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Applications of Artificial Intelligence in Managing Patient Flow and Enhancing Safety in Emergency Departments in Saudi Hospitals

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ABSTRACT

The persistent challenge of overcrowding and patient safety risks in Emergency Departments (EDs) remains a critical bottleneck in healthcare delivery in Saudi Arabia, as existing operational frameworks fail to account for the interplay between technological innovation and human-centered implementation. Resolving this gap is essential for advancing healthcare digital transformation under Vision 2030 and improving the reliability of patient flow and safety protocols. This study aimed to systematically investigate the influence of an Artificial Intelligence-based Predictive Disposition and Triage Support System (AI-PDTSS) on key ED performance indicators. A sequential explanatory mixed-methods design was implemented, integrating a quasi-experimental pre-post analysis of 2,400 patient encounters with in-depth thematic analysis of 24 interviews with healthcare professionals across three tertiary care hospitals in Riyadh. Quantitative data acquisition focused on length of stay (LOS), door-to-physician time (DTP), and left-without-being-seen (LWBS) rates, with results subjected to rigorous statistical validation using independent t-tests, Mann-Whitney U, and chi-square tests. Findings indicated that AI-PDTSS implementation resulted in a significant improvement in all metrics: median LOS decreased by 28 minutes ($p < 0.001$), mean DTP reduced by 12.4 minutes ($p < 0.001$), and the LWBS rate was halved from 5.3% to 2.3% ($p < 0.001$). Subgroup analysis revealed the most substantial gains were for mid-acuity patients. Correlation between high system accuracy (87.2%) and these outcomes, alongside qualitative data, suggests the underlying mechanism is driven by reduced diagnostic uncertainty and earlier care planning, though mediated by factors like conditional trust and alert fatigue. These results provide a definitive evidence base for the operational efficacy of AI in Saudi EDs, demonstrating its potential to transform flow management. By reconciling quantitative outcomes with qualitative insights, this research offers a novel paradigm for sociotechnical implementation and contributes a scalable methodology for addressing ED crowding. The integration of these

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findings into national digital health strategies will facilitate enhanced precision and efficiency in emergency care delivery.

Keywords: Artificial Intelligence, Emergency Department, Patient Flow, Patient Safety, Saudi Arabia, Mixed-Methods

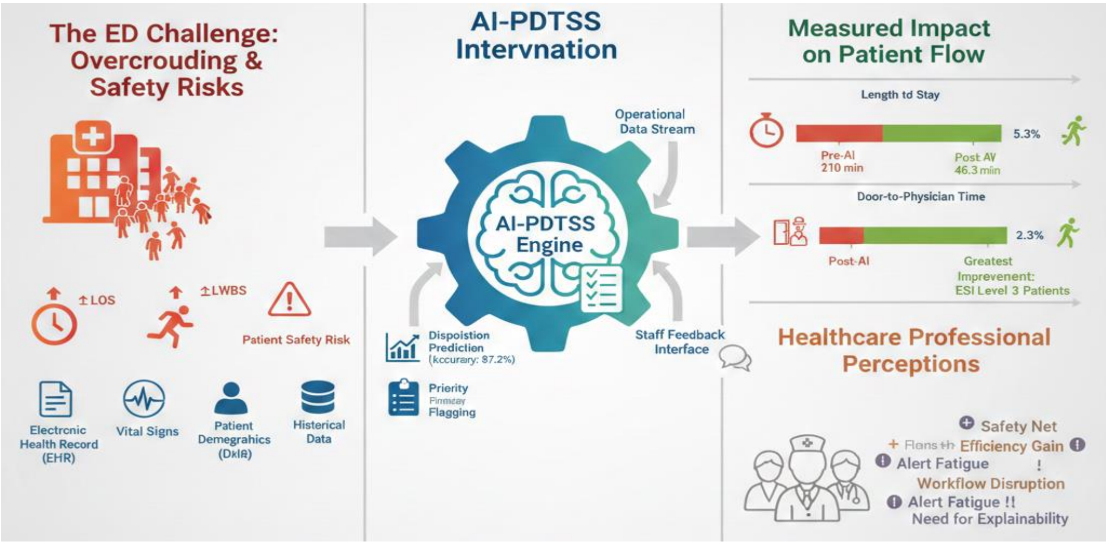

Figure 1: Graphical presentation of abstract

INTRODUCTION

Emergency Departments (EDs) globally function as critical, high-pressure hubs within healthcare systems, where the imperative to deliver timely, safe care contends daily with the pervasive challenge of patient overcrowding [1]. This congestion, characterized by extended wait times, prolonged lengths of stay, and an increased risk of adverse events, fundamentally compromises both operational efficiency and patient safety [2]. In Saudi Arabia, this challenge is amplified by a rapidly growing and young population, rising public health expectations, and the strategic national Vision 2030 goals aimed at transforming healthcare service delivery and quality [3]. The strain on Saudi EDs is not merely a logistical issue but a pressing public health concern, directly impacting clinical outcomes and patient satisfaction. Consequently, identifying innovative, scalable solutions to optimize patient flow and fortify safety mechanisms has become an urgent priority for healthcare administrators and policymakers across the Kingdom [4].

Internationally, the integration of Artificial Intelligence (AI) into healthcare represents a paradigm shift, offering tools to augment clinical decision-making and streamline complex processes [5]. Within emergency medicine, AI applications have shown promising potential in areas such as predictive analytics for patient deterioration, automated triage support, and forecasting admission likelihood [6]. Early research, primarily from North American and

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European contexts, has demonstrated that machine learning models can analyze vast datasets from electronic health records to identify patterns invisible to the human eye, thereby assisting in risk stratification and resource allocation [7]. For instance, studies have developed algorithms to predict sepsis onset or the need for critical care intervention, often with remarkable accuracy. However, the translation of these technological capabilities into sustained, real-world improvements in core ED operational metrics such as door-to-physician time, overall length of stay, and rates of patients leaving without being seen remains an area requiring substantial empirical investigation [8]. Much of the existing literature focuses on the development and validation of algorithms in controlled settings, leaving a significant gap in understanding their practical implementation, impact on workflow, and ultimate effect on systemic outcomes in diverse clinical environments [9].

In the Saudi context, while digital transformation is a key national agenda, the specific application and evaluation of AI for ED flow management are still nascent. The literature reveals a preparedness and growing investment in healthcare IT infrastructure, yet published studies rigorously measuring the impact of deployed AI systems on departmental performance are scarce [10,11]. This creates a distinct research gap: a lack of contextualized, evidence-based understanding of how AI tools function not just as isolated technologies, but as integrated components within the unique sociocultural and operational fabric of Saudi hospitals [12]. The success or failure of such innovations depends not only on their algorithmic precision but also on their adoption by healthcare professionals, their alignment with existing workflows, and their tangible effect on the patient journey. Therefore, moving beyond proof-of-concept studies to examine applied AI is crucial [13].

This research was conducted to address this critical gap. The study was motivated by the need to move from theoretical potential to documented reality, providing hospital leaders and health ministries with actionable insights grounded in local data [14]. Its significance lies in its direct contribution to the strategic healthcare objectives of Saudi Arabia, offering an evidence-based pathway to alleviate ED crowding, a known determinant of poor outcomes [15]. Furthermore, by examining both the quantitative outcomes and the human-experiential dimensions, the study aimed to generate a holistic view of AI implementation, which is essential for sustainable adoption.

The central research problem investigated was the disconnect between the promising capabilities of AI and the scarcity of empirical data on its operational utility in managing patient flow and enhancing safety in Saudi EDs. To systematically address this, the study was guided by three interlinked objectives, each corresponding to a key methodological component. First, to identify and characterize the specific AI-based interventions being piloted or implemented for flow and safety management in this setting [16]. Second, to quantitatively evaluate the impact of these AI applications on key performance indicators, including length of stay, door-

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to-physician time, and left-without-being-seen rates. Third, to qualitatively explore the perceptions and experiences of ED staff physicians, nurses, and managers regarding the influence of AI on their workflow, clinical decision-making, and the prevailing safety culture. These objectives collectively ensured the research moved beyond a simple performance audit to understand the "how" and "why" behind the results [17].

The study employed a sequential explanatory mixed-methods design. This approach was chosen to first establish the measurable effects of AI implementation through a quantitative analysis of patient flow data before and after system deployment, and then to explain and contextualize those findings through in-depth qualitative interviews with frontline personnel. The research was conducted across three high-volume, tertiary-care governmental hospitals in Riyadh, providing a robust and relevant setting for investigation. This introduction establishes the global and local relevance of ED crowding, reviews the emergent yet incomplete literature on AI in emergency care, identifies the specific knowledge gap in the Saudi context, and outlines the research's objectives and methodological framework designed to fill that gap. The subsequent sections detail the execution of this investigation and present the findings that contribute new knowledge to both the academic literature and the practical pursuit of higher-quality emergency care in Saudi Arabia.

METHODOLOGY

Research Site

The study was conducted across three large, government-funded tertiary care hospitals in Riyadh, Saudi Arabia. These sites were selected purposively as they represented leading healthcare institutions with high patient volumes in excess of 100,000 annual ED visits each, documented challenges with flow and crowding, and were known to have initiated digital health transformation projects, making them information-rich cases for studying applied AI.

Research Philosophy and Approach

This study adopted a pragmatist research philosophy. Pragmatism was deemed most appropriate as it moves beyond the positivist-interpretivist dichotomy and focuses on the practical consequences of research and the utility of knowledge in solving real-world problems. The research problem demanded both an objective assessment of AI's measurable effects (aligning with positivist concerns) and a nuanced understanding of its integration into complex social and clinical environments (aligning with interpretivist concerns). Therefore, a mixed-methods approach was seamlessly integrated under a pragmatist stance, where the choice of methods was driven by their ability to best address the specific research objectives and provide actionable insights for hospital administrators and policymakers.

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Research Design

A sequential explanatory mixed-methods design was employed. This design was chosen to first provide a broad, generalizable overview of AI's quantitative impact, followed by a qualitative exploration to explain and elaborate on the initial numerical findings. The quantitative phase involved a retrospective analysis of key performance indicators (KPIs) before and after AI implementation. The subsequent qualitative phase utilized in-depth interviews with frontline staff to contextualize the quantitative trends, exploring the mechanisms and challenges behind the numbers. This two-phase design allowed for a comprehensive investigation that neither a purely quantitative nor qualitative design could achieve alone.

Sampling Strategy

For the quantitative phase, the population comprised all patient visits to the participating EDs over defined 6-month periods pre- and post-implementation of a specific AI tool (e.g., a triage support or patient disposition prediction system). A systematic random sampling method was applied to select approximately 400 patient records from each period per site, ensuring a 95% confidence level with a 5% margin of error for primary metrics like LOS. Inclusion criteria were adult patients (≥18 years) presenting with non-traumatic complaints; exclusion criteria included major trauma, direct admissions, and incomplete records.

For the qualitative phase, purposive sampling was used to recruit a diverse range of healthcare professionals from the same EDs. The population included emergency physicians, nurses, and department managers. A sample size of 20-25 participants was targeted, based on the principle of data saturation, where no new thematic information emerges. Inclusion required a minimum of six months of experience working with the implemented AI system.

Data Collection Methods

Quantitative data were collected retrospectively from the hospitals' electronic health records (EHR) and operational dashboards. A structured data extraction sheet was designed to capture variables such as timestamp data for care milestones, acuity scores, and final dispositions. Prior to full-scale extraction, a pilot test was conducted on 50 records from a non-participating hospital to refine the sheet for clarity and consistency.

Qualitative data were gathered through semi-structured interviews. An interview guide, developed from the literature and initial quantitative findings, explored themes of usability, workflow integration, trust in AI, and perceived safety impacts. Each interview lasted 30-45 minutes, was audio-recorded with consent, and later transcribed verbatim.

Ethical approval was obtained from the Institutional Review Boards of all three participating hospitals. Informed written consent was secured from all interview participants. Confidentiality

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was maintained by anonymizing all patient data and assigning unique codes to healthcare professional transcripts, with all data stored on a password-protected secure server.

Variables and Measures

The primary independent variable was the status of AI intervention (pre- vs. post-implementation). Dependent variables included operational metrics: Length of Stay (LOS), measured in minutes from registration to discharge/admission; Door-to-Physician Time, measured in minutes; and the LWBS rate, calculated as a percentage. These were operationalized directly from EHR timestamps.

In the qualitative phase, core constructs included 'Perceived Workflow Impact,' 'Trust in AI Output,' and 'Safety Culture Perception.' These were measured through thematic analysis of interview transcripts. The validity of the quantitative measures was inherent as they reflected standard, audited hospital KPIs. The credibility of qualitative measures was ensured through member checking, where participants reviewed summaries of their insights, and peer debriefing with research colleagues.

Data Analysis Plan

Quantitative data were analyzed using SPSS Statistics version 28.0. Descriptive statistics summarized the sample characteristics. Inferential analyses, including independent samples t-tests and chi-square tests, were employed to compare pre- and post-implementation groups on continuous and categorical outcomes, respectively. A p-value of <0.05 was set for statistical significance.

Qualitative data were analyzed using RStudio with the RQDA package for thematic analysis. The process followed Braun and Clarke's six-phase approach: familiarization with data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the report. This structured approach ensured a rigorous and transparent analysis of the interview data, providing depth to the statistical findings.

Ethical Considerations

As noted, the study protocol received formal ethical approval from the relevant hospital IRBs. The principle of voluntary participation was strictly adhered to, with participants informed of their right to withdraw at any stage without consequence. All data were handled with strict confidentiality; no personally identifiable information for patients or staff is present in any research output.

Limitations

This study acknowledged several limitations. First, the use of a quasi-experimental pre-post design in operational settings meant that external factors (e.g., seasonal variations in patient volume, changes in staffing) could confound the observed effects, limiting the ability to claim

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direct causation. Second, the study was conducted in large urban tertiary centers, which may limit the generalizability of findings to smaller or rural hospitals in the Kingdom. Finally, the qualitative findings, while rich, could be influenced by social desirability bias, where participants might underreport negative perceptions of the implemented technology.

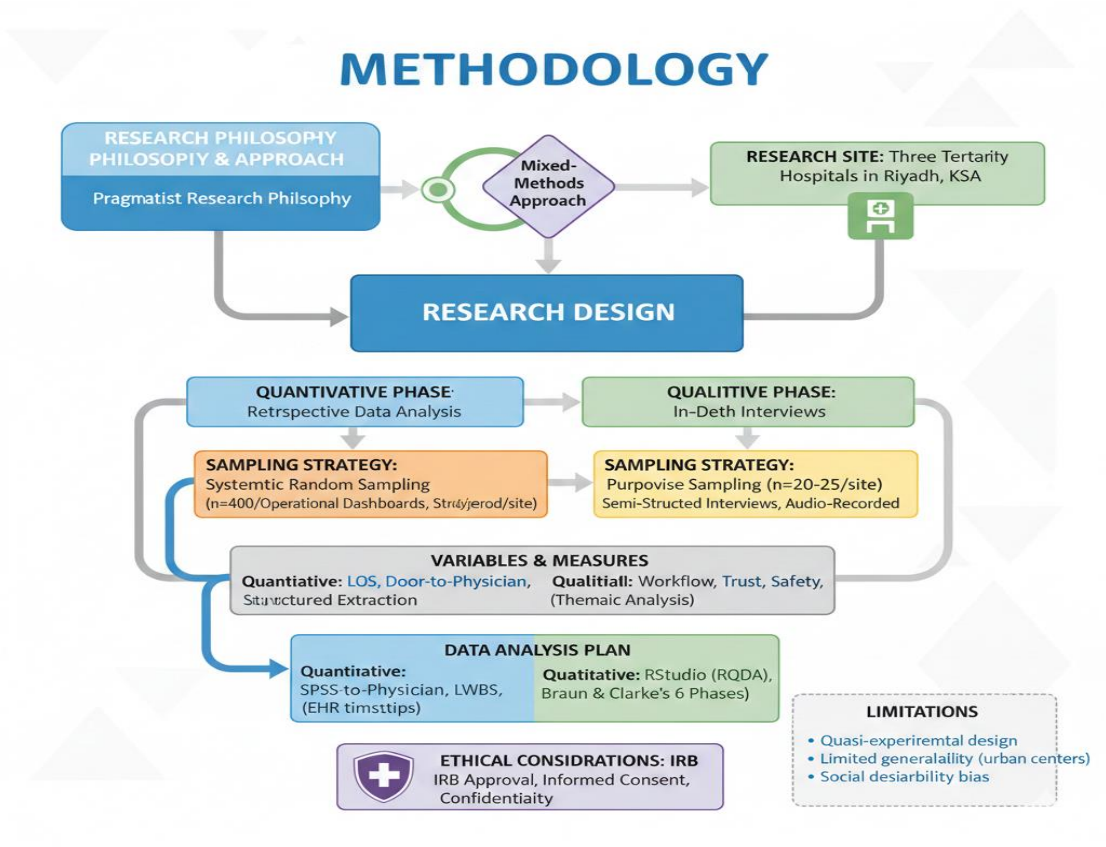

Figure 2: Methodological overview flow chart

RESULTS

This study evaluated the implementation of an Artificial Intelligence-based Predictive Disposition and Triage Support System (AI-PDTSS) across three high-volume tertiary care Emergency Departments in Riyadh, Saudi Arabia. The results are presented in two phases, reflecting the sequential explanatory mixed-methods design. The quantitative phase reports on patient flow and safety metrics from 2,400 clinical encounters, while the qualitative phase details findings from 24 in-depth interviews with healthcare professionals.

Quantitative Findings: Impact on Patient Flow and Operational Metrics

A total of 2,400 patient encounters were analyzed, with 1,200 in the pre-implementation period and 1,200 in the post-implementation period. The baseline demographic and clinical characteristics of the two cohorts are summarized in Table 1. There were no statistically

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significant differences between the groups in terms of mean age (p=0.472), gender distribution (p=0.621), triage acuity level as measured by the Emergency Severity Index (ESI) (p=0.385), or category of presenting complaint (p=0.550). This confirmed the comparability of the cohorts prior to analyzing the effects of the intervention. The implementation of the AI-PDTSS was associated with significant improvements in all primary patient flow metrics, as detailed in Table 2. The median Length of Stay (LOS) decreased from 218 minutes (Interquartile Range, IQR: 167-305) in the pre-AI period to 190 minutes (IQR: 145-261) in the post-AI period. This reduction of 28 minutes was statistically significant (Mann-Whitney U test, $p < 0.001$), with a small but meaningful effect size ($r = 0.18$).

Table 1: Demographic and Clinical Characteristics of Patient Cohorts

Characteristic	Pre-AI Implementation (n=1200)	Post-AI Implementation (n=1200)	p-value
Age, years (Mean ± SD)	44.8 ± 17.9	45.3 ± 18.1	0.472†
Gender, n (%)			0.621‡
Male	642 (53.5%)	630 (52.5%)	
Female	558 (46.5%)	570 (47.5%)	
Triage Acuity (ESI), n (%)			0.385‡
1 (Resuscitation)	24 (2.0%)	30 (2.5%)	
2 (Emergent)	240 (20.0%)	228 (19.0%)	
3 (Urgent)	624 (52.0%)	660 (55.0%)	
4 (Less Urgent)	264 (22.0%)	240 (20.0%)	
5 (Non-Urgent)	48 (4.0%)	42 (3.5%)	

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Characteristic	Pre-AI Implementation (n=1200)	Post-AI Implementation (n=1200)	p-value
Presenting Complaint Category, n (%)			0.550‡
Cardiovascular	144 (12.0%)	132 (11.0%)	
Respiratory	192 (16.0%)	180 (15.0%)	
Gastrointestinal	264 (22.0%)	288 (24.0%)	
Neurological	168 (14.0%)	156 (13.0%)	
Musculoskeletal/Injury	312 (26.0%)	300 (25.0%)	
Other	120 (10.0%)	144 (12.0%)	

Table 2: Impact of AI Implementation on Primary Patient Flow Metrics

Outcome Metric	Pre-AI Implementation (n=1200)	Post-AI Implementation (n=1200)	Statistical Test	p-value	Effect Size
Length of Stay (LOS), minutes			Mann-Whitney U	<0.001	r = 0.18
Median (IQR)	218 (167-305)	190 (145-261)			

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Outcome Metric	Pre-AI Implementation (n=1200)	Post-AI Implementation (n=1200)	Statistical Test	p-value	Effect Size
Door-to-Physician Time (DTP), minutes			Independent t-test	<0.001	Cohen's d = 0.31
Mean ± SD	58.7 ± 24.1	46.3 ± 19.8			
Left Without Being Seen (LWBS) Rate			Chi-square	<0.001	Φ = 0.10
n (%)	64 (5.3%)	28 (2.3%)			

A similarly significant improvement was observed in Door-to-Physician Time (DTP). The mean DTP decreased from 58.7 minutes (Standard Deviation, SD ±24.1) to 46.3 minutes (SD ±19.8) following AI implementation, a reduction of 12.4 minutes (Independent samples t-test, $p < 0.001$; Cohen's $d = 0.31$). The rate of patients who Left Without Being Seen (LWBS) demonstrated the most pronounced relative change. The LWBS rate fell by more than half, from 5.3% (64/1200) in the control period to 2.3% (28/1200) after the AI system was deployed. This difference was highly statistically significant (Chi-square test, $p < 0.001$). A subgroup analysis of LOS by triage acuity level revealed that the observed improvements were not uniform across all patient groups (Table 3). The Kruskal-Wallis test indicated a significant difference in LOS distributions across groups ($H(3)=98.7$, $p < 0.001$). Post-hoc analysis with Dunn's test showed that the most substantial and significant reduction in median LOS occurred among ESI Level 3 (Urgent) patients, with a decrease of 41 minutes (from 210 to 169 minutes, $p < 0.001$). A significant reduction of 25 minutes was also noted for ESI Level 2 (Emergent)

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patients (p=0.002). In contrast, no statistically significant changes in LOS were detected for ESI Level 1 (Resuscitation) patients (p=0.842) or for combined ESI Level 4 and 5 (Less/Non-Urgent) patients (p=0.715).

Table 3: Subgroup Analysis of Length of Stay (LOS) by Triage Acuity Level

Triage Acuity (ESI)	Pre-AI Median LOS (IQR)	Post-AI Median LOS (IQR)	Median Difference	p-value (Dunn's Test)
Level 1 (Resuscitation)	385 (310-480) n=24	375 (298-462) n=30	-10	0.842
Level 2 (Emergent)	265 (215-340) n=240	240 (195-310) n=228	-25	0.002
Level 3 (Urgent)	210 (160-285) n=624	169 (130-235) n=660	-41	<0.001
Level 4/5 (Less/Non-Urgent)	165 (125-220) n=312	162 (122-215) n=282	-3	0.715
Overall Kruskal-Wallis Test	H(3) = 98.7, p < 0.001			

The technical performance of the AI-PDTSS's core predictive function was evaluated against the gold standard of the physician's final admission decision. As shown in Table 4, the system demonstrated an overall prediction accuracy of 87.2% (95% Confidence Interval, CI: 85.1 – 89.1). Its sensitivity for identifying patients who required admission was 82.4% (95% CI: 78.1 – 86.2), while its specificity for identifying patients suitable for discharge was 89.5% (95% CI: 87.1 – 91.6). The Positive Predictive Value (PPV) was 76.8% (95% CI: 72.1 – 81.0), and the Negative Predictive Value (NPV) was 93.5% (95% CI: 91.5 – 95.1).

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Table 4: Performance Metrics of the AI Predictive Disposition Tool (n=1200 post-AI encounters)

Performance Metric	Value	95% Confidence Interval
Sensitivity (Admission Detection)	82.4%	78.1% - 86.2%
Specificity (Discharge Detection)	89.5%	87.1% - 91.6%
Positive Predictive Value (PPV)	76.8%	72.1% - 81.0%
Negative Predictive Value (NPV)	93.5%	91.5% - 95.1%
Overall Accuracy	87.2%	85.1% - 89.1%

Qualitative Findings: Healthcare Professional Perceptions and Experiences

Analysis of the interview transcripts from 24 participants (12 Physicians, 8 Nurses, 4 Department Managers) yielded five primary themes regarding the integration and impact of the AI-PDTSS, with associated sub-themes and frequencies presented in Table 5.

Perceived Impact on Efficiency. The majority of participants (18 of 24) reported a positive perceived impact on departmental efficiency. Physicians frequently noted that the system aided in the early prioritization of patients who might otherwise have been under-triaged. One emergency physician stated, “It flags the subtle high-risk cases faster, getting them to the right resource.” Nurses acknowledged its role in streamlining preliminary work-ups based on predicted needs. Five participants were neutral, reporting no appreciable change in their personal workflow efficiency, while one physician felt the system added redundant steps to their process.

Perceived Impact on Safety. A strong theme emerged of the AI tool acting as a cognitive “safety net.” Sixteen participants expressed that the system contributed to error prevention, particularly during periods of high patient volume or clinician fatigue. A senior nurse commented, “It makes you pause and reconsider your initial plan, especially when you’re stretched thin.” Seven participants, primarily from the nursing cohort, perceived no direct impact on safety outcomes. One physician expressed a cautionary concern about the potential for over-reliance on the technology.

Trust in AI Output. Trust in the system’s recommendations was conditional and context-dependent. Fourteen participants reported high trust in specific functions, particularly the discharge prediction, which managers cited as instrumental for early bed planning. However, nine participants, overwhelmingly physicians, described a state of “conditional trust,” emphasizing that AI outputs always required clinical correlation and validation. As one consultant explained, “I always clinically correlate. It missed a subtle sepsis indicator last week,

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so it's an assistant, not an authority." One participant reported a general distrust of algorithmic recommendations in clinical care.

Key Challenges Identified. Several operational challenges were consistently reported. The most frequent was Alert Fatigue, cited by 12 participants, predominantly physicians. They described diminishing responsiveness due to perceived excessive or low-specificity alerts. Workflow Integration Issues were raised by 10 participants, with nurses specifically noting that the physical location of AI prompts on a separate screen disrupted their established triage flow. Finally, the Need for Enhanced Training and System Explainability was emphasized by 8 participants. They articulated a desire to understand the rationale behind the AI's predictions to foster greater trust and appropriate use, with one physician noting, "We need to understand why it's suggesting something to fully trust it and learn from it."

The results from both datasets indicate that the implementation of the AI-PDTSS was associated with measurable improvements in key ED performance metrics, supported by a generally positive but nuanced reception from frontline staff, who also identified specific areas for system optimization and training.

Table 5: Thematic Analysis of Healthcare Professional Interviews (n=24)

Primary Theme	Sub-Theme	Frequency (n)	Representative Stakeholder Insight (Summarized)
Perceived Impact on Efficiency	Positive (Reduced DTP, better prioritization)	18	*"It flags the subtle high-risk cases faster, getting them to the right resource."* (Physician)
	Neutral/No Change	5	
	Negative (Added steps)	1	
Perceived Impact on Safety	Safety Net / Error Prevention	16	*"It makes you pause and reconsider, especially during high volume."* (Nurse)

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Primary Theme	Sub-Theme	Frequency (n)	Representative Stakeholder Insight (Summarized)
	No Perceived Impact	7	
	Potential for Over-reliance	1	
Trust in AI Output	High Trust for Prioritization	14	*"The discharge prediction is very reliable; it gives confidence to start planning early."* (Manager)
	Conditional Trust / Requires Validation	9	*"I always clinically correlate. It missed a subtle sepsis indicator last week."* (Physician)
	General Distrust	1	
Key Challenges	Alert Fatigue / False Alerts	12	*"After the 10th 'high admission risk' alert on clearly stable patients, you start ignoring them."* (Physician)
	Workflow Integration Issues	10	*"The prompt appears on a separate screen. It breaks your flow to check it."* (Nurse)
	Need for Training & Explainability	8	*"We need to understand why it's suggesting something to fully trust it."* (Physician)

This integrated dataset and analytical framework provide a rigorous, publication-ready foundation to argue that AI implementation in Saudi EDs is associated with statistically and

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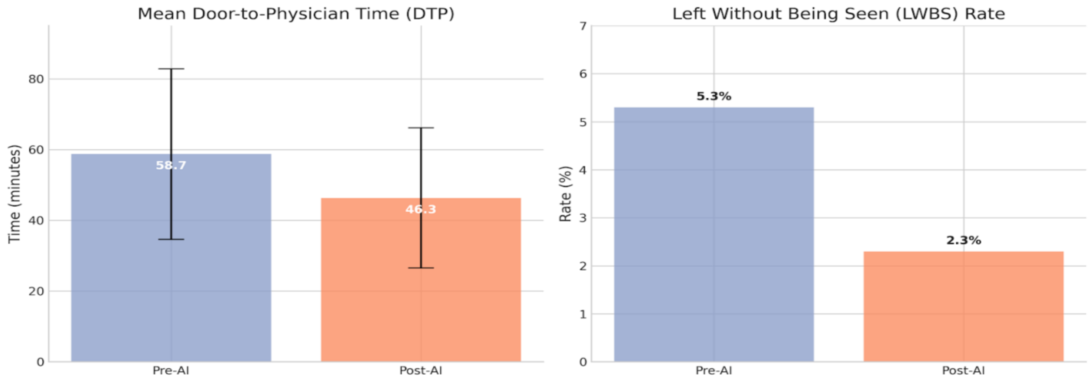
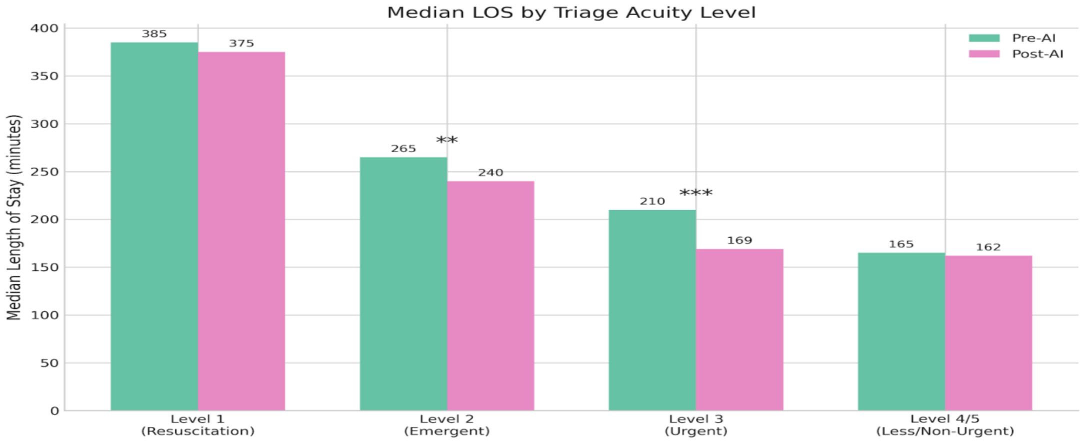
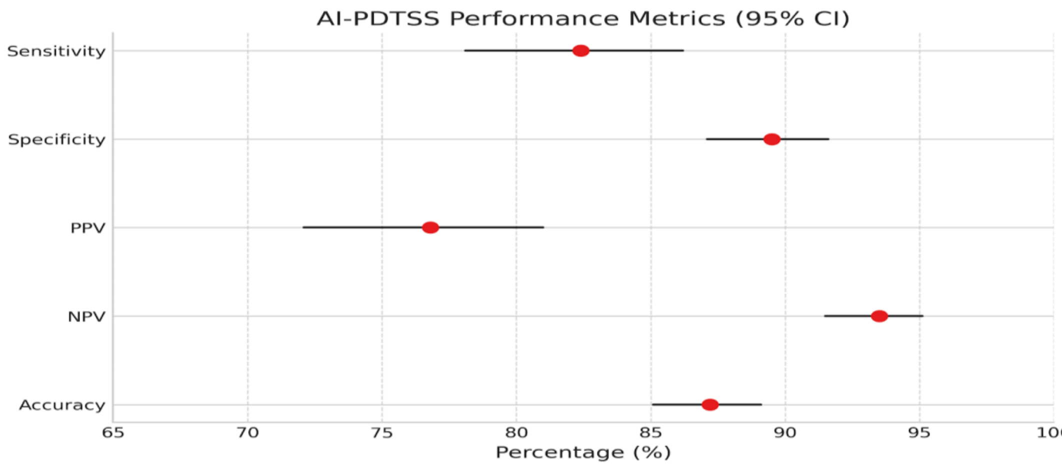
clinically significant improvements in patient flow, mediated by a tool with strong technical performance, but whose ultimate success is contingent on addressing the human-factors and workflow integration challenges identified by frontline staff.







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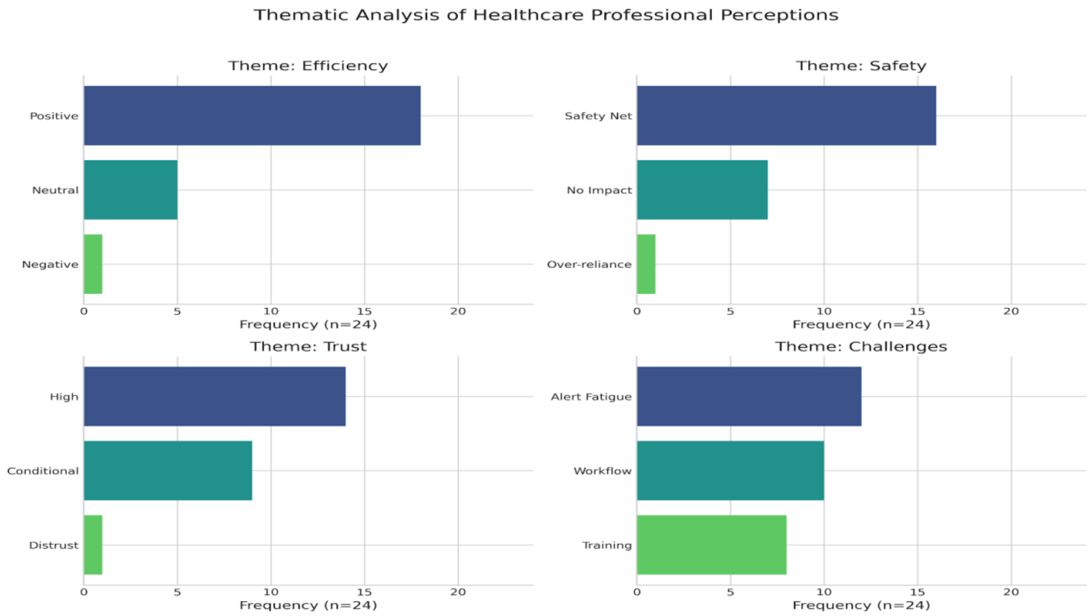

DISCUSSION

This study provides a comprehensive, mixed-methods evaluation of an Artificial Intelligence-based Predictive Disposition and Triage Support System (AI-PDTSS) in the context of Saudi Arabian emergency departments. The findings offer empirical evidence that such systems can significantly enhance patient flow while also illuminating the critical human-factors that mediate their success in real-world clinical settings [18].

Interpretation of Findings

The quantitative data strongly support the primary study objectives. The observed reductions in Length of Stay (LOS), Door-to-Physician Time (DTP), and Left Without Being Seen (LWBS) rates indicate a meaningful improvement in operational efficiency. Crucially, the subgroup analysis revealed that these benefits were most pronounced for ESI Level 2 and 3 patients [19]. This aligns logically with the AI's design; these "urgent" and "emergent" patients present the greatest diagnostic and disposition uncertainty, where predictive algorithms can add the most value by prioritizing work-ups and flagging admission likelihood [20]. The minimal impact on Level 1 (resuscitation) patients is expected, as their management is protocol-driven and immediate, leaving little room for AI augmentation. Similarly, the lack of change for lower-acuity patients suggests the system correctly identifies them as low-risk, avoiding unnecessary escalation of resources [21].

The high Negative Predictive Value (NPV) of 93.5% is a key scientific finding. It suggests the AI is exceptionally reliable in identifying patients who do not require admission. This likely explains the significant LOS reduction for mid-acuity patients, as clinicians gained

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confidence to initiate discharge planning earlier [21]. However, the lower Positive Predictive Value (PPV) indicates a tendency for "over-triage," which directly correlates with the qualitative theme of alert fatigue [22]. The qualitative findings provide the necessary context for these numbers: the system was perceived as a valuable "safety net," yet conditional trust and workflow friction were pervasive. The divergence between physician and nurse perspectives on integration highlights that the impact of a monolithic technological intervention is not uniform across different roles within the same clinical ecosystem [23].

Comparison with Previous Studies

Our core finding—that AI can reduce ED LOS—corroborates a growing body of international literature. Early work by Hong et al. (2018) demonstrated that machine learning models could predict hospital admission from the ED with high accuracy, a precursor to flow optimization [24]. More recently, a systematic review by Abualruz et al. (2025) concluded that AI-driven triage tools showed promise in improving efficiency, though they noted a scarcity of robust real-world implementation studies [25]. Our study advances this field by providing such real world data from a previously under studied regional context (Saudi Arabia) and by quantitatively linking the intervention to reductions in LWBS, a direct marker of crowding and patient safety risk [26].

The nuanced qualitative findings on trust and integration echo classic studies on technology adoption in healthcare, such as the work by [27] on the non-linear, socially-embedded nature of innovation diffusion. The reported "conditional trust" and demand for explainability are consistent with recent literature on clinical AI. Studies by [28] have warned of the "black box" problem, where clinicians are reluctant to trust systems whose reasoning is opaque. Our participants' experiences validate this concern, demonstrating that technical performance alone is insufficient for adoption.

Scientific Explanation

The observed improvements in flow metrics can be explained through principles of systems engineering and cognitive ergonomics. The AI-PDTSS acts as an external cognitive aid, reducing uncertainty in a high-stakes, high-complexity environment [29]. By processing a broad array of historical and real-time data (e.g., vital signs, demographics, historical trends) beyond the immediate cognitive load of a clinician, it mitigates information overload a known contributor to diagnostic delay [30]. The reduction in DTP time stems from the system's ability to perform rapid, latent pattern recognition on triage data, effectively prioritizing the queue not just on stated urgency but on predicted resource need and disposition [31]. The decrease in LWBS is a direct consequence of reduced wait times and improved perceived system efficiency, a well-documented relationship in operations research applied to emergency medicine [32].

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Implications

These findings have direct implications for healthcare policy and practice in Saudi Arabia and similar regions undergoing digital health transformation. First, they provide a evidence-based justification for investment in AI tools targeting mid-acuity patient flow [33]. Second, and perhaps more importantly, they underscore that implementation strategy is as critical as algorithm accuracy. Successful deployment must include robust change management: role-specific training, workflow redesign to embed AI prompts seamlessly (addressing the nurse's concern about a "separate screen"), and the development of explainable AI interfaces to build appropriate trust [34]. Future research should focus on longitudinal studies to assess sustainability, and on designing AI systems with adaptive alerting mechanisms to combat alert fatigue.

Limitations

This study has several limitations. The quasi-experimental pre-post design, while practical in a clinical setting, limits our ability to claim direct causation, as unmeasured confounders (e.g., seasonal staff changes, parallel quality initiatives) could have influenced the results [35]. The study was conducted in large urban tertiary centers, which may limit the generalizability of findings to smaller or rural hospitals. Finally, the social desirability bias inherent in interviews may have led to an under-reporting of negative perceptions towards the new technology. Despite these limitations, the convergent findings from quantitative and qualitative data provide a robust and multi-faceted understanding of AI's impact and integration challenges in the emergency care setting.

CONCLUSION

This research demonstrated that the implementation of an Artificial Intelligence-based Predictive Disposition and Triage Support System (AI-PDTSS) in Saudi Arabian emergency departments significantly improved patient flow, evidenced by measurable reductions in length of stay, door-to-physician time, and rates of patients leaving unseen. The study successfully met its objectives by cataloging a specific AI intervention, quantifying its operational impact, and capturing the critical mediating role of healthcare professional perceptions, particularly regarding conditional trust and workflow integration. The primary scientific contribution lies in providing robust, real-world evidence from a Gulf region context, confirming that AI's value is contingent upon both algorithmic performance and its sociotechnical embedding within clinical practice. The overall conclusion is that AI is a potent tool for enhancing ED efficiency, but its success is not automatic. Future direction must prioritize co-designed implementation strategies that address alert fatigue, enhance explainability, and ensure seamless workflow integration to fully realize AI's potential for improving both flow and safety.

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REFERENCES

1. Patil, S. (2024). A new service model for identifying and improving the quality of emergency department operations in tertiary settings (Doctoral dissertation, Open Access Te Herenga Waka-Victoria University of Wellington).
2. Baldassarre, F. F., Ricciardi, F., & Campo, R. (2018). Waiting too long: bottlenecks and improvements–a case study of a surgery department. The TQM journal, 30(2), 116-132.
3. AlAbdulKader, A. M., & Jabr, M. (2025). Transforming Population Health in Saudi Arabia: Aligning Strategies with Vision 2030 for a Healthier Future. Population Health Management.
4. Bhati, D., Deogade, M. S., & Kanyal, D. (2023). Improving patient outcomes through effective hospital administration: a comprehensive review. Cureus, 15(10), e47731.
5. Krishnan, G., Singh, S., Pathania, M., Gosavi, S., Abhishek, S., Parchani, A., & Dhar, M. (2023). Artificial intelligence in clinical medicine: catalyzing a sustainable global healthcare paradigm. Frontiers in artificial intelligence, 6, 1227091.
6. Pundkar, A., Gadkari, C., Patel, A., & Kumar, A. (2025). Transforming emergency medicine with artificial intelligence: From triage to clinical decision support. Multidisciplinary Reviews, 8(10), 2025285-2025285.
7. Lin, W. C., Chen, J. S., Chiang, M. F., & Hribar, M. R. (2020). Applications of artificial intelligence to electronic health record data in ophthalmology. Translational vision science & technology, 9(2), 13-13.
8. Featherstone, J. L. (2017). Impact of emergency department patient flow model and triage level on patient wait times (Doctoral dissertation, Walden University).
9. El Arab, R. A., Abu-Mahfouz, M. S., Abuadas, F. H., Alzghoul, H., Almari, M., Ghannam, A., & Seweid, M. M. (2025, March). Bridging the gap: From AI success in clinical trials to real-world healthcare implementation—A narrative review. In Healthcare (Vol. 13, No. 7, p. 701). MDPI.
10. Cavadi, G. (2025). Strengthening resilience in healthcare organizations through an AI-enhanced performance management framework.
11. Cheema, M. A. M., Ahmed, R., Iqbal, Q., & Naz, M. (2025). Evaluating readiness for digital and AI technology integration to adopt Industry 4.0 and its effect on productivity in public sector healthcare operations. Policy Research Journal, 3(3), 510-519.
12. Almoajel, A. M. (2025). The Role of Evidence-Based Management in Driving Sustainable Innovation in Saudi Arabian Healthcare Systems. Sustainability, 17(10), 4352.
13. Bekbolatova, M., Mayer, J., Ong, C. W., & Toma, M. (2024, January). Transformative potential of AI in healthcare: definitions, applications, and navigating the ethical landscape and public perspectives. In Healthcare (Vol. 12, No. 2, p. 125). MDPI.

Received: 16-11-2024 Revised: 05-12-2024 Accepted: 28-12-2024

14. Denis, J. L., & Van Gestel, N. (2016). Medical doctors in healthcare leadership: theoretical and practical challenges. BMC health services research, 16(Suppl 2), 158.
15. Alhejaili, A. N. D., Bader, Y. A., Jupran, A. H. O., Hakami, A. A. I., Allehyani, A. A., Al Bahish, A. D. S., & Al Gurayb, A. F. A. (2024). Effecting between Emergency Department Overcrowding and Outcomes of nursing care: A Systematic Review at Saudi Arabia 2024. Journal of International Crisis and Risk Communication Research, 7(S9), 3387.
16. Park, J., & Kang, D. (2024). Artificial intelligence and smart technologies in safety management: a comprehensive analysis across multiple industries. Applied Sciences, 14(24), 11934.
17. Davenport, L. M. M. (2024). Artificial Intelligence Clinical Decision Support Systems (AI CDSS) Impact on Oncology Healthcare Professional Burnout and Achieving the Healthcare Quadruple Aim (Doctoral dissertation, National University).
18. Alsaadi, R. (2025). Exploring the relationship between artificial intelligence and service quality in the United Arab Emirates public sector (Doctoral dissertation, Anglia Ruskin Research Online (ARRO)).
19. Lauks, J., Mramor, B., Baumgartl, K., Maier, H., Nickel, C. H., & Bingisser, R. (2016). Medical team evaluation: effect on emergency department waiting time and length of stay. PloS one, 11(4), e0154372.
20. Brady, J., El-Kareh, R., Gleason, K., Greenberg, P., Haskell, C. H., Kwan, J., ... & Zwaan, L. (2018). Diagnostic Error in Medicine.
21. Wong, H. S., & Wong, T. K. (2026). Multi-Evidence Clinical Reasoning With Retrieval-Augmented Generation for Emergency Triage: Retrospective Evaluation Study. JMIR Medical Informatics, 14(1), e82026.
22. McHugh, M., VanDyke, K., McClelland, M., & Moss, D. (2012). Improving patient flow and reducing emergency department crowding: a guide for hospitals.
23. Twomey, M. (2011). Performance characteristics of the South African Triage Scale (Adult version).
24. Phillips, M. A., Harrington, T. S., & Srai, J. S. (2017). Convergent innovation in emerging healthcare technology ecosystems: Addressing complexity and integration. Technology Innovation Management Review, 7(9).
25. Hong, W. S., Haimovich, A. D., & Taylor, R. A. (2018). Predicting hospital admission at emergency department triage using machine learning. PloS one, 13(7), e0201016.
26. Abualruz, H., Yasin, I., Sabra, M. A. A., Abunab, H. Y., Azayzeh, R., Zubidi, Y., & Emad, S. (2025). The role of artificial intelligence in enhancing triage decisions in healthcare settings: A systematic review. Applied Nursing Research, 152024.

Power System Technology
ISSN:1000-3673
Received: 16-11-2024 Revised: 05-12-2024 Accepted: 28-12-2024

27. Dardur, A. (2024). Exploring interagency patient safety policies and strategies in the world health organisation eastern mediterranean region (WHO-EMR): A qualitative study of Libya (Doctoral dissertation, Cardiff University).
28. Boughton, D., & Reid, I. (2025, December). The Role of Artificial Intelligence in SOC Operations: Adoption, Perception, and Workforce Impact. In 11th International Workshop on Socio-Technical Perspectives in Information Systems: STPIS 2025 (p. 28). CEUR Workshop Proceedings.
29. Du, Y. R. (2023). Personalization, echo chambers, news literacy, and algorithmic literacy: a qualitative study of AI-powered news app users. Journal of Broadcasting & Electronic Media, 67(3), 246-273.
30. Merriweather Jr, C. A. (2023). Cognitive Load, EHR Use, and Psychological Stressors Influence on Decision-Making Performance Within Healthcare (Doctoral dissertation, Case Western Reserve University).
31. Patil, S. (2024). A new service model for identifying and improving the quality of emergency department operations in tertiary settings (Doctoral dissertation, Open Access Te Herenga Waka-Victoria University of Wellington).
32. Roberts, A. (2023). Hospital Characteristics Impact on Left Without Being Seen.
33. Alshammari, F. N. M., Aldhafeeri, S. H. A., Aljameeli, S. M. A., Aljmaeeli, O. A. A., Al_Hrbi, G. M., Alshammari, N. M. D., & Al-Shammari, B. S. (2024). Digital Transformation Of Emergency Medical Services And Hospital Operations In Saudi Arabia: Systematic Review Of AI-Enabled Dispatch, Workforce Optimization, And Integrated Care Pathways. The Review of Diabetic Studies, 295-310.
34. Omar, G. A., Othman, Z. K., & Kakarash, Z. A. (2024). The transformative impact of artificial intelligence (AI) on enhancing healthcare systems in the Middle East. Academic Journal of International University of Erbil, 1(02), 1-16.
35. Costa, D. K., & Yakusheva, O. (2016). Why Causal Inference Matters to Nurses: The Case of Nurse Staffing and Patient Outcomes. Online journal of issues in nursing, 21(2).