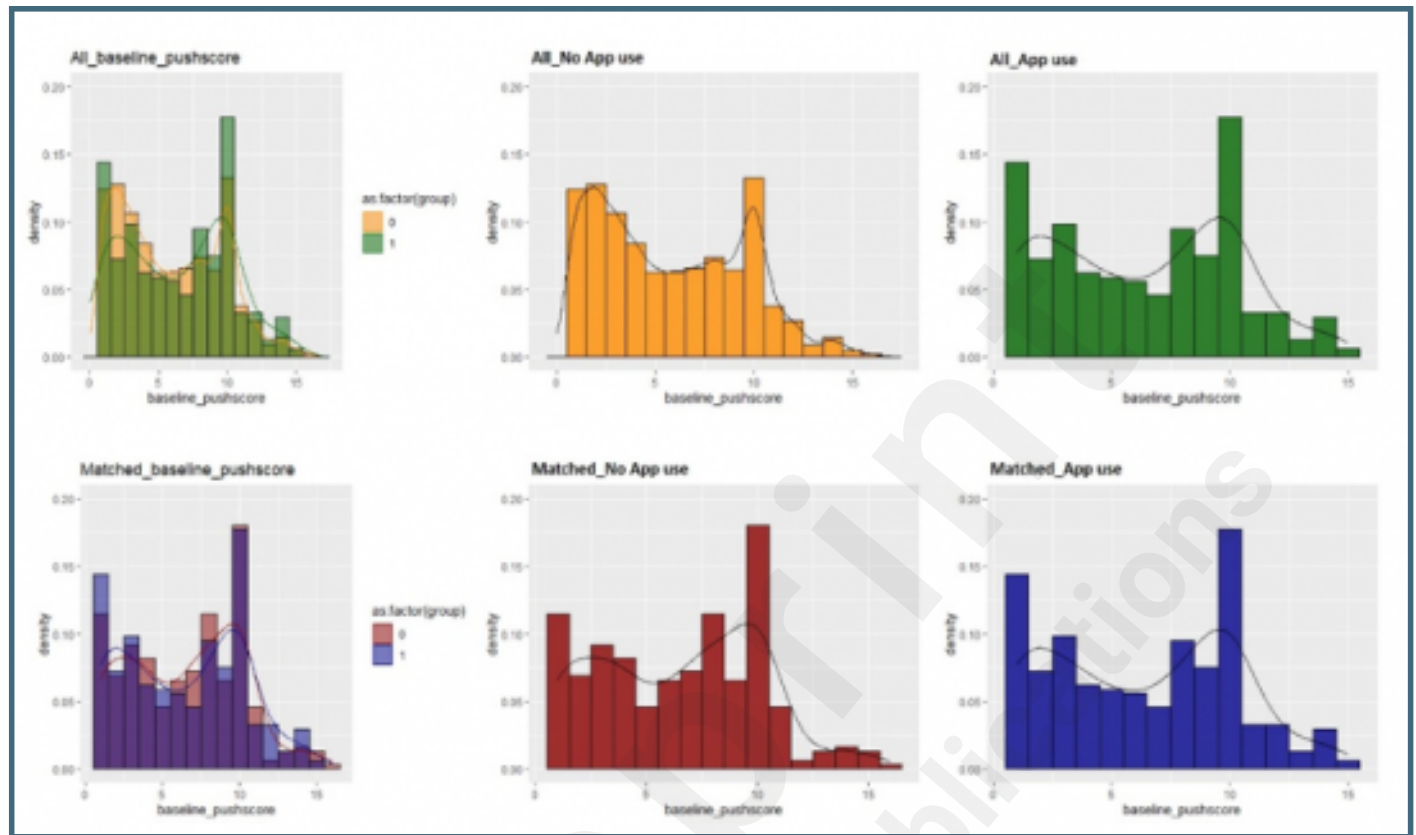


Illustration of the distribution of PUSH scores in the app-use and non-app-use groups before and after propensity score matching (PSM).



Multimedia Appendixes

Comparability Between the Non-app-use and app-use groups by Hospital Unit.

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Comparability analysis of subgroups.

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Balance assessment after matching.

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