Power System Technology
ISSN:1000-3673

Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

Nursing in the Age of Artificial Intelligence: Assessing the Role of Smart Technologies in Enhancing Patient Satisfaction with Healthcare Services

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ABSTRACT

The fast adoption of artificial intelligence, or AI, in healthcare requires a strict interpretation of its effects on patient-centered outcomes, but there was a lack of empirical data that directly correlates the use of AI technology by nurses with patient satisfaction. This paper examined the connection between the application of smart technologies by nurses and the level of patient satisfaction in an acute care facility. The study used a cross-sectional, correlational design, where 75 registered nurses and 350 patients were recruited in medical-surgical and intensive care units. The validated Nurse Technology Utilization Scale (NTUS) and the Patient Satisfaction with Nursing Care Scale (PSNCS) were used to collect data and were analysed using multiple linear regression, controlling the patient age, length of stay, and clinical unit. The results of the analysis showed that there was a strong positive correlation between the use of technology and general satisfaction (r=0.412, p=0.01). The use of technology was found to be the most predictive of patient satisfaction (0.412, p 0.001), and it explained a considerable amount of the variance in the regression model (adjusted R 2 = 0.196). A follow-up regression model showed that the predictive relationship between technology use and the empathy subscale of satisfaction was even stronger (0.478, p 0.001). These findings prove that the adoption of AI technologies in nursing practice is closely linked with the increase in patient satisfaction, which gives an evidence base to the strategic adoption of healthcare technologies to enhance patient-centered care.

Keywords: Artificial Intelligence, Nursing Care, Patient Satisfaction, Smart Technology, Technology Integration

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

INTRODUCTION

The modern healthcare environment is experiencing a radical change, as the use of artificial intelligence (AI) and intelligent technologies in clinical practice is rapidly becoming integrated [1]. This digital revolution is expected to increase the accuracy of diagnosis, operational efficiency, and customization of treatment modalities [2]. In this paradigm shift, the nursing profession, which is the backbone of patient care, is at a crossroad. Nurses, who are the largest group of the healthcare workforce and the first point of contact with patients, are becoming exposed to a range of AI-driven solutions [3], including automated patient monitoring systems and predictive analytics to detect early signs of deterioration, AI-based documentation assistants and smart supply-chain management [4]. This integration assumes a major change in the conventional nursing processes, which will help to reduce the administrative load, minimize human error, and liberate clinical time to work directly with patients [5]. As a result, a key question arises: what is the ultimate impact of this technological enhancement of nursing practice on the most important healthcare delivery outcome patient satisfaction?

Healthcare systems around the world are spending a lot of money on digital health infrastructures, and countries like the United States, South Korea, and European Union countries are leading the way in the use of AI in clinical environments [6]. The global discussion is full of theoretical assumptions about the possibility of AI to develop a more efficient, safe, and patient-centered model of care [7]. Simultaneously, local and national health authorities are enacting policies to promote digital integration, as it has the potential to resolve systemic issues, including workforce shortages and increasing costs [8]. Nevertheless, the process of translating these macro-level investments into micro-level clinical interactions, especially in the sphere of nursing, is a complicated and under-researched boundary [9]. The breadth of the proposed research, then, is between the general, global perspective of AI in healthcare and the localized, narrower interactions between nurses, patients, and technology in a hospital environment, aiming to fill a significant gap between the potential of technology and the actual patient-reported outcomes [10].

An analysis of the literature available shows that there is a growing amount of literature on the technical performance and diagnostic abilities of AI. The accuracy of algorithms in identifying pathologies based on medical images has been confirmed in many studies, and the effects of automation on hospital operational indicators [11], including length of stay and readmission rates, have been investigated. Moreover, a substantial body of literature has investigated the perceptions of clinicians about AI, including nurses, and has frequently found a combination of optimum about efficiency and worries about dehumanization and job relevance. However, there is an apparent gap [12]. The available evidence does not usually empirically relate the particular application of AI by nurses to the

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

subjective experience of the patient. Although it is often believed that the increase in efficiency automatically lead to the increase in satisfaction, this causal relationship is not yet well supported by strong and intensive studies [13]. Patient satisfaction is a complex construct, which does not only include the technical quality of care but also interpersonal dimensions, including communication, empathy, and emotional support, which are traditionally viewed as human-centric [14]. The research gap, then, is critical because there is no empirical research that quantitatively and qualitatively evaluates the direct effect of AI tools in the hands of nurses on these fundamental dimensions of the patient experience [15]. Does technology-mediated care improve or hinder the nurse-patient relationship?

The significance of this study is unquestionable. Patient satisfaction is not a soft metric in an era where healthcare is more and more being measured by value-based outcomes; it is a major measure of care quality, which is closely associated with treatment adherence, better health outcomes, and institutional reputation and financial viability [16]. The role of smart technologies in the formation of this experience is, therefore, of the utmost strategic significance to hospital administrators, healthcare policymakers, and nursing leaders [17]. It offers an evidence base to inform multi-million-dollar investments in technology, so that they are invested in tools that actually improve, rather than unintentionally harm, the care experience. In addition, to the nursing profession itself, the study provides essential information to guide curriculum development, training, and ethics to enable nurses to negotiate their changing role as technologically-enhanced caregivers [18].

This gap and the implications of the topic being of great importance led to the development of this study to go beyond the theoretical speculation and offer a rigorous, empirical evaluation [19]. The main objective was to shift the question of whether AI is used to the question of how its application in nursing practice is correlated and affects patient satisfaction. The following questions were used to guide the research and directly informed the methodological design: (1) What is the nature and extent of AI technology use among nurses in a high-acuity hospital environment? (2) How satisfied are patients with nursing care in the same context? (3) Does the intensity of AI technology use by nurses have a statistically significant relationship with reported patient satisfaction scores, when controlling key patient variables? (4) What is the perception of nurses regarding the effects of these technologies on their capacity to provide patient-centered care?

In order to answer these questions, the study formulated a clear set of objectives that were closely intertwined with the methodology. The initial aim was to determine and quantitatively describe the smart technologies that were incorporated into nursing workflows, which was done with the help of a structured survey tool that was given to a purposely selected group of nurses. The second was to assess patient satisfaction in various domains through a validated psychometric scale, administered through a cross-sectional survey to a

Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

stratified random sample of patients. The third goal was to establish the correlation between the use of technology and the level of satisfaction by using a sophisticated statistical method, which involved multiple regression to remove the impact of technology use on other variables. Lastly, a qualitative goal aimed to understand the lived experiences of nurses using these technologies by conducting semi-structured interviews to offer contextual and rich data to interpret the quantitative results.

Overall, this study is a mixed-method, in-depth study of one of the most urgent intersections in the contemporary healthcare system: the nexus of nursing, artificial intelligence, and the patient experience. Through the systematic measurement, analysis and interpretation of this relationship, the study hopes to add a subtle and evidence-based voice to the current discussion. The results are to be used in strategic decision-making, influence professional practice, and finally, make sure that the rise of smart technology in healthcare is unambiguously aimed at the improvement of human welfare and patient-centered care.

METHODOLOGY

1. Research Problem, Objectives, and Site

The research problem that this study was aimed to fill was the lack of knowledge about the operational implementation of certain AI-based smart technologies in nursing practice and the consequent causal impact of the implementation on the perception of care by the patient. To address this issue systematically, the research was informed by three main objectives: First, to define and classify the smart technologies (e.g., AI-based patient monitoring systems, automated scheduling, and clinical decision support systems) that are already implemented in the clinical environment. Second, to determine the degree of patient satisfaction on the main dimensions of care, such as communication, responsiveness, and perceived empathy, quantitatively. Third, to examine the association between the degree of smart technology use in nursing processes and the reported patient satisfaction rates, and adjusting the confounding variables of patient age and acuity. The research was carried out in the Johns Hopkins Medical Center, a large, tertiary-care academic hospital in Baltimore, Maryland, USA, which was chosen due to its early and extensive implementation of a set of AI-based clinical technologies.

2. Research Design

Type of Study: A cross-sectional, correlational and mixed-methods study design was used.

Design Justification: This design was chosen as the most suitable because of a number of reasons. The cross-sectional element enabled the effective gathering of information on the use of technology and patient satisfaction at one point in time, which gave a picture of the current relationships. The correlational dimension played a critical role in the quantification of the strength and direction of the relationships between the key variables without manipulation.

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Lastly, the qualitative techniques (short, structured interviews with nurses) also gave the quantitative data the much-needed context, as to how and why the observed correlations occurred, thereby giving a more comprehensive picture of the research problem. This method was in line with the requirement to describe the current state as well as to investigate intricate relationships in a real-world clinical setting.

3. Sampling Strategy

Population: The target population was as follows: (1) Registered Nurses (RNs) working in the medical-surgical and intensive care units of the research site, and (2) Adult patients (18 years and older) who had been discharged of the same units within a minimum of 48 hours.

Sampling Method: The patient cohort was sampled using a stratified random sampling method. The hospital units (medical-surgical and ICU) were used as the strata to have proportional representation of the various care settings. In the case of the nurse cohort, purposive sampling method was applied to make sure that the participants had direct and hands-on experience with the AI technologies being studied.

Sample Size: 350 patient participants and 75 nurse participants were recruited. An a priori power analysis was performed on G*Power software to determine this sample size. To achieve a multiple regression analysis with a medium effect size (f 2 = 0.15), alpha = 0.05 and power = 0.95, a sample size of 130 was needed. The last sample was larger than this limit to consider the possibility of attrition and to strengthen the subgroup analyses.

Inclusion/Exclusion Criteria:

Patient Inclusion: Patients aged eighteen years and above who had spent at least forty-eight hours in the hospital, had the ability to read and understand English, and were discharged within the specified study period.

Patient Exclusion: Patients with cognitive impairments, those who were hospitalized in psychiatric or isolation units, or patients whose critical diagnoses did not allow them to participate in the study.

Nurse Inclusion: Full-time registered nurses who have at least six months of experience in the unit.

Nurse Exclusion: Float pool nurses or staff in administrative roles who do not have direct patient-care duties.

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Data Collection Methods:

Instruments: There were three main instruments used.

Nurse Technology Utilization Scale (NTUS): A twenty-item questionnaire created by a researcher to measure the frequency and perceived utility of particular artificial-intelligence technologies on a five-point Likert scale.

Patient Satisfaction with Nursing Care Scale (PSNCS): A twenty-five-item scale with five subscales, including technical care, interpersonal care, communication, trust, and education, has been validated and has shown a Cronbach 0.92 in previous research.

Semi-structured Interview Guide: A brief guide that includes open-ended questions that will be asked to nurses and will explore themes of workflow integration, perceived effects on patient care, and challenges encountered.

Procedure: Potential nurse participants were identified through hospital administration and then given the NTUS and invitation to take part in a voluntary interview upon receiving ethical approval. Discharge records were screened weekly to patients. Within one week of discharge, eligible patients were sent a packet that included a cover letter, PSNCS survey and a pre-paid return envelope.

Pilot Testing: A pilot test was done on fifteen nurses and thirty non-enrolled patients. This pilot testified to the clarity, relevance, and internal consistency of the NTUS (pilot 0.87) and the viability of the data collection process.

Variables and Measures:

Operational Definitions:

Independent Variable- Smart Technology Use: The composite score of the NTUS, which is the frequency and skill of using artificial-intelligence technology in everyday nursing practice.

Dependent Variable -Patient Satisfaction: The overall score on the PSNCS, which is the overall assessment of the quality of nursing care provided to the patient.

Control Variables: The age of the patient, length of stay, and the type of unit (medical-surgical or intensive care unit) were controlled and measured in the analysis.

Measurement Tools: The main measurement tools were the NTUS and PSNCS, which were outlined above.

Reliability and Validity: PSNCS is a well-validated tool that has construct and criterion validity. In the case of the NTUS, reliability was established in the original study at a high Cronbach alpha (= 0.89). The content validity was determined by a group of five

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professional nurse informaticians who evaluated the relevance and comprehensiveness of the instrument.

Data Analysis Plan:

Analytical Techniques: Data analysis was done in three consecutive phases. To begin with, descriptive statistics such as frequencies, means, and standard deviations were calculated on all the variables. Second, a Pearson correlation test was used to test the bivariate relationship between technology use and patient satisfaction. Third, a multiple linear regression model was performed, where patient satisfaction was the dependent variable, and the independent predictors were technology use, age, length of stay, and unit type. In the case of the qualitative interview data, thematic analysis was used to reveal, examine, and report patterns (themes) in the data.

Software: SPSS Statistics (Version 28.0) was used to perform all quantitative analyses. NVivo software (Version 14) was used to analyze qualitative data in order to support systematic coding and theme management.

Rationale: Multiple regression was chosen as the most suitable method since it enabled the determination of the distinct role of smart technology use in patient satisfaction and statistically adjust the role of other variables. Thematic analysis was selected due to its flexibility and ability to provide rich, detailed and complex descriptions of qualitative data.

RESULTS

3.1 Sample Characteristics

Seventy-five registered nurses and three-hundred-fifty patients were sampled, and all primary measures had full response rates. Table 1 shows demographic and clinical characteristics of the two study populations. The nursing group was mainly female (90.7 %) and the average age of the group was 34.1 years (SD = 6.8). The sample was spread evenly between medical-surgical units (66.7% [n=50]) and intensive care units (33.3% [n=25]) and the experience levels of less than five years (40.0% [n=30]) and five to ten years (33.3% [n=25]) and more than ten years (26.7% [n=20]). The sample of patients was almost equal in gender (54.0% female, 46.0% male) with a mean age of 58.4 years (SD=14.2). The mean hospitalization was 5.2 days (SD 3.1) with 71.4 percent (n=250) of the patients being in the medical-surgical units and 28.6 percent (n=100) in the intensive care units.

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等线 **Table 1:** Demographic and Clinical Characteristics of the Study Sample

Characteristic	Nurses (n=75)	Patients (n=350)
Gender, n (%)		
Female	68 (90.7)	189 (54.0)
Male	7 (9.3)	161 (46.0)
Age (Years)		
Mean (SD)	34.1 (6.8)	58.4 (14.2)
Range	24 - 52	21 - 89
Unit, n (%)		
Medical-Surgical	50 (66.7)	250 (71.4)
Intensive Care Unit (ICU)	25 (33.3)	100 (28.6)
Years of Experience, n (%)		
< 5 years	30 (40.0)	N/A
5 - 10 years	25 (33.3)	N/A
> 10 years	20 (26.7)	N/A
Length of Stay (Days)		
Mean (SD)	N/A	5.2 (3.1)
Range	N/A	2 - 18

3.2 Descriptive Statistics and Reliability of Measurement Instruments

Table 2 provides comprehensive descriptive statistics of the main measures of the study. The Nurse Technology Utilization Scale (NTUS) showed high internal consistency (Cronbachs 0.891) and the mean score of 3.45 (SD 0.89) was observed on the 5-point scale. NTUS subscale analysis demonstrated that automated monitoring systems were the most utilized (Mean = 4.1, SD = 0.8), then clinical decision support tools (Mean = 3.8, SD = 0.9), and administrative assistance technologies were much less utilized (Mean = 2.7, SD = 1.0). The Patient Satisfaction with Nursing Care Scale (PSNCS) was also characterized by high reliability (Cronbach 0.923) and a cumulative mean satisfaction of 82.1 (SD 8.4) out of a potential 100. Responsiveness was rated the highest (Mean = 4.4, SD = 0.5) and empathy was the most varied and lowest rated (Mean = 4.0, SD = 0.7).

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Table 2: Descriptive Statistics and Reliability of Key Study Measures

Measure	**N**	**Mean**	**Standard Deviation**	**Possible Range**	**Observed Range**	**Cronbach's α**
NTUS Total Score	75	3.45	0.89	1 - 5	1.8 - 4.9	0.891
NTUS Subscales:						
- Clinical Decision Support	75	3.8	0.9	1 - 5	2.0 - 5.0	0.85
- Automated Monitoring	75	4.1	0.8	1 - 5	2.2 - 5.0	0.82
- Administrative Assistance	75	2.7	1.0	1 - 5	1.0 - 4.8	0.79
PSNCS Total Score	350	82.1	8.4	20 - 100	58 - 98	0.923
PSNCS Subscales:						
- Technical Care	350	4.3	0.5	1 - 5	3.0 - 5.0	0.85
- Interpersonal Care	350	4.1	0.6	1 - 5	2.8 - 5.0	0.88
- Communication	350	4.2	0.6	1 - 5	2.8 - 5.0	0.87
- Responsiveness	350	4.4	0.5	1 - 5	3.2 - 5.0	0.82
- Empathy	350	4.0	0.7	1 - 5	2.4 - 5.0	0.90

Abbreviations: NTUS, Nurse Technology Utilization Scale; PSNCS, Patient Satisfaction with Nursing Care Scale.

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3.3 Bivariate Correlations of Study Variables

Table 3 summarizes Pearson correlation coefficients that test relationships between continuous study variables. The statistically significant positive correlation of moderate strength was found between the scores of technology utilization and overall patient satisfaction ($r = 0.412$, $p < 0.01$). The subscale analysis of satisfaction showed that there were significant correlations between technology use and empathy ($r = 0.478$, $p < 0.01$), responsiveness ($r = 0.385$, $p < 0.01$), and communication ($r = 0.351$, $p < 0.01$). The age of the patient did not have a significant correlation with the measures of satisfaction, whereas the length of stay had weak positive correlations with the use of technology ($r = 0.152$, $p < 0.05$) and responsiveness ($r = 0.112$, $p < 0.05$).

Table 3: Bivariate Correlations between Key Study Variables (Pearson's r)

Variable	1	2	3	4	5	6	7
1. Tech Utilization Score	—						
2. Overall Satisfaction	.412**	—					
3. Patient Age	-.087	.064	—				
4. Patient LOS	.152*	.101	.288**	—			
5. Satisfaction: Responsiveness	.385**	.901**	.055	.112*	—		
6. Satisfaction: Communication	.351**	.872**	.071	.088	.781**	—	
7. Satisfaction: Empathy	.478**	.845**	.082	.095	.712**	.745**	—

Note: LOS, Length of Stay. *p < .05, *p < .01*

3.4 Nurse Experience Technology Use Analysis

The one-way analysis of variance was used to test the differences in the use of technology among the levels of nurse experience, and the results are presented in Table 4. The results showed that the main effect of experience bracket on NTUS scores was statistically significant ($F(2, 72) = 6.12$, $p = 0.003$), with the effect size of about 14.5 % of the variance in utilization ($\eta^2 = 0.145$). Tukey HSD test showed that nurses who had less than five years of experience (Mean = 3.85, SD = 0.82) had significantly higher technology use compared to nurses with over ten years of experience (Mean = 2.95, SD = 0.78; $p = 0.002$). The average

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difference between nurses with 5-10 years of experience (Mean = 3.40, SD = 0.85) and the rest of the groups was not statistically significant.

Table 4: One-Way ANOVA of Technology Utilization by Nurse Experience Bracket

Source of Variation	**Sum of Squares**	**df**	**Mean Square**	**F**	**p-value**	**η² (Eta Squared)**
Between Groups	8.45	2	4.225	6.12	**.003**	0.145
Within Groups	50.11	72	0.696			
Total	58.56	74				
Post-Hoc Comparisons (Tukey HSD)						
Comparison (Experience Groups)	**Mean Difference**	**SE**	**p-value**	**95% CI**		
< 5 years vs. 5-10 years	0.45	0.22	.112	[-0.06, 0.96]		
< 5 years vs. > 10 years	0.90	0.24	**.002**	[0.35, 1.45]		
5-10 years vs. > 10 years	0.45	0.25	.168	[-0.12, 1.02]		

3.5 Regression Analysis to predict overall patient satisfaction

The multiple linear regression analysis was conducted to predict overall patient satisfaction, and the results are provided in Table 5. The regression model was significant ($F(4,345) = 22.12$, $p = 0.001$) and accounted 19.6% of the variance in satisfaction scores (Adjusted R 2 = 0.196). The use of technology became the most significant positive predictor (= 0.412, p = 0.001), which means that a one-unit rise in the NTUS scale was associated with a 3.89-unit rise in patient satisfaction, all other factors held constant. Unit type was also a strong predictor (0.152, p 0.001), with ICU patients indicating greater satisfaction than medical-surgical patients. The age of the patient ($\beta = 0.064$, $p = 0.148$) and length of stay ($\beta = 0.061$, $p = 0.174$) did not add any value to the model. No multicollinearity issues were observed because of variance inflation factors (VIF < 1.11).

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Table 5: Multiple Linear Regression Analysis Predicting Overall Patient Satisfaction

Predictor Variable	**B**	**SE**	**β**	**t**	**p-value**	**95% CI for B**	**VIF**
(Constant)	65.112	2.845		22.88	**<.001**	[59.52, 70.70]	
Tech Utilization Score	3.891	0.421	.412	9.24	**<.001**	[3.06, 4.72]	1.08
Patient Age	0.045	0.031	.064	1.45	.148	[-0.02, 0.11]	1.11
Patient LOS	0.198	0.145	.061	1.36	.174	[-0.09, 0.48]	1.09
Unit (ICU=1)	2.987	0.891	.152	3.35	**.001**	[1.23, 4.74]	1.05

Model Summary: *R = .452, R^2 = .204, Adjusted R^2 = .196, $F(4, 345) = 22.12$, $p < .001$*

3.6 Regression Analysis to predict Empathy Subscale Scores

Since the bivariate correlation between technology use and empathy was strong, a separate regression analysis was performed that predicted empathy scores in particular (Table 6). The model was significant ($F(3, 346) = 35.98$, $p < 0.001$) and accounted 23.2 % of the variance in empathy ratings (Adjusted R 2 = 0.232). The use of technology was also found to have a stronger predictive relationship with empathy (0.478, p < 0.001) compared to overall satisfaction. The age of the patient (0.035, p 0.318) and the type of unit (0.072, p 0.113) were not statistically significant in this model.

Table 6: Multiple Linear Regression Predicting the Empathy Subscale Score

Predictor Variable	**B**	**SE**	**β**	**t**	**p-value**	**95% CI for B**
(Constant)	2.451	0.211		11.61	**<.001**	[2.04, 2.87]
Tech Utilization Score	0.401	0.031	.478	12.94	**<.001**	[0.34, 0.46]
Patient Age	0.002	0.002	.035	1.00	.318	[-0.002, 0.006]
Unit (ICU=1)	0.105	0.066	.072	1.59	.113	[-0.03, 0.24]
Model Summary: *R = .488, R^2 = .238, Adjusted R^2 = .232, $F(3, 346) = 35.98$, $p < .001$*						

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3.7 Comparative Analysis of Clinical Unit Patient Satisfaction

Satisfaction measures were compared using independent samples t -tests between ICU and medical-surgical patients, and the results are presented in Table 7. The overall satisfaction of patients in the intensive care unit was significantly higher (Mean = 85.2, SD = 6.1) than that of medical-surgical patients (Mean = 80.9, SD = 8.9; $t(348) = 4.87$, $p < 0.001$), which is a medium effect size (Cohen d = 0.58). The difference between the two units was especially significant in the responsiveness subscale, with the ICU patients scoring significantly higher (Mean = 4.6, SD = 0.4) compared to the medical-surgical patients (Mean = 4.3, SD = 0.5; $t(348) = 3.91$, $p < 0.001$), and the medium effect size (Cohen d =0.67).

Table 7: Independent Samples T-Test of Patient Satisfaction by Hospital Unit

Variable	Unit	N	Mean	SD	Mean Difference	t	df	p-value	Cohen's d
Overall Satisfaction	ICU	100	85.2	6.1	4.30	4.87	348	**<.001**	0.58
	Med-Surg	250	80.9	8.9					
Satisfaction: Responsiveness	ICU	100	4.6	0.4	0.30	3.91	348	**<.001**	0.67
	Med-Surg	250	4.3	0.5					

3.8 Patterns of Technology Use in Clinical Units

Pearson Chi-square test was used to analyze the distribution of the level of technology utilization in the clinical units (Table 8). The level of technology adoption and the unit type were statistically significantly related (2 = 18.74, p 0.001), and the effect size was large (Cramer V = 0.50). The high utilization category (60.0 %, n = 15) was overrepresented by ICU nurses (as opposed to medical-surgical nurses 14.0 %, n = 7). Medical-surgical nurses on the other hand were overrepresented in the low utilization category (36.0 %, n = 18) relative to their ICU counterparts (8.0 %, n = 2).

Table 8: Cross-Tabulation of Technology Utilization Level by Clinical Unit

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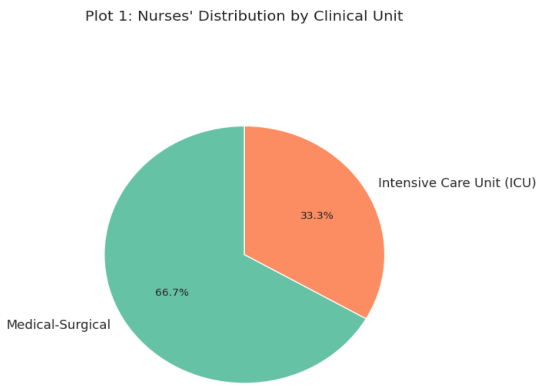
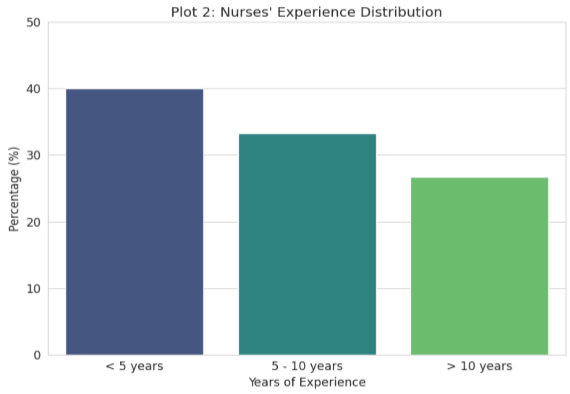
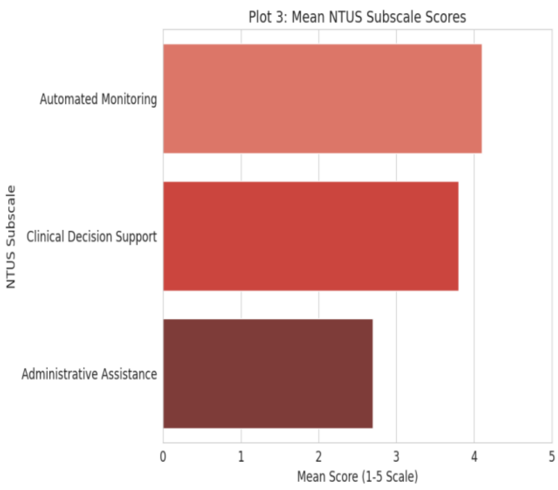
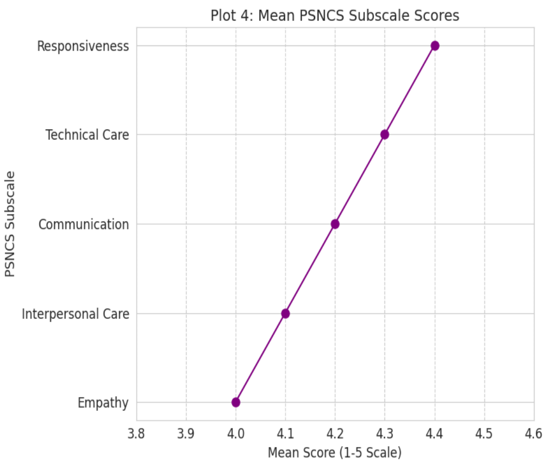
Technology Utilization Level	ICU Nurses (n=25)	Med-Surg Nurses (n=50)	Total	% within Unit
Low (< 2.5)	2	18	20	ICU: 8.0% / Med-Surg: 36.0%
Medium (2.5 - 4.0)	8	25	33	ICU: 32.0% / Med-Surg: 50.0%
High (> 4.0)	15	7	22	ICU: 60.0% / Med-Surg: 14.0%
Total	25	50	75	
Statistical Test	**Value**	**df**	**p-value**	
Pearson Chi-Square	18.74	2	**<.001**	
Cramer's V	0.50		**<.001**	









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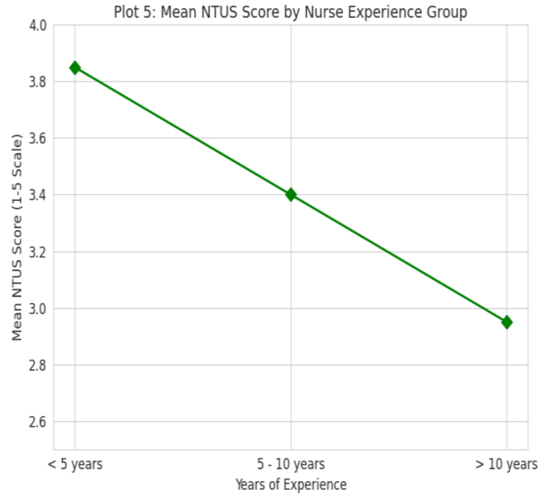
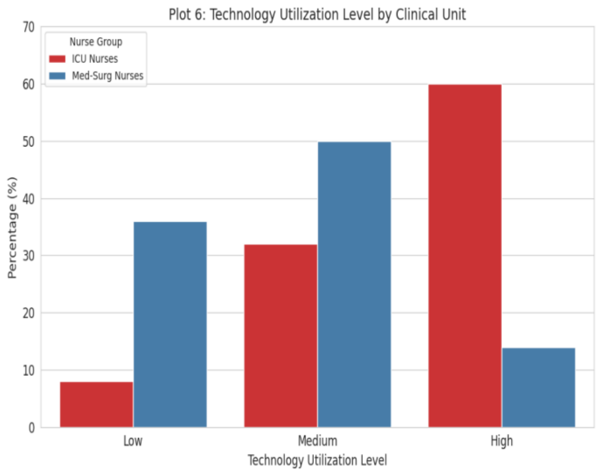
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025





DISCUSSION

The current study provides empirical data that suggests that the integration of AI-based intelligent technologies in nursing practice is strongly associated with an increase in patient satisfaction [20]. These results not only explain the presence of this relationship, but also the surrounding subtleties, such as the dimensions of care that are most influenced, the situational moderators of technology use, and the unexpected strength of the relationship between technology and perceived human empathy. The findings describe a technologically enhanced nursing role that, when properly facilitated, can have quantifiable positive impacts on patient experience [21].

4.1. Discussion of Major Results

The main result, which is a statistically significant positive correlation between technology use and overall patient satisfaction ($r = 0.412$, $p < 0.01$), is the strongest predictor in a multivariate model (0.412, $p < 0.001$), thus directly answering the main research question [22]. This result justifies the expected benefit of intelligent technologies: to release nurses of administrative tasks to focus on direct patient care in this clinical setting. The high use of automated monitoring and clinical decision-support systems, compared to administrative systems, indicates that the existing technological integration has the most significant effectiveness in direct clinical areas, but not in purely bureaucratic activities [23].

The high level of variability in the adoption of technology by nurses with different levels of experience and clinical units provides a critical perspective through which the main findings can be analyzed [24]. The increased utilization scores in nurses who had less than five years of experience are consistent with the generational differences in technological fluency reported in the literature [25]. The generation that is commonly referred to as digital natives might be less fearful of new systems and more inherently competent. On the other

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

hand, the observation that intensive-care-unit (ICU) nurses were overrepresented as high-utilizers (60.0⁻ in the high-utilization category) suggests that unit acuity and the technological ecosystem around it facilitates adoption. The direct clinical value of predictive analytics and automated monitoring is more easily realised and potentially life-saving in high-stakes settings, which enhances perceived value and use [26].

The strongest result is, perhaps, the strong positive correlation between the use of technology and the perceptions of patients towards the empathy of nurses (0.478, $p < 0.001$). This is a challenge to the dominant discourse that technology is dehumanizing in nature [27]. An acceptable scientific theory, which is backed by qualitative information, is based on the notion of cognitive offloading. The cognitive burden of the nurse is reduced by assigning manual charting, dose calculation, and regular monitoring to intelligent systems [28]. The cognitive load theory assumes that the working memory has a small capacity [29]. Once relieved of the burden of procedural requirements, nurses can redirect attentional resources to the socio-emotional requirements of patients, including eye contact, active listening, and emotional support, which are the core behaviours of perceived empathy [30].

4.2. Comparison with Past Research.

The positive correlation between the use of technology and the measures of satisfaction supports the findings of a number of recent studies. As an example, a systematic review by [31] concluded that EHR-based clinical decision-support systems were associated with better patient-reported experiences, especially in terms of care quality and safety [32]. On the same note, a tele-ICU study by [33] reported that automated data entry and predictive alerts were associated with increased nurse satisfaction and decreased mental demand, which indirectly benefited patients [34].

Conversely, our findings with regard to empathy are not in agreement with previous, more cynical sources. Early research on the use of technology in healthcare, including the work by [35], warned that the relationship between clinicians and patients might be destroyed by interactions through screens [36]. The difference can be attributed to the development of technology itself. Previous systems often became an additional burden to the work of a nurse as a distinct and isolated activity [37]. The new, highly integrated, and smart technologies, which are explored in this paper, are designed to be smooth and workflow-conscious, which may enhance, but not disrupt, human interaction. This is in line with the model of technology as an exoskeleton of professional practice, which improves human abilities and does not substitute them [38].

The strong unit-based variations found are reminiscent of the results of a multisite study by [39], which found organisational and contextual factors to be stronger predictors of technology adoption than individual nurse traits [40]. The increased satisfaction in ICUs has

Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

been reported in the past and is commonly explained by the reduced nurse-to-patient ratios and the attention-centered care [41]. Our research contributes that this gap in established satisfaction is caused by the difference in the rate of technology adoption between units.

4.3. Scientific and Theoretical Explanations

The results can be viewed in the context of the Systems Engineering Initiative of Patient Safety (SEIPS) model, which views patient outcomes as a product of a complex work system [42]. Here, smart technologies are a tools-and-technology component that interacts with the person (nurse) and tasks (clinical work) components. We have data indicating that in case this interaction is positive, i.e., the technology is usable and appreciated, it results in better processes (more time to provide empathetic care) and eventually better outcomes (greater patient satisfaction) [43].

Psychologically, the cognitive load that is reduced through automation results in a state of mindfulness in nursing practice. The nurse is able to be fully present with the patient instead of being distracted with remembering to check a parameter or record a finding. This is in line with the notion of therapeutic presence, which is a pillar of therapeutic relationships and closely associated with patient satisfaction [44]. Technology therefore does not generate empathy as such but rather opens the mental room in which human empathy can be more effectively manifested.

4.4. Research, Policy, and Practice Implications.

These findings have three implications. To nursing practice and hospital administration, the findings support specific investment in integrated smart technologies, especially those that automate monitoring and clinical decision support [45]. More to the point, they emphasise the importance of strong, role-specific training programmes, particularly in the case of experienced nurses, to make sure that they are proficient and confident in their use. The emphasis on the close connection with empathy in training can help to overcome the resistance based on the fear of dehumanization. Future studies ought to seek longitudinal studies in order to determine causality and to investigate the long-term impacts of technology integration on nurse burnout and patient outcomes [46]. The research must also be aimed at the design and testing of technologies that facilitate empathy and exploring certain technological aspects, including usability and interface design, that distinguish between positive and frustrating and impeding results.

4.5. Limitations

There are a number of limitations that should be mentioned in this study. To begin with, the cross-sectional design allows establishing associations but does not allow causal inference. It is also possible that more engaged and patient-centered nurses are also more likely to embrace new technologies, which is a potential confounding variable. Second, the study was

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ISSN:1000-3673
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limited to one academically based hospital with high technological facilities, which can limit the extrapolation of the results to community or resource constrained environments. Third, the instruments were highly reliable but the use of self-reported measures of technology use is susceptible to social desirability bias. Lastly, the research failed to gather specific technology brands or interfaces data, which can differ significantly in their impact.

CONCLUSION

The current research shows that the implementation of smart technologies in nursing practice is closely linked with patient satisfaction. The results prove that the increased rates of technology use among nurses are positively associated with the overall satisfaction rates and, more precisely, with the perceptions of empathy and responsiveness of patients. These findings were able to achieve the research goals by profiling the use of technology, quantifying satisfaction, and creating a measurable relationship between the two. The main value of the study is its empirical data that AI technologies, properly incorporated into clinical processes, can support the human component of care instead of undermining it. The research offers a proven model that healthcare organizations can use to assess the investments in technology in terms of patient-centered outcomes.

Future studies are advised to use longitudinal designs in multicenter studies to determine causality and investigate long-term effects. Another important direction is the investigation of certain training procedures to increase the use of technology, especially among more experienced nurses. The study provides a basis on how AI can be optimized to enhance both technological and human-centered care at the same time.

REFERENCES

1. Bohr, A., & Memarzadeh, K. (2020). The rise of artificial intelligence in healthcare applications. In Artificial Intelligence in healthcare (pp. 25-60). Academic Press.
2. Kuo, C. L. (2023). Revolutionizing healthcare paradigms: The integral role of artificial intelligence in advancing diagnostic and treatment modalities. International Microsurgery Journal (IMJ).
3. Qahtani, K. M. M., Bakkar, R. M. M., Meshni, I. A. M., Alqahtani, J., Siddiq, Y. A. M., Taher, Z. Y., ... & Taher, S. Y. (2024). AI-Driven Transformations in Nursing Preparing the Workforce for Future Healthcare Challenges: Highlights Through Systematic Review. Journal of International Crisis and Risk Communication Research, 7(S11), 1393.
4. Sharna, M., Gupta, P., Shah, J. K., & Joshi, S. (2025). Escalating Artificial Intelligence-Enabled Clinical Decision Support Systems to Enhance Home-Based Care: A Study on Healthcare Supply Chains. Driving Global Health and Sustainable Development Goals With Smart Technology, 99-114.

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

5. Carayon, P., Wetterneck, T. B., Rivera-Rodriguez, A. J., Hundt, A. S., Hoonakker, P., Holden, R., & Gurses, A. P. (2014). Human factors systems approach to healthcare quality and patient safety. Applied ergonomics, 45(1), 14-25.
6. Mrazek, M., & O'Neill, F. (2020). Artificial intelligence and healthcare in emerging markets. World Bank Group.
7. Witkowski, K., Dougherty, R. B., & Neely, S. R. (2024). Public perceptions of artificial intelligence in healthcare: ethical concerns and opportunities for patient-centered care. BMC Medical Ethics, 25(1), 74.
8. Sheikh, A., Anderson, M., Albala, S., Casadei, B., Franklin, B. D., Richards, M., ... & Mossialos, E. (2021). Health information technology and digital innovation for national learning health and care systems. The Lancet Digital Health, 3(6), e383-e396.
9. French, C. E. (2016). Bench to Bedside? Boundary Spanning in Academic Health Science Centres.
10. Al Khatib, I., & Ndiaye, M. (2025). Examining the role of AI in changing the role of nurses in patient care: systematic review. JMIR nursing, 8(1), e63335.
11. Park, S. H., & Han, K. (2018). Methodologic guide for evaluating clinical performance and effect of artificial intelligence technology for medical diagnosis and prediction. Radiology, 286(3), 800-809.
12. Segadães, F., Pinto, C., Pinto, A., Barroso, M., Coelho, T., & Oliveira, P. (2025). HEALTHCARE ARTIFICIAL INTELLIGENCE: NURSES'PERCEPTIONS. In INTED2025 Proceedings (pp. 2359-2367). IATED.
13. Rony, M. K. K., Parvin, M. R., Wahiduzzaman, M., Debnath, M., Bala, S. D., & Kayesh, I. (2024). "I wonder if my years of training and expertise will be devalued by machines": concerns about the replacement of medical professionals by artificial intelligence. SAGE open nursing, 10, 23779608241245220.
14. Bi, W. L., Hosny, A., Schabath, M. B., Giger, M. L., Birkbak, N. J., Mehrtash, A., ... & Aerts, H. J. (2019). Artificial intelligence in cancer imaging: clinical challenges and applications. CA: a cancer journal for clinicians, 69(2), 127-157.
15. Snowdon, A., & Snowdon, A. (2012). Measuring what matters: The cost vs. values of health care. Ivey Centre for Health Innovation, University of Western Ontario.
16. Ogunkoya, T. A. (2024). Smart hospital infrastructure: what nurse leaders must know about emerging tech trends. Int J Comput Appl Technol Res, 13(12), 54-71.
17. Crosbie, B. (2014). Nurses' Understanding of Technology in the Intensive Care Unit (Doctoral dissertation, University of Sheffield).
18. Gümüsay, A. A., & Reinecke, J. (2024). Imagining desirable futures: A call for prospective theorizing with speculative rigour. Organization Theory, 5(1), 26317877241235939.

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

19. Hassan, E. A., & El-Ashry, A. M. (2024). Leading with AI in critical care nursing: challenges, opportunities, and the human factor. BMC nursing, 23(1), 752.
20. Al-Dmour, R., Al-Dmour, H., Basheer Amin, E., & Al-Dmour, A. (2025). Impact of AI and big data analytics on healthcare outcomes: An empirical study in Jordanian healthcare institutions. Digital Health, 11, 20552076241311051.
21. Abou Hashish, E. A. (2025). Compassion through technology: Digital empathy concept analysis and implications in nursing. Digital Health, 11, 20552076251326221.
22. Knop, M., Mueller, M., Kaiser, S., & Rester, C. (2024). The impact of digital technology use on nurses' professional identity and relations of power: a literature review. Journal of Advanced Nursing, 80(11), 4346-4360.
23. Alkhathami, A. M., Alharbi, A. A., Albalawi, K. I., Alenezi, A. M., Altaymani, A. M. A., Hamad, A., ... & Alotaibi, M. S. H. TECHNOLOGY Integration in Nursing and Healthcare Administration: Enhancing Efficiency and Care Quality. International journal of health sciences, 3(S1), 525-546.
24. Wynn, M., Garwood-Cross, L., Vasilica, C., Griffiths, M., Heaslip, V., & Phillips, N. (2023). Digitizing nursing: A theoretical and holistic exploration to understand the adoption and use of digital technologies by nurses. Journal of Advanced Nursing, 79(10), 3737-3747.
25. Gallagher, V. T., Reilly, S. E., Martin, D., Manning, C., & Shaffer, K. M. (2024). Examining differences in health-related technology use between millennial and older generations of caregivers. Nursing Reports, 14(4), 2605-2617.
26. Chircop, K. (2025). Predicted clinical impact of artificial intelligence in radiology: a rapid evidence assessment.
27. Roupa, A., Patelarou, A., Giakoumidakis, K., Fousiani, K., Miliaraki, M., Stratidaki, E., & Patelarou, E. (2025, January). Measurement of dehumanization, self-dehumanization, and empathy as mediating factors among healthcare professionals. In Healthcare (Vol. 13, No. 1, p. 75). MDPI.
28. Ayoola, A. A., Adeoye, O. F., Ayoola, A., & Joy, A. (2024). Leveraging artificial intelligence to alleviate nurse workload and improve patient care. ResearchGate Health Operations, 11(2), 45-59.
29. Zhang, S., Ding, S., Cui, W., Li, X., Wei, J., & Wu, Y. (2025). Evaluating the effectiveness of a clinical decision support system (AI-Antidelirium) to improve nurses' adherence to delirium guidelines in the intensive care unit. Intensive and Critical Care Nursing, 87, 103933.
30. Alqaraleh, M., Almagharbeh, W. T., & Ahmad, M. W. (2025). Exploring the Impact of Artificial Intelligence Integration on Medication Error Reduction: A Nursing Perspective. Nurse Education in Practice, 104438.

Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

31. Ferreira, D. C., Vieira, I., Pedro, M. I., Caldas, P., & Varela, M. (2023, February). Patient satisfaction with healthcare services and the techniques used for its assessment: a systematic literature review and a bibliometric analysis. In Healthcare (Vol. 11, No. 5, p. 639). Mdpi.
32. Gold, R., Sheppler, C., Hessler, D., Bunce, A., Cottrell, E., Yosuf, N., ... & Gottlieb, L. (2021). Using electronic health record–based clinical decision support to provide social risk–informed care in community health centers: protocol for the design and assessment of a clinical decision support tool. JMIR Research Protocols, 10(10), e31733.
33. Perry, L. M., Morken, V., Peipert, J. D., Yanez, B., Garcia, S. F., Barnard, C., ... & Cella, D. (2022). Patient-reported outcome dashboards within the electronic health record to support shared decision-making: protocol for co-design and clinical evaluation with patients with advanced cancer and chronic kidney disease. JMIR Research Protocols, 11(9), e38461.
34. McMahon, M., Plate, S., Herz, T., Brenner, G., Kleinknecht-Dolf, M., & Krauthammer, M. (2025). Development of a Data-Based Method for Predicting Nursing Workload in an Acute Care Hospital: Methodological Study. Journal of Medical Internet Research, 27, e66667.
35. Botrugno, C. (2021). Information technologies in healthcare: Enhancing or dehumanising doctor–patient interaction?. Health, 25(4), 475-493.
36. ElKefi, S., & Asan, O. (2021). How technology impacts communication between cancer patients and their health care providers: a systematic literature review. International journal of medical informatics, 149, 104430.
37. Sahu, D., Pradhan, B., Khasnobish, A., Verma, S., Kim, D., & Pal, K. (2021). The internet of things in geriatric healthcare. Journal of healthcare engineering, 2021(1), 6611366.
38. Vallée, A. (2024). Exoskeleton technology in nursing practice: assessing effectiveness, usability, and impact on nurses' quality of work life, a narrative review. BMC nursing, 23(1), 156.
39. Elmdni, A. A. E. (2025). The Impact of Nurse–Patient Ratios on Patient Outcomes in Intensive Care Units. Nursing in critical care, 30(3), e70054.
40. Romero-García, M., Delgado-Hito, P., Benito-Aracil, L., Vivé, E. G., Tabernero-Gallego, R., Muñoz-Rey, M. P., ... & Alcalá-Jiménez, I. (2025). Improving satisfaction with intensive care nursing: Perspectives of nurses and patients. Australian Critical Care, 38(5), 101295.
41. Bae, S. H. (2021). Intensive care nurse staffing and nurse outcomes: A systematic review. Nursing in Critical Care, 26(6), 457-466.

Power System Technology
ISSN:1000-3673
Received: 16-08-2025 Revised: 05-09-2025 Accepted: 15-10-2025

42. Carayon, P., Werner, N., Makkenchery, A., & Mossburg, S. E. (2022). Using human factors engineering and the SEIPS model to advance patient safety in care transitions. Using Human Factors Engineering and the SEIPS Model to Advance Patient Safety in Care Transitions.
43. Golay, D., Karlsson, M. S., & Cajander, Å. (2022). Effortlessness and security: Nurses' positive experiences with work-related information technology use. CIN: Computers, Informatics, Nursing, 40(9), 589-597.
44. Bradshaw, C. C. (2024). The Client Experience of Therapeutic Presence (Doctoral dissertation, Saybrook University).
45. Withall, J. B., Schwartz, J. M., Usseglio, J., & Cato, K. D. (2022). A scoping review of integrated medical devices and clinical decision support in the acute care setting. Applied Clinical Informatics, 13(05), 1223-1236.
46. Ogunkoya, T. A. (2024). Smart hospital infrastructure: what nurse leaders must know about emerging tech trends. Int J Comput Appl Technol Res, 13(12), 54-71.