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Integrating artificial intelligence into nursing practice: Development and clinical evaluation of the NURSYA care model based on Levine's Conservation Principles☆

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ABSTRACT

Background: Although artificial intelligence (AI) is increasingly used in healthcare, its integration with established nursing theories remains limited. Levine's Conservation Model provides a holistic framework for nursing care, yet its routine application can be challenging without structured decision support.

Purpose: This study aimed to develop and evaluate NURSYA, a theory-based AI-supported nursing care system grounded in Levine's Conservation Model, and to examine changes in nursing outcomes following its implementation.

Methods: A single-group pre-post intervention study was conducted with 300 nurses working in diverse clinical settings in Türkiye. Nurses used NURSYA for three months. Data were collected using a nursing model evaluation scale assessing planning, implementation, evaluation, and usability. Paired *t*-tests and effect size analyses were performed.

Results: Perceived effectiveness scores increased significantly after implementation ($p < 0.001$), with improvements observed across all domains. The evaluation scale showed high internal consistency (Cronbach's $\alpha = 0.92$).

Conclusion: NURSYA was associated with significant improvements in nurses' perceived effectiveness in care planning and clinical decision-making. Theory-based AI systems may support evidence-based and patient-centered nursing practice, although patient-level outcomes require further investigation.

1. Introduction

Artificial intelligence (AI) is increasingly being integrated into healthcare systems, particularly through clinical decision support tools designed to assist with data analysis, risk prediction, and care optimization. In nursing practice, AI-based systems have demonstrated potential to support early warning detection, real-time patient monitoring, workflow efficiency, and decision-making in complex clinical environments (Almagharbeh, 2025; Austin, 2020; Moore et al., 2021). Despite these advances, the development and implementation of AI applications in nursing have largely occurred without systematic alignment with established nursing theories that emphasize holistic, patient-centered care (El Arab et al., 2025; Wei et al., 2025). As a result, many AI-supported systems risk reinforcing task-oriented and disease-focused workflows rather than supporting comprehensive nursing care grounded in theoretical frameworks (Martínez-Ortigosa et al., 2023).

1.1. Theoretical background: Levine's Conservation Model

Nursing theories play a critical role in structuring clinical knowledge, interpreting patient responses, and guiding individualized nursing interventions across diverse care settings (Schaefer & Pond, 1994). Among these, Levine's Conservation Model offers a particularly relevant framework for contemporary nursing practice by emphasizing patient wholeness through four interrelated conservation principles: conservation of energy, structural integrity, personal integrity, and social integrity (Levine, 1996). The model conceptualizes individuals as adaptive systems who continuously respond to internal and external stressors, highlighting the role of nursing interventions in promoting adaptation while minimizing unnecessary energy expenditure. This holistic and

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integrative perspective aligns closely with the goals of modern nursing practice, which increasingly demands comprehensive assessment and individualized care planning in the context of rising patient acuity and workload pressures (Kirca & Özcan, 2023).

1.2. Study purpose and the NURSYA system

Levine's Conservation Model has been applied in various clinical contexts, including neonatal care, geriatric nursing, infertility care, and chronic disease management, demonstrating positive effects on patient outcomes and nursing care quality (Kirca & Özcan, 2023; Mefford, 2004; Nurhidayah et al., 2019). However, its application in routine clinical practice often relies on individual nurse expertise and manual interpretation, which may limit consistency, scalability, and systematic integration across care settings. To date, AI-supported nursing systems have not been comprehensively designed around established nursing theories, resulting in limited theoretical fidelity and reduced support for holistic nursing assessment and care planning (Alruwaili et al., 2025; Bodur et al., 2025; Tabassam et al., 2024).

Recent literature suggests that AI-driven systems may enhance personalized nursing care by integrating individual-level clinical data with population-level evidence, thereby supporting more informed and timely clinical decisions (Brydges, 2025). Nevertheless, existing AI applications in nursing remain predominantly task-specific and disease-oriented, offering limited support for theory-based, comprehensive nursing assessment that encompasses physical, psychological, and social dimensions of patient care. This gap underscores the need for AI systems that are explicitly grounded in nursing theory and designed to support holistic, patient-centered practice.

To address this need, the present study introduces NURSYA (Nursing System with Artificial Intelligence), a digital clinical decision support platform explicitly grounded in Levine's Conservation Model. Levine's Conservation Model was selected over other nursing theories (such as Orem's Self-Care Deficit Theory, Roy's Adaptation Model, and Neuman's Systems Model) for several key reasons: (1) its holistic framework explicitly integrates physical, psychological, and social dimensions of patient care, which aligns well with AI's capacity to process multidimensional data; (2) the four conservation principles provide structured yet flexible assessment categories that can be systematically operationalized through algorithmic decision pathways; (3) no prior AI-supported operationalization of Levine's model exists in the literature, representing a significant theoretical and practical gap; and (4) the model's focus on adaptive nursing interventions is particularly relevant for dynamic clinical environments where AI-driven decision support can enhance real-time responsiveness. NURSYA is designed to structure nursing assessment across all four conservation domains, support evidence-based care planning and evaluation, and provide real-time clinical guidance while preserving the core values of holistic and patient-centered nursing practice. In this study, "traditional nursing models" refers to conventional nursing care practices employed at baseline across participating institutions, which varied by site and included unstructured clinical assessments, paper-based documentation, and nurse-initiated care planning without formalized decision support tools or theory-driven frameworks. The aim of this study was to examine changes in nursing practice domains following the implementation of NURSYA, relative to baseline traditional nursing practices in supporting key domains of nursing practice, including planning, implementation, evaluation, and overall care delivery. In addition, the study examined nurses' perceptions of NURSYA, its impact on clinical confidence and workflow efficiency, and its performance across different clinical settings and demographic groups.

2. Methods

2.1. Study design

This study utilized a single-group pre-post intervention design to evaluate the effectiveness of NURSYA, an artificial intelligence-enhanced nursing platform grounded in Levine's Conservation Model. Data were collected between July 2024 and March 2025 across multiple healthcare institutions in Turkey. Ethical approval was obtained from the Institutional Review Board (IRB Protocol No. 2024-NURSYA-001), and all participants provided written informed consent prior to participation.

2.2. Setting and sample

The study was conducted in four major healthcare facilities, including two university hospitals, one general state hospital, and one private hospital. The target population consisted of registered nurses employed in acute care, intensive care, emergency departments, and outpatient clinics.

Sample size was determined using G*Power 3.1 with an effect size of $d = 0.5$, $\alpha = 0.05$, and power of 0.95 for paired *t*-tests, resulting in a minimum requirement of 273 participants. To account for attrition, 320 nurses were recruited, and 300 completed the study (93.75% retention rate).

Participants were included if they:

(a) were registered nurses actively providing direct patient care,
(b) had at least six months of clinical experience, and
(c) had no prior exposure to AI-based nursing platforms.

Nurses on administrative leave or not engaged in clinical duties were excluded.

2.3. Intervention: NURSYA AI-enhanced care platform

NURSYA is an artificial intelligence-supported clinical decision support system designed to systematize patient assessment, care planning, implementation, and evaluation based on the four conservation principles of Levine's model. The AI component of NURSYA employs a hybrid rule-based and machine learning architecture. The system uses a decision tree classifier (scikit-learn RandomForestClassifier, Python 3.11) trained on a dataset of 5247 anonymized nursing care records collected from three Turkish university hospitals between 2022 and 2024. Training data included patient demographics, vital signs, Levine-based assessment inputs, documented nursing diagnoses, and care plan outcomes. The model was validated using 5-fold cross-validation (mean accuracy = 0.87, SD = 0.03) and tested on a held-out set of 1049 records (accuracy = 0.85, sensitivity = 0.83, specificity = 0.88). Care recommendations are generated through a three-stage process: (1) structured data entry by nurses following Levine's four conservation domains, (2) algorithmic risk stratification based on clinical thresholds and predictive scoring, and (3) rule-based mapping to evidence-based nursing interventions derived from clinical practice guidelines and expert consensus. The intervention involved:

- Structured assessment modules aligned with conservation of energy, structural integrity, personal integrity, and social integrity. Each conservation principle was operationalized as follows: (a) Energy conservation: assessment of fatigue, activity tolerance, sleep patterns, nutrition, and metabolic demands; (b) Structural integrity: evaluation of tissue condition, wound status, mobility limitations, physical function, and anatomical integrity; (c) Personal integrity: assessment of self-concept, identity, autonomy, emotional status, coping mechanisms, and psychological adaptation; and (d) Social integrity: evaluation of family relationships, social support systems,

cultural considerations, communication patterns, and role functions. These domains were embedded as structured input fields within the NURSYA platform, with predefined assessment categories, scoring rubrics, and prompt-based data entry interfaces designed to ensure systematic and comprehensive evaluation across all four conservation areas.
- Automated care plan generation based on patient inputs and clinical guidelines.
- Real-time decision support for prioritization, risk detection, and procedural guidance.
- Evaluation dashboards to standardize outcome assessment and documentation.

Participants received a standardized 60-minute training session, followed by a two-week supervised familiarization phase to ensure proficiency with the system. During the familiarization phase, each nurse was supervised by a trained study coordinator who provided real-time guidance on data entry, system navigation, and interpretation of AI-generated recommendations. Proficiency was assessed using a standardized checklist requiring successful completion of five simulated patient cases with ≥90% accuracy in data entry and appropriate selection of care interventions. System usage was monitored through automated logging, with weekly feedback provided to participants. Adherence was defined as completing at least 80% of required assessments during the familiarization period; all 300 participants met this threshold. After this phase, NURSYA was actively integrated into routine clinical practice and used for three consecutive months across participating units prior to post-intervention data collection.

In the NURSYA system, machine learning components were used primarily for risk stratification and pattern recognition based on multidimensional nursing assessment data. Clinical decision-making and care recommendations were subsequently guided by a rule-based layer grounded in Levine's Conservation Principles, ensuring clinical safety, interpretability, and theoretical fidelity.

2.4. Data collection instruments

Three instruments were used for data collection:

- Demographic Information Form including age, education level, years of experience, and work department.
- Baseline conventional nursing practices
- Effectiveness Evaluation Form (19 items; Cronbach's $\alpha = 0.89$).
- NURSYA Effectiveness Evaluation Form (19 items; Cronbach's $\alpha = 0.92$). Both evaluation forms were newly developed for this study based on established nursing effectiveness frameworks and Levine's Conservation Model principles. Item generation was conducted through a three-stage process: (1) literature review of nursing care model evaluation instruments, (2) expert panel review by five nursing faculty members with expertise in nursing theory and informatics, and (3) pilot testing with 30 nurses not included in the main study sample. Content validity was established through expert panel ratings (Content Validity Index = 0.91). Internal consistency reliability was assessed in the pilot sample (Baseline conventional nursing practices $\alpha = 0.87$; NURSYA Model $\alpha = 0.90$) and confirmed in the full study sample as reported above. Sample items from the evaluation forms are available in supplementary materials.

Both effectiveness instruments used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree) and assessed four domains: (a) planning, (b) implementation, (c) evaluation, and (d) general review.

2.5. Data collection procedure

Participants first completed the baseline conventional nursing practices Effectiveness Evaluation Form to establish baseline perceptions of conventional nursing practices. After the intervention phase, participants completed the NURSYA Effectiveness Evaluation Form using the same 19-item structure. Qualitative feedback regarding usability, perceived benefits, and challenges was collected through open-ended survey questions at the end of the post-intervention assessment.

Post-intervention assessments were conducted after the three-month clinical use period to capture stabilized user experience rather than initial learning effects.

2.6. Statistical analysis

Quantitative data were analyzed using IBM SPSS Statistics 28.0 and Python 3.11. Descriptive statistics summarized demographic characteristics. Pre-post differences were evaluated using paired-samples *t*-tests, and effect sizes were calculated using Cohen's d. A priori power analysis was conducted using G*Power 3.1 assuming a medium effect size ($d = 0.5$), alpha = 0.05, and power = 0.95, yielding a required sample of 273 participants. Post-hoc power analysis confirmed adequate power (>0.99) given the observed large effect sizes ($d = 1.06–2.16$). For the 19 paired *t*-tests, a Bonferroni-corrected significance threshold of $p < 0.0026$ (0.05/19) was applied to control for multiple pre-post change; all pre-post change remained statistically significant after correction. Missing data were minimal ($n = 7$ items across all participants, 0.12% of total data points) and handled via listwise deletion. No participants withdrew after enrollment.

Subgroup analyses assessed whether changes differed by age, education, clinical experience, or department using one-way ANOVA. Effect sizes for ANOVA analyses were calculated using partial eta-squared ($\eta^2 p$), with values of 0.01, 0.06, and 0.14 interpreted as small, medium, and large effects, respectively. Statistical significance was set at $p < 0.05$ (two-tailed).

Internal consistency reliability was assessed through Cronbach's alpha coefficients for each instrument.

Qualitative data were analyzed using conventional content analysis to identify recurring themes and representative statements.

2.7. NURSYA digital platform structure

The NURSYA system was designed as an AI-supported digital nursing platform that enables structured data entry, automated assessment, and risk analysis grounded in Levine's Conservation Model. The platform consists of three integrated modules: (1) Patient Data Entry, (2) Levine Conservation Assessment, and (3) AI-Generated Summary and Care Recommendations. The system workflow is illustrated in Fig. 1.

The first module includes the demographic and clinical information interface, which allows nurses to enter patient identifiers, demographic details, and primary clinical data in a standardized format. The layout of this interface is illustrated in Fig. 2.

Vital signs-including blood pressure, pulse, temperature, respiratory rate, oxygen saturation, and pain level-are collected through a structured input screen, as shown in Fig. 3.

In the second module, the system conducts a comprehensive assessment based on Levine's four conservation principles. Nurses input patient data related to energy conservation, structural integrity, personal integrity, and social integrity.

The assessment interface, which guides the nurse through each conservation domain, is presented in Fig. 4. The third module, which provides the AI-generated risk summary and care recommendations, is described in the Results section.

2.8. Ethical approval

Ethics approval was granted for this study (Decision No: 2025/05/51, Date: May 22, 2025). Written informed consent was obtained from all participating nurses prior to data collection. Participation was

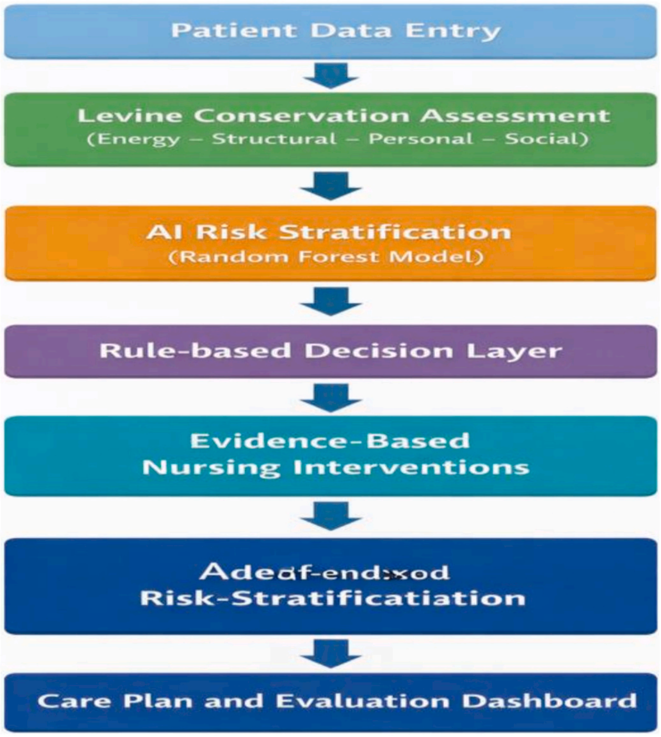

Fig. 1. NURSYA system workflow.
NURSYA system workflow illustrating patient data entry, Levine conservation assessment, AI risk stratification, rule-based decision layer, and evidence-based care planning.

voluntary, and participants were informed that they could withdraw from the study at any time without any consequences.

The study did not involve direct patient participation, and no identifiable patient data were collected, recorded, or used during the development or evaluation of the NURSYA system. All data were collected anonymously and analyzed in aggregate form to ensure confidentiality.

3. Results

3.1. Sample characteristics

The final sample consisted of 300 nurses representing a wide range of demographic characteristics. Detailed demographic information is presented in Table 1.

3.2. Primary outcomes: pre-post changes in overall effectiveness

Table 2 summarizes the item-level pre-post changes in effectiveness scores from baseline traditional nursing practices following NURSYA implementation across all 19 evaluation items. All items showed statistically significant improvements following implementation of NURSYA (all $p < 0.001$), with very large effect sizes, particularly in priority identification and gap identification.

3.3. Domain-specific analyses

Table 3 presents the domain-level effectiveness scores comparing traditional nursing models and NURSYA, and high levels of improvement were observed following NURSYA implementation across all four assessment domains.

3.3.1. Planning phase effectiveness

The planning domain showed substantial improvements following NURSYA implementation. The mean planning score increased from 3.29 (SD = 0.44) to 4.23 (SD = 0.35), representing a 28.6% improvement ($t(299) = 28.44$, $p < 0.001$, Cohen's $d = 2.16$). All five planning items demonstrated statistically significant improvements, with *gap identification* showing the largest effect size ($d = 2.27$).

3.3.2. Implementation phase effectiveness

Implementation domain scores increased from 3.31 (SD = 0.49) to 4.25 (SD = 0.41), corresponding to a 28.4% improvement ($t(299) = 23.97$, $p < 0.001$, Cohen's $d = 1.93$). Improvements were observed across all implementation items, with emergency decision-making showing a marked increase ($\Delta = 0.94$, $d = 1.91$).

3.3.3. Evaluation phase effectiveness

The evaluation domain demonstrated the largest improvement among all domains. Mean scores increased from 3.28 (SD = 0.47) to 4.27 (SD = 0.39), reflecting a 30.2% improvement ($t(299) = 28.83$, $p < 0.001$, Cohen's $d = 2.10$). Professional confidence showed the greatest increase, with scores rising by 1.01 points ($d = 2.15$).

3.3.4. General review effectiveness

General review scores increased from 3.30 (SD = 0.48) to 4.27 (SD = 0.39), representing a 29.4% improvement ($t(299) = 26.89$, $p < 0.001$, Cohen's $d = 2.03$). Among general review items, *team communication* demonstrated a particularly strong improvement ($\Delta = 0.98$, $d = 2.08$).

3.4. Subgroup analyses

Table 4 presents the effectiveness improvements across different demographic subgroups.

All demographic subgroups demonstrated significant improvements with NURSYA (all $p < 0.001$). One-way ANOVA revealed no significant interactions between demographic characteristics and effectiveness improvements (Age: $F(3,296) = 1.84$, $p = 0.14$, $\eta^2p = 0.018$; Education: $F(2,297) = 0.76$, $p = 0.47$, $\eta^2p = 0.005$; Experience: $F(3,296) = 2.13$, $p = 0.10$, $\eta^2p = 0.021$; Department: $F(3,296) = 0.52$, $p = 0.67$, $\eta^2p = 0.005$), indicating comparable effectiveness improvements across subgroups. All effect sizes were small ($\eta^2p < 0.06$), confirming the absence of clinically meaningful subgroup differences.

3.5. Reliability and validity

Internal consistency reliability was excellent for both evaluation instruments. The baseline scores reflecting traditional practices Effectiveness Evaluation Form demonstrated good reliability (Cronbach's $\alpha = 0.89$, 95% CI [0.87, 0.91]), with item-total correlations ranging from 0.62 to 0.78. The NURSYA Effectiveness Evaluation Form showed even higher reliability (Cronbach's $\alpha = 0.92$, 95% CI [0.90, 0.93]), with item-total correlations ranging from 0.67 to 0.82. These high reliability coefficients indicate that the instruments consistently measured the intended constructs.

3.6. Qualitative feedback and satisfaction

In addition to quantitative measures, participants provided qualitative feedback regarding their use of NURSYA. Table 5 summarizes the main themes identified and representative participant quotations.

Overall satisfaction with NURSYA was high. A total of 87.3% of participants reported that they would be willing to continue using the system in the future, while 91.7% indicated that they would recommend NURSYA to their colleagues. Only 3.3% of participants stated that they would not continue using the system. These findings demonstrate high user acceptance of the NURSYA platform and support the feasibility of integrating theory-based, AI-supported decision support systems into

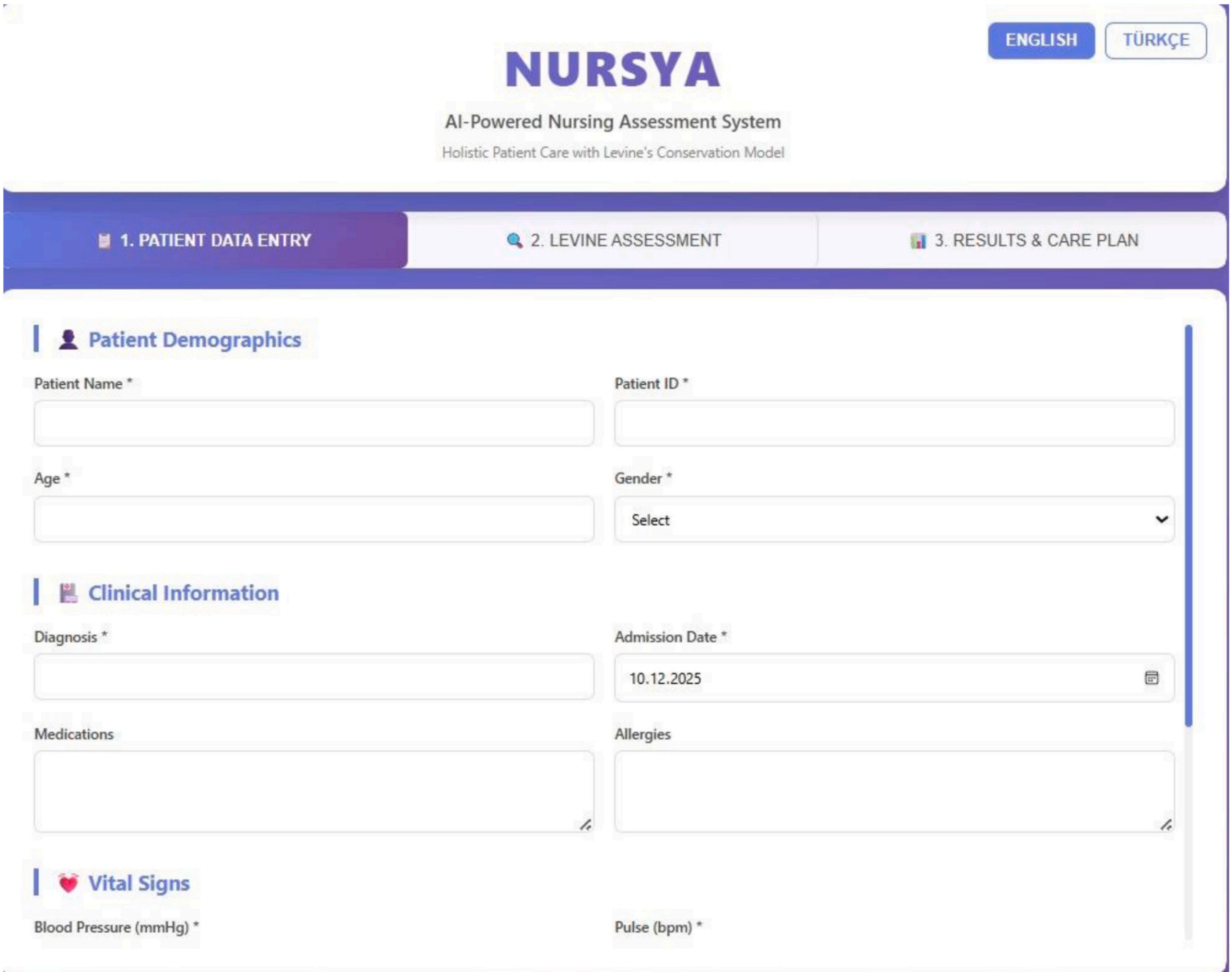

Fig. 2. NURSYA patient data entry interface (demographics and clinical information).
The figure presents the initial data entry screen of the NURSYA system, where nurses input patient demographic characteristics and key clinical information required for subsequent assessment and analysis.

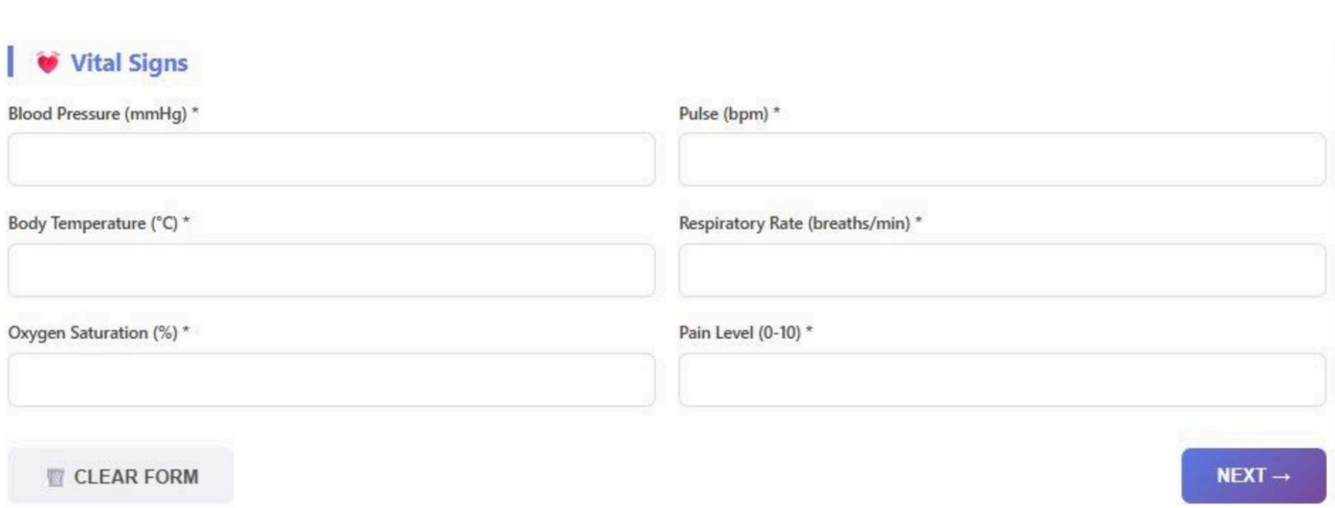

Fig. 3. NURSYA patient data entry interface (vital signs module).
The figure illustrates the vital signs data entry screen of the NURSYA system, where nurses record core physiological parameters used for clinical evaluation and risk assessment.

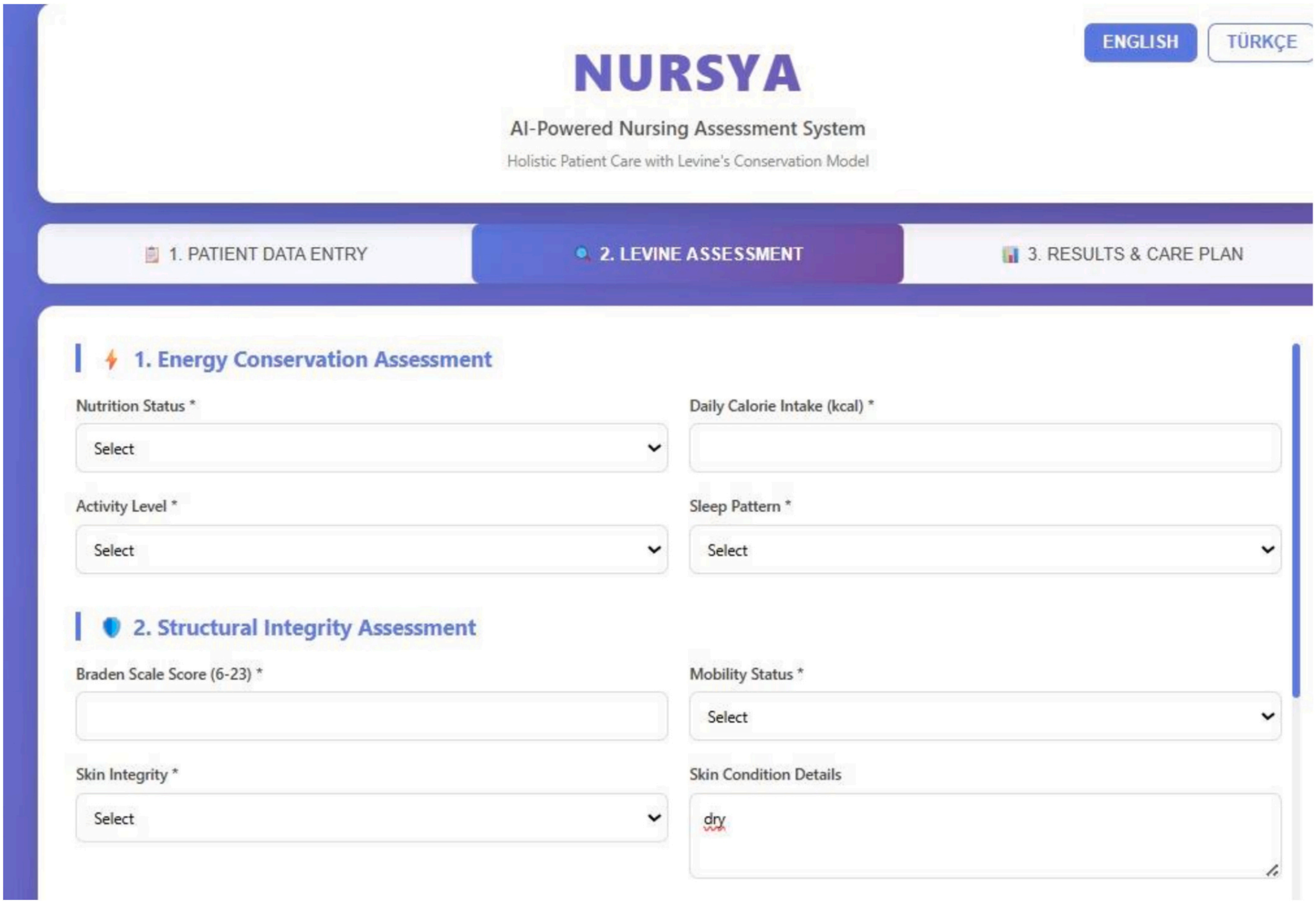

Fig. 4. Levine's Conservation Model-based assessment screen.
The figure displays the structured assessment interface guided by Levine's four conservation principles, including energy conservation, structural integrity, personal integrity, and social integrity, used to support comprehensive nursing assessment.

Table 1
Demographic characteristics of participants.

Characteristic (N = 300)	n	%
Age group		
18–25 years	48	16.0
25–35 years	129	43.0
35–50 years	94	31.3
50–65 years	29	9.7
Education level		
Bachelor's degree	205	68.3
Master's degree	72	24.0
Doctoral degree	23	7.7
Years of experience		
0–5 years	89	29.7
6–10 years	108	36.0
11–15 years	64	21.3
≥16 years	39	13.0
Department/unit		
Emergency services	93	31.0
Intensive care units	91	30.3
Outpatient clinics	61	20.3
Other departments	55	18.3

n = number of participants; % = percentage.

routine nursing practice.

3.7. AI-supported clinical output

After completing the data entry and Levine-based assessment, the NURSYA system automatically produced individualized patient summaries integrating vital signs, clinical history, Braden scores, and conservation-based assessment findings. The AI model generated a narrative analysis highlighting risk factors, clinical priorities, and recommended nursing interventions. An example of the AI-generated summary and risk stratification output is presented in Fig. 5. This module provided nurses with an immediate and comprehensive overview of patient status, including overall risk level, contributing factors, and suggested interventions. According to participant feedback collected through post-intervention open-ended responses, this feature was perceived to support clinical decision-making, reduce time spent on assessment synthesis, and increase confidence in managing complex patient cases. Together, these quantitative and qualitative findings provide a converging picture of NURSYA's impact across multiple domains of nursing practice, which is interpreted in detail in the Discussion section below.

4. Discussion

This study demonstrated statistically significant pre-post improvements across all evaluated domains following the implementation of NURSYA, relative to baseline nursing practices, highlighting the practical value of theory-based artificial intelligence (AI) systems in clinical nursing practice. Very large effect sizes across individual items indicate

Table 2
Item-level pre-post changes in effectiveness scores following NURSYA implementation (N = 300).

Item	Traditional M (SD)	NURSYA M (SD)	Difference	t	*p*-Value
Planning domain					
1.Work process organization	3.31 (1.02)	4.25 (0.85)	0.94	24.16	<0.001
2.Care plan development	3.28 (0.98)	4.22 (0.82)	0.94	26.35	<0.001
3.Examination process clarity	3.27 (1.01)	4.19 (0.87)	0.92	25.71	<0.001
4.Priority identification	3.30 (0.99)	4.26 (0.83)	0.96	27.42	<0.001
5.Gap identification	3.31 (1.03)	4.31 (0.81)	1.00	28.08	<0.001
Implementation domain					
6.Care consistency	3.29 (1.05)	4.23 (0.89)	0.94	22.45	<0.001
7.Procedural guidance	3.35 (0.97)	4.28 (0.84)	0.93	24.12	<0.001
8.Emergency decision-making	3.28 (1.08)	4.22 (0.91)	0.94	21.87	<0.001
9.Patient education	3.32 (1.00)	4.27 (0.86)	0.95	25.43	<0.001
Evaluation domain					
10.Professional confidence	3.30 (1.02)	4.31 (0.82)	1.01	29.15	<0.001
11.Feedback analysis	3.27 (0.99)	4.25 (0.85)	0.98	27.92	<0.001
12.Performance assessment	3.29 (1.01)	4.28 (0.83)	0.99	28.47	<0.001
13.Quality measurement	3.28 (1.00)	4.26 (0.84)	0.98	29.03	<0.001
14.Care standardization	3.27 (0.98)	4.24 (0.87)	0.97	27.58	<0.001
General review domain					
15.Learning facilitation	3.31 (1.03)	4.29 (0.85)	0.98	27.35	<0.001
16.Monitoring and revision	3.29 (0.99)	4.26 (0.83)	0.97	26.21	<0.001
17.Team communication	3.32 (1.04)	4.30 (0.86)	0.98	27.88	<0.001
18.Health monitoring	3.28 (0.97)	4.25 (0.82)	0.97	26.49	<0.001
19.Overall care approach	3.31 (1.02)	4.25 (0.84)	0.94	25.93	<0.001
Overall effectiveness score	**3.29 (1.00)**	**4.26 (0.84)**	**0.96**	**35.82**	**<0.001**

Values are presented as mean (M) and standard deviation (SD). Difference represents the mean pre-post difference from baseline traditional practices. Paired-samples *t*-tests were used for within-group analyses. All *p*-values remained significant after Bonferroni correction (adjusted $\alpha = 0.0026$).

Table 3
Domain-level pre-post changes in effectiveness scores relative to baseline practices (*N* = 300).

Domain	Traditional M (SD)	NURSYA M (SD)	Difference	% increase	t	p-Value	Cohen's d
Planning	3.29 (0.44)	4.23 (0.35)	0.94	28.6%	28.44	<0.001	2.16
Implementation	3.31 (0.49)	4.25 (0.41)	0.94	28.4%	23.97	<0.001	1.93
Evaluation	3.28 (0.47)	4.27 (0.39)	0.99	30.2%	28.83	<0.001	2.10
General Review	3.30 (0.48)	4.27 (0.39)	0.97	29.4%	26.89	<0.001	2.03
Overall	**3.29 (1.00)**	**4.26 (0.84)**	**0.96**	**29.2%**	**35.82**	**<0.001**	**1.06**

Values are presented as mean (M) and standard deviation (SD). Difference represents the mean pre-post difference relative to baseline traditional practices. Percentage increase was calculated based on baseline scores reflecting traditional practices scores. Paired t-tests were used for pre-post change. Cohen's d indicates effect size.

Table 4
Effectiveness improvements by demographic subgroups following NURSYA implementation.

Category	Subgroup	n	Mean improvement	p-Value
Age group	18–25 years	48	1.03	<0.001
	25–35 years	129	0.98	<0.001
	35–50 years	94	0.94	<0.001
	50–65 years	29	0.87	<0.001
Education level	Bachelor's	205	0.95	<0.001
	Master's	72	0.99	<0.001
	Doctoral	23	0.93	<0.001
Experience	0–5 years	89	1.03	<0.001
	6–10 years	108	0.97	<0.001
	11–15 years	64	0.91	<0.001
	≥16 years	39	0.88	<0.001
Department	Emergency	93	0.98	<0.001
	Intensive care unit	91	0.97	<0.001
	Outpatient	61	0.93	<0.001
	Other	55	0.95	<0.001

Mean improvement represents the pre–post difference in overall effectiveness scores within each subgroup. p-Values refer to within-group paired-samples *t*-tests. One-way ANOVA indicated no statistically significant differences in improvement magnitude across demographic subgroups (all $p > 0.05$).

that NURSYA was associated with consistent improvements across

Table 5
Qualitative feedback themes and representative quotes.

Theme	% mentioned	Representative quote
Improved Clinical Assessment	92%	"NURSYA helped me systematically assess all aspects of patient needs that I might have overlooked."
Improved Time Efficiency	87%	"The AI-generated care plans saved significant time while being comprehensive and evidence-based."
Enhanced Clinical Confidence	89%	"Having instant risk assessments improved my confidence in clinical decision-making."
Care Standardization	85%	"The system helped standardize our team's approach while allowing individualization."
Educational Support	78%	"NURSYA taught me to apply Levine's model more systematically than I learned in school."
Implementation Challenges	23%	"Initial data entry took longer than expected, though this improved with practice."

Percentages represent the proportion of participants who mentioned each theme in post-intervention open-ended responses. Participants could report more than one theme; therefore, percentages do not sum to 100%. Representative quotes were selected to illustrate each theme.

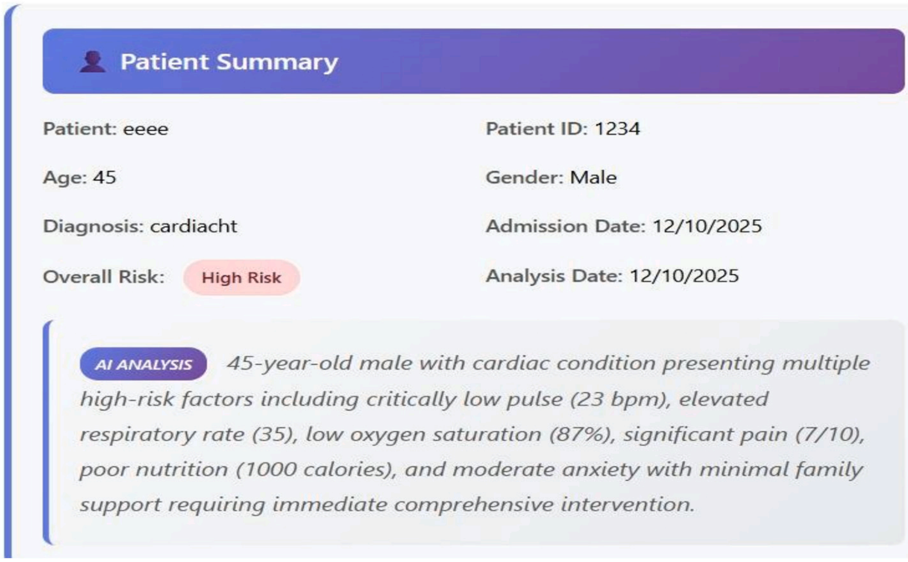

Fig. 5. AI-generated patient summary and risk analysis (case example 1).
The figure presents an example of the AI-generated narrative summary and risk stratification produced by the NURSYA system, integrating patient data, clinical history, and assessment findings to support nursing decision-making.

multiple aspects of nursing care. Although the composite effectiveness score showed a relatively smaller effect size, this is likely attributable to score aggregation across heterogeneous domains, whereas item-level analyses revealed pronounced gains in key clinical processes. Specifically, composite effect sizes ($d = 1.06$) reflect variance pooled across all 19 items spanning four distinct clinical domains, while item-level effect sizes (up to $d = 2.16$) capture concentrated improvements in specific practice areas. This discrepancy is methodologically expected when aggregating diverse subscales and does not indicate inconsistency in the data; rather, it underscores that certain clinical processes (e.g., risk detection, outcome evaluation) benefited most substantially from NURSYA implementation. Both composite and item-level effect sizes are large by conventional standards (Cohen, 1988) and are considered clinically meaningful in the context of nursing care improvements.

These findings should be interpreted within the context of a single-group pre-post design, in which observed changes reflect improvements relative to baseline nursing practices rather than direct pre-post change with an external control group.

4.1. Integration of theory-based AI into clinical nursing practice

The findings provide empirical support for integrating AI systems with established nursing theories to enhance practice effectiveness. Unlike many AI-supported tools that operate independently of nursing frameworks, NURSYA was grounded in Levine's Conservation Model, enabling structured clinical reasoning while preserving holistic and patient-centered care. Concerns that AI may reinforce task-oriented or biomedical workflows when not theoretically aligned have been noted in prior research (Martínez-Ortigosa et al., 2023; Tabassam et al., 2024). In contrast, the present results demonstrate that theory-based AI can reinforce nursing's conceptual foundations while improving clinical performance.

By operationalizing Levine's four conservation principles into actionable assessment and decision-making steps, NURSYA addressed a persistent gap between nursing theory and routine clinical application, a challenge long recognized in the literature.

4.2. Impact on clinical decision-making and care planning

One of the most clinically meaningful findings was the substantial improvement observed in care planning and evaluation. Nurses using NURSYA demonstrated greater effectiveness in identifying clinical priorities, recognizing gaps in care, and evaluating patient outcomes. These findings are consistent with previous research indicating that structured and technology-supported decision processes enhance nurses' clinical reasoning and care coordination by synthesizing complex patient information (Moore et al., 2021).

The largest gains were observed in professional confidence and evaluative processes, suggesting that NURSYA functioned not only as a technical support system but also as a cognitive aid. Similar improvements in professional confidence and situational awareness have been reported in studies examining clinical decision support systems and human-centered health information technologies (Austin, 2020; Carayon et al., 2020). However, unlike disease-specific systems, NURSYA supported comprehensive nursing judgment across multiple domains of care, consistent with the holistic intent of Levine's model.

4.3. Workflow efficiency and standardization

In addition to improving decision-making, NURSYA enhanced workflow efficiency and care standardization. Participants reported perceived time savings, improved communication, and greater workflow clarity, findings consistent with prior research on AI-enabled workflow optimization in nursing practice (Alruwaili et al., 2025; Bodur et al., 2025). Importantly, standardization did not result in rigid or impersonal care. Instead, NURSYA supported individualized planning within a consistent theoretical framework, aligning with contemporary calls for AI systems that balance safety, quality, and personalization (Wei et al., 2025).

4.4. Feasibility and user acceptance

High levels of user acceptance observed across demographic groups and clinical settings underscore the feasibility and scalability of the NURSYA model. Although some participants initially reported challenges related to data entry, these concerns diminished with experience and did not negatively affect overall acceptance. Similar learning-curve effects have been widely reported in digital health and nursing informatics implementations and are generally considered manageable through training, user-centered design, and system refinement (Bodur et al., 2025; Carayon et al., 2020; Topaz et al., 2019). A notable methodological strength of this study is its mixed-methods design, which triangulated quantitative effectiveness data (paired *t*-tests, effect sizes) with qualitative thematic findings from open-ended participant responses. This convergence of evidence strengthens the credibility of the findings and provides a more comprehensive understanding of NURSYA's impact than quantitative data alone could afford.

4.5. Implications for nursing practice and research

The findings of this study have direct implications for nursing practice and informatics. First, they suggest that AI systems grounded in nursing theory can enhance clinical effectiveness while preserving holistic, patient-centered care. For clinical practice, NURSYA demonstrates how theory-based AI can support priority setting, care planning, and outcome evaluation, particularly in complex or high-acuity environments.

Second, the observed improvements in professional confidence indicate that such systems may serve as valuable cognitive and educational supports for both novice and experienced nurses. Embedding theoretical reasoning into routine clinical workflows may contribute to workforce development, support clinical consistency, and reduce cognitive burden.

From a research perspective, this study provides a replicable model for the development and evaluation of theory-based AI systems in nursing. Future studies should examine patient outcomes, cost-effectiveness, and long-term sustainability, as well as cross-cultural applicability in different healthcare systems.

4.6. Limitations and future research

This study has limitations. First, the single-group pre-post design limits causal inference; observed improvements may reflect Hawthorne effects, practice effects, or temporal confounders rather than true intervention effects. Future studies employing randomized controlled trials with parallel control groups are needed to isolate the specific impact of NURSYA. Second, all sites were located in Türkiye, which may limit generalizability to other healthcare systems, cultural contexts, and resource settings. Third, the study focused exclusively on Levine's Conservation Model, and findings may not extend to AI implementations grounded in other nursing theories. Fourth, traditional nursing models varied across sites at baseline and were not standardized, introducing potential heterogeneity in pre-post change conditions. Fifth, the clinical accuracy and validity of AI-generated recommendations were not independently assessed against expert clinical judgment, and no direct validation against patient outcomes was conducted. Sixth, although system usage was monitored during familiarization, consistency of NURSYA usage during the three-month intervention period was not systematically measured or verified. Seventh, outcomes were primarily nurse-reported and based on subjective self-assessment rather than objective performance metrics; therefore, future research should include patient-level outcomes, safety indicators, and long-term impacts on care quality. Finally, the three-month follow-up period may be insufficient to assess sustained adoption, long-term workflow integration, or delayed effects on clinical practice patterns. Further evaluation of integration with electronic health record systems and implementation in diverse clinical contexts is also warranted.

5. Conclusion

This study provides preliminary evidence from a single-group design that implementation of NURSYA, an AI-supported clinical decision support system grounded in Levine's Conservation Model, was associated with significant improvements in nurses' perceived effectiveness across multiple domains of practice. NURSYA represents a promising example of how theory-based AI systems can support holistic, patient-centered, and evidence-based nursing care while improving efficiency and confidence in clinical decision-making. As this represents the first systematic operationalization of Levine's model into an AI platform, further research with controlled designs is essential to establish causal effects and to determine impacts on patient-level clinical outcomes, safety, and quality of care. Validation of AI recommendation accuracy, assessment of implementation fidelity, and evaluation across diverse cultural and healthcare contexts are critical next steps for advancing this line of research.

CRediT authorship contribution statement

Şeyda Öztuna: Writing – review & editing, Writing – original draft, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Cihangir Işık:** Writing – review & editing, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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