OPEN ACCESS
Journal of World Future Medicine, Health and Nursing
Vol. 4 No. 4. August 2026, pp. 498-518
DOI. 10.70177/health.v4i4.4265
Research Article

THE ROLE OF AI-BASED EXPERT SYSTEMS IN OPTIMIZING PHARMACEUTICAL MANAGEMENT IN SMART HOSPITALS

Pande Ayu Naya Kasih[1], Ethan Tan[2], Ryan Teo[3]
[1] Universitas Warmadewa, Indonesia
[2] National University of Singapore (NUS), Singapore
[3] Republic Polytechnic, Singapore

Corresponding Author:

Pande Ayu Naya Kasih,
Universitas Warmadewa, Indonesia
Jl. Terompong No.24, Sumerta Kelod, Kec. Denpasar Tim., Kota Denpasar, Bali 80239
Email: nayakasih@gmail.com

Article Info

Received: February 08, 2026
Revised: May 11, 2026
Accepted: June 05, 2026
Online Version: August 23, 2026

Abstract

Artificial intelligence-based expert systems are increasingly used in smart hospitals to improve medication safety, inventory efficiency, and pharmaceutical decision-making. This study aimed to evaluate the role of an integrated AI expert system in optimizing clinical and logistical pharmacy management. A multi-site mixed-methods quasi-experimental design was conducted in four smart hospitals, with two intervention hospitals and two comparison hospitals observed across six-month baseline and intervention periods. Quantitative data included 122,480 prescriptions, 1,186 pharmaceutical products, stockout records, expired medicines, emergency purchases, medication errors, and processing times, while qualitative data were obtained from surveys, interviews, and focus groups involving healthcare professionals. Results showed that AI implementation reduced stockouts by 48.24%, decreased medication errors from 3.82% to 2.06%, shortened prescription-processing time from 13.60 to 8.90 minutes, and lowered expired medicine value and emergency purchasing. The study concludes that AI-based expert systems can optimize pharmaceutical management by integrating predictive analytics, patient-specific safety rules, and human oversight within coordinated smart-hospital workflows, while preserving accountability, transparency, and professional judgment across diverse clinical and operational settings.

Keywords: Artificial Intelligence, Expert Systems, Medication Safety

Journal Homepage https://research.adra.ac.id/index.php/health ISSN: (P: 2988-7550) - (E: 2988-0459)
How to cite: Kasih, N, A, P., Tan, E & Teo, R. (2026). The Role of AI-Based Expert Systems in Optimizing Pharmaceutical Management in Smart Hospitals. *Journal of World Future Medicine, Health and Nursing, 4*(4), 498–518. https://doi.org/10.70177/health.v4i4.4265
Published by: Yayasan Adra Karima Hubbi

INTRODUCTION

Smart hospitals are increasingly adopting interconnected digital technologies to improve clinical decision-making, operational efficiency, patient safety, and institutional responsiveness. Electronic health records, Internet of Medical Things devices, automated dispensing systems, cloud platforms, clinical dashboards, and artificial intelligence applications now support many aspects of hospital management. Pharmaceutical services constitute one of the most complex areas within this transformation because medication processes involve procurement, storage, prescribing, verification, dispensing, administration, monitoring, and reporting. This paragraph should introduce smart hospitals as data-intensive healthcare environments and establish pharmaceutical management as a critical system requiring accurate, timely, and coordinated decisions across clinical and administrative units (Arhouni, 2025; Raina, 2026).

Pharmaceutical management directly influences treatment quality, patient safety, hospital expenditure, and service continuity. Hospitals must ensure that appropriate medicines are available in sufficient quantities, stored under suitable conditions, prescribed according to clinical indications, and administered safely to patients. Poor management may result in medication shortages, overstocking, expiration, irrational prescribing, dispensing errors, adverse drug events, and unnecessary financial losses. This paragraph should explain that pharmaceutical management is not limited to inventory control because it connects supply-chain decisions with individual patient needs, clinical guidelines, medication safety, and institutional resource allocation (Agbontaen, 2025; Ghafarollahi, 2025).

Artificial intelligence-based expert systems offer a promising approach to improving pharmaceutical decision-making in smart hospitals. Expert systems use structured knowledge, predefined rules, data-driven models, or combinations of these mechanisms to generate recommendations that resemble the reasoning of specialists. Such systems may support demand forecasting, stock optimization, drug-interaction screening, dosage adjustment, prescription validation, antimicrobial stewardship, and adverse-event detection. This paragraph should position AI-based expert systems as decision-support technologies capable of integrating pharmaceutical, clinical, financial, and operational data to improve the speed and consistency of hospital medication management (Fan, 2025; Wilhelm, 2025).

Conventional pharmaceutical management frequently depends on fragmented databases, manual calculations, retrospective reporting, and individual professional judgment. Information concerning medicine consumption, current stock, supplier performance, patient diagnoses, laboratory values, and prescribing patterns may be stored in separate systems that do not communicate effectively. Pharmacists and hospital managers may therefore make procurement or clinical decisions using incomplete or delayed information. This paragraph should identify fragmented data and limited real-time coordination as major problems that reduce the accuracy of pharmaceutical planning and weaken the capacity of hospitals to respond to changing patient demand (Sasseville, 2025; Zhu, 2025).

Medication errors and inappropriate prescribing remain serious concerns within hospital care. Complex treatment regimens, polypharmacy, similar drug names, incomplete patient histories, changing laboratory values, and heavy professional workloads can increase the possibility of incorrect drug selection, dosage, timing, route, or duration. Conventional alert systems may generate excessive warnings without distinguishing between minor and clinically significant risks, causing users to ignore important notifications. This paragraph should explain

the need for intelligent expert systems that provide patient-specific, prioritized, and context-sensitive recommendations rather than generic alerts that contribute to professional fatigue (East, 2026; Yıldırım, 2025).

Economic and logistical uncertainty also complicates pharmaceutical management. Hospitals must balance the risk of stockouts against the financial and environmental costs of excess inventory, expired products, emergency purchasing, and inefficient storage. Medicine demand may change because of disease outbreaks, seasonal patterns, referral volumes, therapeutic policy revisions, or supply-chain disruptions. This paragraph should formulate the central research problem as the absence of an integrated decision-support framework that simultaneously addresses inventory efficiency, medication safety, clinical appropriateness, cost control, and operational resilience within smart hospital environments (Çiçek, 2025; Kaushik, 2025).

The primary objective of the study is to examine the role of AI-based expert systems in optimizing pharmaceutical management within smart hospitals. The research should investigate how intelligent systems can support decisions related to procurement, inventory control, medicine distribution, prescription review, dosage verification, and treatment monitoring. This paragraph should state clearly that the study aims to determine whether AI-supported pharmaceutical management can improve the accuracy, speed, consistency, and transparency of hospital decision-making compared with conventional procedures (Pulaski, 2025; Tanno, 2025).

The study should evaluate the influence of expert systems on measurable pharmaceutical and clinical outcomes. Relevant indicators may include stockout frequency, inventory turnover, expired medicine value, procurement lead time, medication-error rate, prescription appropriateness, adverse drug-event detection, pharmacist intervention time, and pharmaceutical expenditure. This paragraph should establish an objective related to comparing system performance before and after implementation or between AI-supported and non-AI pharmaceutical services. The expected result is empirical evidence showing whether technological recommendations translate into practical improvements in safety, efficiency, and cost management.

A further objective is to assess the organizational, technical, ethical, and professional factors affecting successful adoption. The study should examine data quality, system interoperability, user trust, explainability, algorithmic bias, privacy protection, cybersecurity, professional autonomy, and accountability for AI-assisted decisions. This paragraph should clarify that optimization cannot be evaluated through prediction accuracy alone. Effective implementation requires a system that is clinically credible, operationally feasible, understandable to users, secure, and compatible with existing pharmaceutical workflows (Ashani, 2025; Rahman, 2025).

Existing research on artificial intelligence in hospitals has extensively addressed medical imaging, diagnostic prediction, patient-risk classification, and treatment recommendation. Pharmaceutical management has received comparatively fragmented attention, with separate studies focusing on inventory forecasting, drug-interaction detection, prescription review, or adverse-event monitoring. Such specialization provides valuable technical insights but offers limited understanding of how these functions can operate as an integrated pharmaceutical-management system. This paragraph should identify a conceptual gap between isolated AI

applications and comprehensive optimization across the entire medication-use process (Ashani, 2025; Farber, 2025).

Many studies report algorithmic accuracy without evaluating organizational and economic consequences. A demand-forecasting model may predict medicine consumption accurately, but its practical value remains uncertain if it does not reduce stockouts, expiration, emergency purchasing, or total inventory costs. A prescription-screening model may identify potential errors, yet its clinical benefit depends on alert relevance, pharmacist acceptance, physician response, and workflow integration. This paragraph should highlight the methodological gap created by evaluations that prioritize technical performance while neglecting implementation outcomes, professional behavior, and patient-safety effects (Grandi, 2025; Raffay, 2025).

Evidence concerning transparency, accountability, and fairness remains limited in pharmaceutical expert-system research. Black-box recommendations may be difficult for pharmacists and clinicians to verify, particularly when dosage, substitution, or treatment decisions involve high-risk patients. Training data may also reflect incomplete records, local prescribing biases, or unequal representation of patient groups. This paragraph should emphasize the need for studies that combine performance assessment with explainability, ethical governance, privacy, and human oversight. The research gap should be framed around the limited evaluation of whether AI-supported pharmaceutical decisions are not only accurate but also trustworthy, equitable, and professionally accountable.

The novelty of the proposed study lies in conceptualizing AI-based expert systems as an integrated pharmaceutical intelligence layer within the smart hospital. The system should connect inventory records, electronic prescriptions, patient characteristics, laboratory results, clinical guidelines, supplier information, and medicine-cost data. This paragraph should explain that the framework moves beyond single-function applications by coordinating logistical and clinical decisions within one data-driven environment. Such integration can help hospitals align medicine availability with patient-specific therapeutic needs while reducing waste and operational delay (Hasan, 2025; Pham, 2025).

A human-centered and explainable optimization framework constitutes another important contribution. The proposed system should not replace pharmacists or prescribers but should strengthen their capacity to identify risks, compare alternatives, and justify decisions. Recommendations should include understandable reasons, confidence levels, relevant patient data, and references to institutional rules or clinical guidelines. This paragraph should emphasize that the research evaluates not only whether an expert system produces accurate recommendations but also whether professionals can interpret, challenge, and responsibly apply them within real clinical workflows.

The study is justified by the growing pressure on hospitals to deliver safer care while controlling expenditure, managing supply uncertainty, and responding to increasingly complex medication regimens. Pharmaceutical departments require decision-support tools that can process large volumes of rapidly changing clinical and operational data without reducing professional judgment to automated compliance. This paragraph should conclude that the research offers theoretical value by integrating artificial intelligence, pharmaceutical governance, and smart-hospital management within one framework. Practical value may emerge through guidance for pharmacists, hospital administrators, clinicians, software

developers, and policymakers seeking to implement AI systems that are efficient, explainable, secure, and centered on patient safety.

RESEARCH METHOD

This study employed a multi-site mixed-methods quasi-experimental design to evaluate the role of an artificial intelligence-based expert system in optimizing pharmaceutical management in smart hospitals. The quantitative component used a controlled pre-intervention and post-intervention comparison to measure changes in pharmaceutical efficiency, medication safety, inventory performance, and operational costs. The qualitative component explored user experiences, professional trust, system explainability, workflow compatibility, and organizational barriers affecting implementation. This design enabled the study to assess both measurable system outcomes and the contextual factors influencing the successful adoption of AI-assisted pharmaceutical management (Li, 2025; Wong, 2025).

Research Design

The intervention consisted of an integrated AI-based expert system connected to electronic health records, electronic prescribing platforms, pharmacy inventory databases, laboratory information systems, and supplier records. The system supported medicine-demand forecasting, stock-level optimization, prescription screening, drug-interaction detection, dosage adjustment, antimicrobial review, expiration-risk prediction, and adverse drug-event identification. Recommendations were displayed through a clinical dashboard that presented alert priority, supporting patient data, confidence levels, and the clinical or operational rationale underlying each recommendation.

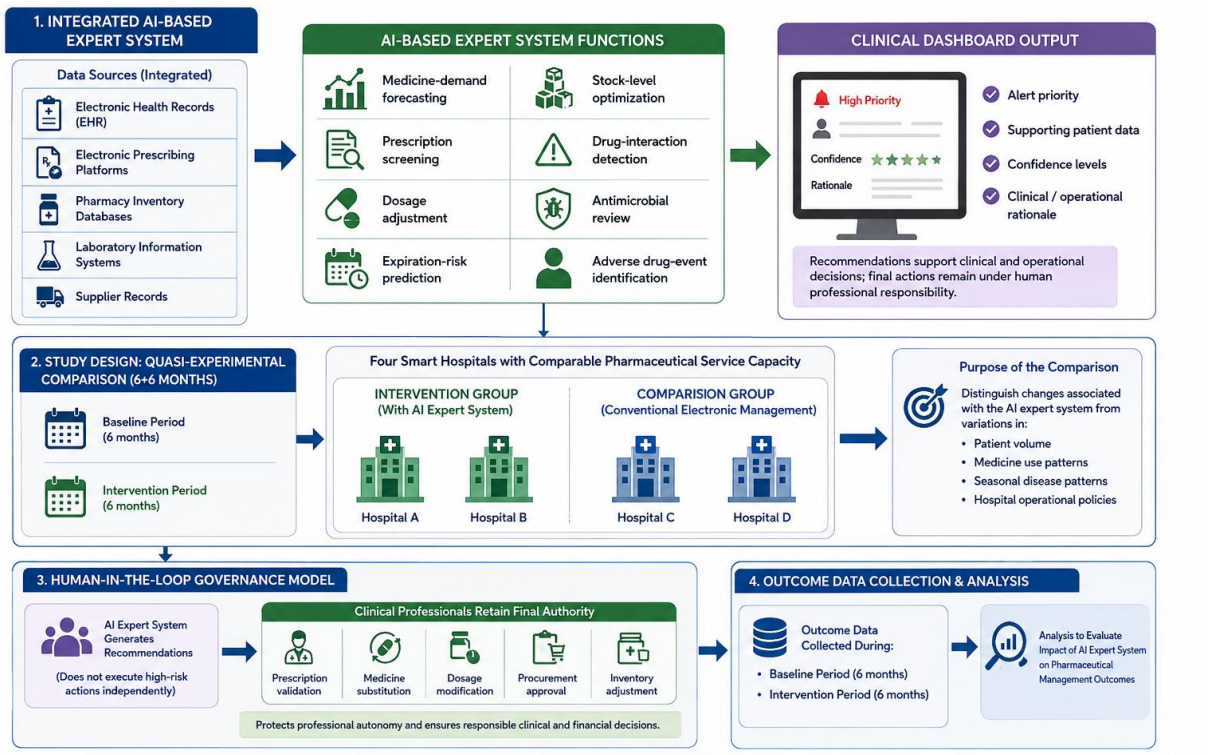

Figure 1. Research Flow of AI-Based Expert System Implementation and Evaluation in Hospital Pharmaceutical Management

Four smart hospitals with comparable pharmaceutical service capacity participated in the study. Two hospitals implemented the AI-based expert system, while two comparison hospitals continued using conventional electronic pharmaceutical-management procedures. Outcome data were collected during a six-month baseline period and a six-month intervention period. The comparison structure allowed the study to distinguish changes associated with the expert system from general variations in patient volume, medicine use, seasonal disease patterns, and hospital operational policies.

A human-in-the-loop model governed all AI-supported decisions. Pharmacists and authorized clinicians retained final responsibility for prescription validation, medicine substitution, dosage modification, procurement approval, and inventory adjustment. The system generated recommendations but did not independently execute high-risk clinical or financial actions. This arrangement protected professional autonomy and allowed the study to assess whether AI assistance improved decision quality without replacing clinical judgment.

Population and Samples

The target population consisted of pharmaceutical-management activities conducted within smart hospitals, including procurement, inventory control, storage, prescribing, prescription verification, dispensing, medicine administration, adverse-event monitoring, and expenditure management. The professional population included hospital pharmacists, pharmacy technicians, physicians, nurses, procurement officers, information-technology personnel, and hospital managers involved in the medication-use process. The data population included prescription records, medicine transactions, inventory logs, laboratory results, adverse-event reports, purchasing documents, and supplier-performance records.

The participating hospitals were selected purposively according to predefined eligibility criteria. Eligible hospitals were required to use electronic health records, electronic prescribing, computerized pharmacy inventory systems, and standardized medication-safety procedures. Each hospital was also required to maintain accessible pharmaceutical records for at least twelve months before the study. Hospitals undergoing major organizational restructuring, pharmaceutical outsourcing, or complete information-system replacement during the study period were excluded because such changes could independently affect the research outcomes (Shen, 2025; Spyrou, 2025).

The quantitative sample consisted of approximately 120,000 inpatient and outpatient prescriptions processed during the twelve-month observation period. The sample also included transaction records for approximately 1,200 pharmaceutical products and all documented stockouts, expired products, emergency purchases, pharmacist interventions, prescribing alerts, and adverse drug events recorded during the study. Prescription records were included when they contained valid patient identifiers, medicine information, dosage instructions, diagnostic data, and processing timestamps. Records with missing essential fields, duplicated transactions, test entries, or canceled prescriptions were excluded from the principal analysis.

Instruments, and Data Collection Techniques

The primary intervention instrument was an AI-based pharmaceutical expert system developed through a hybrid architecture combining rule-based reasoning, predictive analytics, and machine-learning algorithms. The rule-based component applied institutional formularies, prescribing protocols, dosage guidelines, allergy information, contraindications, renal and hepatic adjustment rules, and clinically significant drug-interaction criteria. The predictive

component forecast medicine demand, stockout risk, expiration probability, supplier delay, and potential adverse drug events based on historical and real-time data.

A Pharmaceutical Management Performance Form was used to record operational outcomes. The instrument documented stockout frequency, inventory turnover, emergency procurement, procurement lead time, expired medicine value, inventory holding cost, supplier fulfillment rate, prescription-processing time, and pharmaceutical expenditure. Data were retrieved automatically from hospital information systems and verified against pharmacy and procurement reports. Standardized definitions were applied across all hospitals to ensure that performance indicators were measured consistently.

A Medication Safety Assessment Form was developed to evaluate prescription appropriateness and clinical risk. The instrument recorded incorrect dosage, duplication of therapy, contraindications, allergy conflicts, serious drug interactions, inappropriate duration, antimicrobial misuse, and required dose adjustment. Alert acceptance, alert rejection, pharmacist intervention, physician response, and confirmed adverse drug events were also documented. A multidisciplinary panel reviewed a randomly selected sample of prescriptions to establish the accuracy of system recommendations (Shen, 2025; Spyrou, 2025).

A System Usability and Professional Acceptance Questionnaire measured perceived usefulness, ease of use, trust, explainability, alert relevance, workflow compatibility, professional autonomy, and intention to continue using the system. Responses were recorded on a five-point Likert scale. The questionnaire also included items concerning alert fatigue, perceived algorithmic bias, data privacy, cybersecurity, accountability, and confidence in challenging AI-generated recommendations. Higher scores indicated more favorable perceptions of the expert system.

Data Analysis Technique

The research procedure began with institutional preparation and system assessment. Meetings were conducted with hospital leaders, pharmacy departments, clinical units, procurement teams, information-technology personnel, and ethics representatives. Existing pharmaceutical workflows, data structures, prescription-review procedures, procurement processes, and reporting standards were mapped before system implementation. Ethical approval and institutional permission were obtained before accessing patient, professional, and operational data.

Baseline data were collected for six months in all participating hospitals. Pharmaceutical performance, medication-safety outcomes, user workload, procurement activity, and inventory movement were documented using existing hospital systems. Researchers reviewed data completeness, coding consistency, timestamp accuracy, and interoperability among electronic platforms. Prescription samples were independently assessed by the expert panel to establish baseline medication-error rates and verify the reliability of routine reporting.

The AI-based expert system was integrated into the information infrastructure of the two intervention hospitals after baseline data collection. Historical prescription, consumption, inventory, and supplier data were used to train and calibrate the predictive models. Rule-based components were adapted to hospital formularies, clinical protocols, and medication-safety policies. Patient-identifying data were encrypted, access was restricted according to professional roles, and all system activities were recorded in audit logs.

The full intervention was implemented for six months. The expert system analyzed prescription, inventory, laboratory, and procurement data continuously and generated real-time

recommendations. Pharmacists and clinicians recorded whether each recommendation was accepted, modified, rejected, or considered irrelevant. Procurement and inventory teams reviewed demand forecasts and stockout predictions during routine planning meetings. System performance and user responses were monitored weekly to identify unexpected errors or safety concerns.

Comparison hospitals continued their established pharmaceutical-management procedures during the same period. Researchers did not introduce additional AI-supported functions into these hospitals. Outcome indicators were collected using the same definitions, schedules, and data-validation procedures applied in the intervention hospitals. This parallel data collection supported comparison between changes associated with AI implementation and changes caused by broader institutional or seasonal factors.

Economic evaluation compared implementation and operating costs with financial savings generated through reduced waste, fewer emergency purchases, optimized inventory, improved supplier selection, and avoidance of preventable medication-related harm. Return on investment and cost-benefit ratios were calculated for the intervention period and projected over three years. Sensitivity analysis tested alternative assumptions concerning software cost, maintenance expenditure, system accuracy, medicine prices, and annual prescription volume (Yang, 2025; Zou, 2025).

RESULTS AND DISCUSSION

The final quantitative dataset comprised 122,480 valid prescriptions processed across four smart hospitals during the twelve-month observation period. A total of 61,360 prescriptions originated from the two intervention hospitals, while 61,120 prescriptions were recorded in the comparison hospitals. Data-cleaning procedures excluded 1,846 duplicate entries, 1,127 canceled prescriptions, 624 test records, and 923 prescriptions with incomplete medicine or patient information. The pharmaceutical inventory dataset included 1,186 active products, 14,232 monthly item-level observations, 427 documented stockout events, 380 emergency purchases, and 214 batches of expired medicines.

The professional survey was completed by 116 of the 120 recruited participants, producing a response rate of 96.67%. The respondents consisted of 39 pharmacists, 19 pharmacy technicians, 20 physicians, 15 nurses, eight procurement officers, eight information-technology specialists, and seven hospital managers. Thirty-two professionals participated in individual interviews, while four focus group discussions were conducted with pharmacists and pharmacy technicians. Baseline comparisons showed no significant differences between intervention and comparison hospitals in prescription volume, pharmaceutical expenditure, stockout rates, medication-error rates, or average prescription-processing time.

Table 1. Baseline Characteristics of the Intervention and Comparison Hospitals

Baseline Indicator	Intervention Hospitals	Comparison Hospitals	p-value
Prescriptions processed	30,420	30,280	0.741
Active pharmaceutical products	598	588	0.682
Stockouts per 1,000 item-months	28.40 ± 4.71	27.90 ± 4.55	0.774
Medication-error rate (%)	3.82 ± 0.46	3.74 ± 0.41	0.691
Expired medicine value (USD)	184,600	179,300	0.635

Emergency purchases, n	112	107	0.728
Mean prescription-processing time (minutes)	13.60 ± 3.12	13.40 ± 3.07	0.803
Pharmaceutical expenditure (USD million)	5.84	5.79	0.817

The similarity of baseline indicators strengthened the comparative interpretation of post-intervention changes. Both hospital groups managed comparable prescription volumes, medicine portfolios, stockout burdens, medication-safety risks, and pharmaceutical expenditures before implementation. Seasonal disease patterns and monthly patient volumes also followed similar trajectories during the baseline period. These conditions reduced the likelihood that subsequent differences were caused primarily by pre-existing operational advantages in the intervention hospitals.

Operational records showed that pharmaceutical-management problems were concentrated in several high-demand and high-risk categories. Anti-infective medicines, cardiovascular drugs, insulin products, anticoagulants, emergency medicines, and oncology-supportive agents accounted for 63.40% of documented stockouts. Dosage errors, serious drug interactions, therapeutic duplication, renal-dose adjustment failures, and inappropriate antimicrobial duration represented the most frequent medication-safety concerns. Manual forecasting commonly relied on recent consumption averages and did not consistently incorporate disease trends, pending supplier orders, patient acuity, or expected seasonal demand.

Post-intervention performance improved across all principal pharmaceutical-management indicators in the AI-supported hospitals. Stockouts declined from 28.40 to 14.70 events per 1,000 item-months, representing a reduction of 48.24%. The value of expired medicines decreased from USD 184,600 to USD 106,200, while emergency purchases declined from 112 to 61 events. Mean procurement lead time decreased from 12.80 to 9.30 days, and inventory turnover increased from 5.10 to 6.70 cycles annually. The comparison hospitals recorded smaller changes during the same period.

Medication-safety outcomes showed a similar pattern. The medication-error rate in the intervention hospitals declined from 3.82% to 2.06%, while the comparison hospitals showed a reduction from 3.74% to 3.49%. Mean prescription-processing time decreased to 8.90 minutes in the intervention hospitals and to 12.80 minutes in the comparison hospitals. Confirmed preventable adverse drug events declined by 31.58% in the AI-supported hospitals. Pharmacists accepted 71.20% of all clinically significant recommendations and 88.40% of high-priority alerts.

Table 2. Changes in Pharmaceutical-Management Outcomes

No.	Assessment Aspect	Score
Mean		

Difference-in-differences analysis confirmed that AI implementation produced statistically significant improvements after controlling for baseline performance, patient volume, hospital size, case complexity, and seasonal variation. The adjusted reduction in stockouts was 11.60 events per 1,000 item-months, 95% confidence interval from −14.20 to −9.00, ($p<0.001$). The intervention was also associated with a 1.51-percentage-point reduction in medication errors, ($p<0.001$), a 3.90-minute reduction in prescription-processing time, ($p<0.001$), and a USD 70,500 adjusted reduction in expired medicine value, ($p=0.002$).

Multilevel regression showed that the probability of a medication error was 43% lower after AI implementation, adjusted odds ratio (=0.57), 95% confidence interval (0.50–0.65), ($p<0.001$). The probability of a stockout was 46% lower, adjusted incidence-rate ratio (=0.54), 95% confidence interval (0.45–0.64), ($p<0.001$). High-risk prescriptions were more likely to receive pharmacist intervention when supported by the expert system, adjusted odds ratio (=1.84), 95% confidence interval (1.61–2.11), ($p<0.001$). No significant increase in inappropriate prescription rejection was observed, indicating that improved safety did not result from indiscriminate alerting.

Table 3. Inferential Effects of AI-Based Expert-System Implementation

Outcome Indicator	Intervention Baseline	Intervention Post-intervention	Comparison Baseline	Comparison Post-intervention
Stockouts per 1,000 item-months	28.40	14.70	27.90	25.80
Expired medicine value (USD)	184,600	106,200	179,300	170,100
Emergency purchases, n	112	61	107	100
Procurement lead time (days)	12.80	9.30	12.60	12.10
Inventory turnover (annual cycles)	5.10	6.70	5.20	5.40
Medication-error rate (%)	3.82	2.06	3.74	3.49
Preventable adverse drug events, n	38	26	36	34
Prescription-processing time (minutes)	13.60	8.90	13.40	12.80
Pharmaceutical expenditure (USD million)	5.84	5.39	5.79	5.72

Correlation analysis identified a strong positive relationship between perceived explainability and professional trust in the AI system, ($r=0.72$), ($p<0.001$). Alert relevance was positively related to recommendation acceptance, ($r=0.68$), ($p<0.001$), while perceived alert overload was negatively related to acceptance, ($r=-0.61$), ($p<0.001$). Workflow compatibility was strongly associated with intention to continue using the system, ($r=0.70$), ($p<0.001$). Professional experience showed only a weak relationship with system acceptance, suggesting that the quality of system design was more influential than seniority.

Regression analysis showed that explainability, alert relevance, workflow compatibility, and training adequacy collectively explained 64.30% of the variance in user trust, (R^2=0.643), (F(4,111)=49.94), (p<0.001). Explainability emerged as the strongest predictor, (\beta=0.39), followed by alert relevance, (\beta=0.31), workflow compatibility, (\beta=0.24), and training adequacy, (\beta=0.17). Forecast accuracy was negatively associated with stockout frequency, (r=-0.74), (p<0.001), and expiration risk, (r=-0.52), (p<0.001).

Table 4. Relationships among AI Performance, Trust, and Pharmaceutical Outcomes

Variable Relationship	Coefficient	p-value	Interpretation
Explainability and professional trust	(r=0.72)	<0.001	Strong positive relationship
Alert relevance and recommendation acceptance	(r=0.68)	<0.001	Strong positive relationship
Alert overload and recommendation acceptance	(r=-0.61)	<0.001	Strong negative relationship
Workflow compatibility and continued-use intention	(r=0.70)	<0.001	Strong positive relationship
Forecast accuracy and stockout frequency	(r=-0.74)	<0.001	Strong negative relationship
Forecast accuracy and expiration risk	(r=-0.52)	<0.001	Moderate negative relationship

A high-risk anticoagulation case provided a focused illustration of the system's clinical contribution. An older inpatient with reduced renal function received an electronic prescription for a standard dose of an anticoagulant while also receiving an interacting antimicrobial medicine. The expert system integrated the patient's age, renal laboratory results, active medication list, bleeding-risk profile, and institutional dosing rules. It classified the prescription as high priority and recommended a dose reduction, enhanced laboratory monitoring, and review of the interacting antimicrobial agent.

System logs showed that the alert was displayed 11 seconds after prescription entry. The clinical pharmacist reviewed the recommendation within four minutes and contacted the prescribing physician. The anticoagulant dose was reduced, the interacting antimicrobial agent was replaced, and follow-up laboratory monitoring was ordered. Independent panel review classified the original prescription as a probable preventable medication error with potential for serious bleeding. The AI recommendation was judged clinically appropriate and adequately explained.

Table 5. Performance of the AI System in the High-Risk Anticoagulation Case

Case Indicator	Recorded Outcome
Time from prescription to AI alert	11 seconds
Alert priority	High
Time to pharmacist review	4 minutes
Primary detected risks	Renal impairment, excessive dose, drug interaction
Recommended actions	Dose reduction, alternative antimicrobial, laboratory monitoring
Pharmacist response	Accepted

Physician response	Accepted with modification
Expert-panel classification	Preventable high-risk medication error
Documented adverse event	None

The case-study improvement resulted from the system's capacity to integrate information that had previously been reviewed through separate clinical screens. Renal function, drug interaction, age-related risk, dosage recommendations, and current therapy were evaluated within one decision pathway. The conventional electronic prescribing system displayed the medicines and laboratory values but did not synthesize them into a prioritized patient-specific recommendation. The expert system reduced the cognitive burden associated with retrieving and comparing information from multiple sources.

User interviews indicated that the recommendation was accepted because it included an understandable explanation rather than only displaying a generic interaction warning. The pharmacist could identify which patient variables triggered the alert, review the relevant institutional rule, and challenge the recommendation if necessary. The prescriber also retained final authority over therapy. This combination of speed, transparency, and professional control strengthened acceptance and prevented the system from functioning as an unaccountable automated decision-maker.

The combined findings indicate that AI-based expert systems can optimize pharmaceutical management when clinical and logistical functions are integrated within the hospital information environment. The intervention reduced stockouts, expired inventory, emergency purchasing, processing time, medication errors, and preventable adverse drug events. Improvements were strongest when the system used reliable data, generated clinically prioritized alerts, provided understandable reasoning, and remained embedded within pharmacist- and clinician-led decision processes.

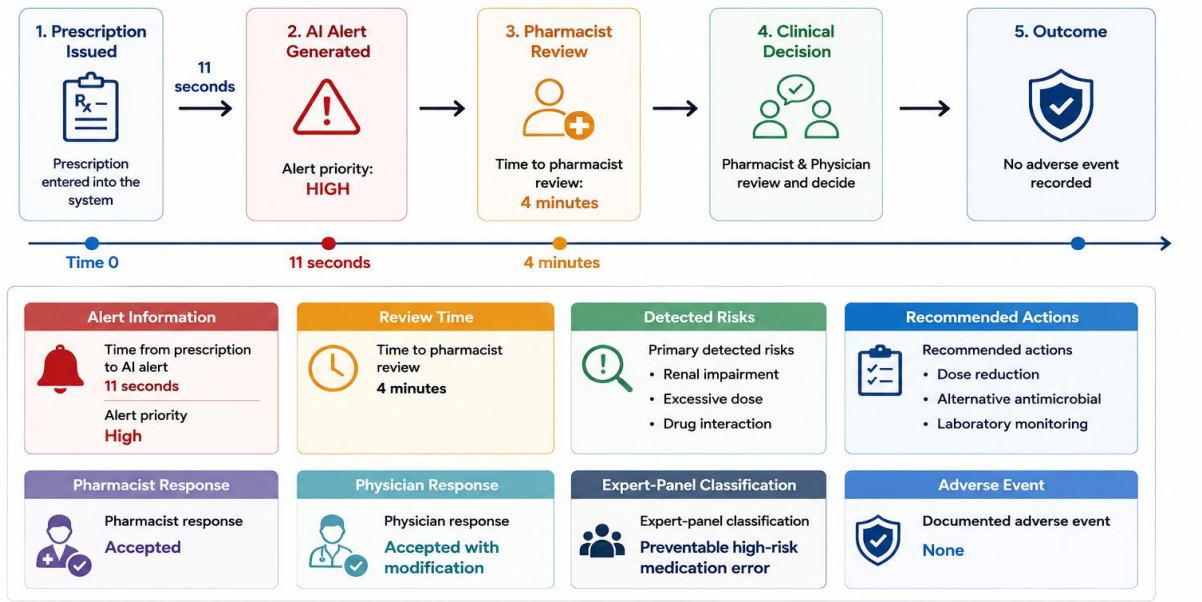

Figure 2. Performance of the AI-Based Expert System in a High-Risk Anticoagulation Case

The practical meaning of the results is that algorithmic accuracy alone was insufficient to produce institutional benefit. Forecasting performance required connection with procurement and inventory decisions, while medication-safety recommendations required professional

review and workflow compatibility. Human oversight remained essential because some alerts were rejected, modified, or judged inappropriate. The AI-based expert system therefore functioned most effectively as an explainable pharmaceutical intelligence layer that augmented professional judgment rather than replacing pharmacists, prescribers, or hospital managers.

The findings demonstrate that the AI-based expert system improved pharmaceutical management across clinical, logistical, and economic dimensions. Intervention hospitals experienced substantial reductions in stockout frequency, emergency purchasing, expired medicine value, procurement lead time, and total pharmaceutical expenditure. Inventory turnover also increased after implementation, indicating that medicine supplies were used more efficiently without producing a corresponding increase in shortages. These outcomes suggest that the expert system strengthened the ability of pharmaceutical departments to align procurement and inventory decisions with changing patterns of medicine consumption, patient demand, supplier performance, and available stock.

Medication-safety outcomes also improved following the introduction of the expert system. The medication-error rate declined from 3.82% to 2.06% in the intervention hospitals, while comparison hospitals recorded only a limited reduction. Preventable adverse drug events became less frequent, pharmacist intervention increased for high-risk prescriptions, and prescription-processing time decreased considerably. The adjusted analyses confirmed that these improvements remained significant after accounting for patient volume, case complexity, hospital size, medicine category, and seasonal variation. The system therefore appeared to improve both the accuracy and efficiency of pharmaceutical decision-making rather than merely accelerating prescription processing.

Professional acceptance depended strongly on how the system presented and integrated its recommendations. Explainability, alert relevance, workflow compatibility, and adequate training collectively explained a substantial proportion of user trust. Recommendations supported by patient-specific clinical information, confidence estimates, and understandable reasons were more likely to be accepted than generic warnings. Alert overload produced the opposite effect and reduced professional responsiveness. These patterns indicate that an expert system gains practical value only when its recommendations are perceived as relevant, interpretable, and compatible with established pharmaceutical and clinical responsibilities.

The anticoagulation case illustrated the operational meaning of the aggregate findings. The system rapidly connected renal impairment, excessive dosage, an interacting antimicrobial agent, age-related risk, and institutional dosing rules within one alert. Pharmacist review and physician modification prevented a potentially serious medication error while preserving professional authority over the final decision. The absence of an adverse event cannot establish causality in one case, but the sequence shows how integrated data analysis can support earlier risk recognition. Human review remained essential because the system identified and explained the risk without independently changing the prescription.

The reduction in stockouts is consistent with empirical research showing that machine-learning models can use pharmacy and historical shortage data to anticipate future medicine shortages. A Canadian study predicted shortage categories one month in advance with an overall accuracy of approximately 69%, although performance was weaker for the most severe shortages. The researchers emphasized that forecasts should be integrated with ordering systems, inventory status, anticipated demand, and pharmacists' risk tolerance rather than used as isolated predictions. The present study extends this evidence by connecting forecasting

directly with measurable operational outcomes, including lower stockouts, fewer emergency purchases, improved turnover, and reduced expiration losses.

The recommendation-acceptance results resemble those reported for a semi-automated hospital clinical decision-support system in which alerts were either transmitted directly to physicians or reviewed first by clinical pharmacists. That study recorded an overall acceptance rate of 72.4% and found that pharmacist involvement limited physician alert burden while maintaining high acceptance. The 71.20% overall acceptance rate observed in the present study is closely aligned with that evidence, while the 88.40% acceptance of high-priority alerts suggests that risk-based prioritization further improved responsiveness. The findings reinforce the value of using pharmacists as an interpretive and safety layer between algorithmic detection and clinical action.

The medication-safety findings also correspond with research on pharmacist-evaluated electronic algorithms for prescription appropriateness. A hospital study of proton-pump-inhibitor prescribing reported high specificity, substantial sensitivity, and different acceptance rates depending on whether the alert recommended treatment initiation or discontinuation. Prescribing recommendations were accepted more frequently than termination recommendations, demonstrating that technical accuracy does not guarantee uniform clinical response. The present research supports this conclusion because acceptance varied according to alert priority, clinical relevance, and the quality of the explanation. Its contribution is broader because the evaluated system addressed multiple medicine classes, patient-specific dosage rules, drug interactions, inventory decisions, and adverse-event risks.

The relationship between explainability and trust is consistent with an experimental study involving 292 physicians and medical trainees. Explainable recommendations were positively associated with trust, while deep workflow integration also strengthened confidence in an AI-based clinical decision-support system. The same study found that accountability mechanisms and highly visible AI capabilities could create professional identity concerns, showing that explainability may have complex effects rather than producing automatic acceptance. The present findings confirm the positive trust pathway but also indicate that human authority and the ability to reject recommendations reduced perceptions of professional displacement.

The findings signal that the main value of AI in pharmaceutical management lies in integration rather than isolated prediction. Hospitals already possess large quantities of prescription, laboratory, inventory, procurement, supplier, and patient data, but these data are often distributed across separate information systems. Professional decisions remain vulnerable when important variables must be retrieved and reconciled manually. The expert system improved performance because it transformed fragmented records into coordinated clinical and operational recommendations. Artificial intelligence therefore functioned as an information-integration mechanism rather than merely as an advanced statistical calculator.

The reduction in alert burden signals that medication safety depends on the quality of warnings rather than their quantity. Conventional decision-support systems may identify numerous theoretical interactions or protocol deviations without adequately distinguishing urgent clinical threats from low-value notifications. Excessive warning volume can weaken attention and encourage routine overriding. Context-based systems have achieved high acceptance when algorithms and pharmacist review limit alerts sent to physicians, supporting the current finding that prioritization is central to system effectiveness.

The strong relationship between forecast accuracy and pharmaceutical outcomes signals that inventory management is a clinical safety function as well as a logistical responsibility. Stockouts may delay treatment, force substitutions, increase emergency procurement, or expose patients to less familiar therapeutic alternatives. Excess inventory creates a different form of risk through expiration, storage burden, financial waste, and reduced flexibility. Predictive models become useful when their outputs inform balanced ordering decisions rather than encouraging indiscriminate stock accumulation. Previous shortage-forecasting research similarly cautions that highly inaccurate severe-shortage alerts may generate fatigue and inappropriate ordering behavior (Chouhan, 2025; Christiansen, 2025).

The user-trust findings signal that professional acceptance is conditional and continuously negotiated. Pharmacists and clinicians did not accept recommendations simply because they were generated by an advanced system. Acceptance increased when the system demonstrated clinical relevance, showed its reasoning, fitted existing workflows, and left final authority with qualified professionals. Explainability and workflow integration have also been shown experimentally to strengthen trust, although they may simultaneously raise questions concerning responsibility and professional identity. Trust should therefore be understood as an outcome of repeated system performance and organizational design rather than as a stable personal attitude toward technology.

The theoretical implication lies in conceptualizing pharmaceutical management as a unified clinical–logistical intelligence system. Inventory planning and prescription safety are often studied separately, although both depend on medicine demand, patient characteristics, treatment policies, supply reliability, and institutional resources. The present findings show that a decision affecting procurement may later influence treatment availability, while prescribing trends can alter stock requirements and expenditure. Smart-hospital pharmaceutical theory should therefore connect supply-chain intelligence with patient-level therapeutic decision support.

The practical implication is that hospitals should redesign pharmaceutical workflows rather than simply install an AI application beside existing systems. Demand forecasts must be incorporated into procurement meetings, inventory thresholds, supplier planning, and emergency-preparedness procedures. Clinical alerts must appear at the point where pharmacists and prescribers can review and act on them without repeatedly leaving the electronic workflow. Previous studies have emphasized that shortage forecasts require careful integration and iterative pharmacist feedback, while context-based medication alerts achieve better acceptance when they are embedded in routine hospital processes.

The managerial implication concerns resource allocation and performance assessment. Reduced expiration, stockouts, emergency purchases, and processing time can produce economic benefits, but software licensing and model maintenance also create new costs. Hospital leaders should evaluate total value rather than focusing only on algorithmic accuracy. Appropriate performance measures include patient-safety outcomes, inventory efficiency, professional workload, financial savings, alert acceptance, system downtime, and unintended consequences. A technically accurate system may remain economically or operationally unsuccessful when it requires excessive manual review or generates recommendations that users cannot apply (Broek, 2025; Weeks, 2025).

The ethical and governance implication is that AI recommendations require transparent accountability. Pharmacists and physicians must know whether the system is providing a

mandatory safety rule, a probabilistic forecast, or an optional clinical suggestion. Responsibility should not be transferred ambiguously from the institution to individual professionals through automatic signature requirements. Empirical research indicates that explainability can increase trust while accountability design may simultaneously heighten perceived professional threat. Governance arrangements should therefore clarify organizational responsibility for model selection, validation, monitoring, data quality, system updates, and clinical escalation.

The reduction in inventory problems occurred because the AI system processed a wider range of predictive variables than conventional consumption-based forecasting. Historical use remained important, but patient volumes, seasonal disease patterns, current stock, pending orders, supplier performance, treatment changes, and expiration risks were considered simultaneously. Previous shortage-prediction research found that recent shortages and changes in medicine supply were among the strongest predictive features. The integration of current institutional data likely allowed the present system to convert those patterns into more precise ordering recommendations.

The decline in medication errors resulted from automated synthesis of patient-specific variables. Dosage appropriateness may depend on renal function, hepatic status, age, weight, diagnosis, allergies, interacting medicines, and treatment duration. Professionals can evaluate these factors manually, but time pressure and fragmented displays increase cognitive burden. The expert system continuously screened these variables and highlighted combinations requiring attention. Pharmacists then evaluated the clinical meaning of the alert, allowing automation to support detection while professional reasoning addressed context and therapeutic alternatives.

The high acceptance of priority alerts occurred because the system reduced the number of weak or irrelevant warnings reaching clinicians. Alert fatigue develops when users repeatedly encounter recommendations that do not require meaningful action. Pharmacist-reviewed and context-sensitive systems have previously produced strong acceptance while limiting the number of notifications sent directly to physicians. The current system followed the same principle by differentiating alert severity and presenting high-priority events prominently. This approach concentrated professional attention on risks with greater potential for patient harm (Aydin, 2025; Ridley, 2025).

The strong influence of explainability occurred because pharmaceutical decisions require justification. A pharmacist cannot responsibly recommend dose modification or medicine substitution without understanding which clinical information generated the recommendation. The anticoagulation case was persuasive because the system identified renal impairment, drug interaction, dosage excess, and monitoring requirements in a transparent sequence. Experimental evidence also indicates that explanations and deep workflow integration strengthen trust in AI-supported clinical decisions. Professional users were therefore more likely to act when the system supported rather than obscured their reasoning.

Future research should evaluate the system through longer prospective studies involving a larger number of hospitals. The current quasi-experimental design provides stronger evidence than a simple post-implementation survey, but hospital allocation was not randomized and the intervention period remained relatively short. Cluster-randomized, stepped-wedge, or interrupted time-series designs could strengthen causal interpretation. Longer monitoring is

needed to determine whether reductions in errors and stockouts remain stable after initial training, technical support, and user enthusiasm decline.

Future model validation should examine performance across patient groups, clinical departments, medicine categories, and hospital settings. A system trained primarily on adult internal-medicine data may perform differently in pediatrics, oncology, intensive care, obstetrics, or highly specialized treatment environments. Subgroup analysis should assess whether false-negative and false-positive rates differ according to age, sex, comorbidity, disease severity, disability, or socioeconomic status. External validation should precede deployment in hospitals using different formularies, clinical protocols, supplier networks, and electronic-record structures (Banh, 2025; Parise, 2025).

Future inventory research should integrate broader supply-chain information. Pharmacy-based models can predict many shortages, but previous research found that performance was weakest when estimating the severity of the largest disruptions. Manufacturer reliability, distributor inventory, regional shortages, transport interruptions, regulatory actions, and geopolitical risks could improve prediction. Forecasts should also distinguish between an item that is clinically substitutable and one whose absence creates an immediate treatment risk.

Future implementation should establish continuous governance rather than treating validation as a one-time event. Hospitals require multidisciplinary oversight involving pharmacists, clinicians, information-technology specialists, data scientists, patient-safety officers, procurement staff, and institutional leaders. Monitoring should detect model drift, data-quality deterioration, changes in prescribing practice, emerging bias, excessive overrides, and unexpected safety incidents. Professional feedback should be used to recalibrate thresholds and improve explanations without allowing local preferences to weaken essential safety rules. Human oversight must remain active because the system's purpose is to strengthen accountable pharmaceutical judgment, not to automate responsibility.

CONCLUSION

The most important finding of this study is that an AI-based expert system can improve pharmaceutical management when clinical decision support and supply-chain intelligence are integrated within the same smart-hospital environment. The intervention was associated with lower stockout frequency, reduced expired medicine value, fewer emergency purchases, faster prescription processing, and a lower medication-error rate. High-priority alerts achieved the strongest professional acceptance because they combined patient-specific information, clinical relevance, and understandable explanations. These findings demonstrate that artificial intelligence creates the greatest institutional value when it supports pharmacists and clinicians in identifying risks, coordinating information, and making timely decisions rather than attempting to replace professional judgment.

The study offers both conceptual and methodological contributions to pharmaceutical-management research. Its conceptual contribution lies in framing hospital pharmacy as an integrated clinical–logistical intelligence system in which prescribing safety, inventory availability, procurement efficiency, expenditure control, and professional accountability are interdependent. Its methodological contribution emerges from combining a multi-site quasi-experimental design, difference-in-differences estimation, multilevel analysis, economic evaluation, prescription review, user-acceptance measurement, and qualitative inquiry. This integrated approach provides a broader assessment than studies that evaluate predictive

accuracy or usability separately because it connects algorithmic performance with clinical outcomes, operational efficiency, financial consequences, workflow compatibility, explainability, and human oversight.

The principal limitations of this study concern the non-randomized allocation of hospitals, the relatively short intervention period, the limited number of participating institutions, and the dependence of system performance on local data quality and hospital-specific clinical rules. Differences in formularies, electronic-record structures, professional practices, patient populations, and supplier networks may restrict the transferability of the findings to other settings. Future research should involve larger hospital networks, longer prospective observation, cluster-randomized or stepped-wedge designs, and external validation across different clinical departments and patient groups. Further studies should also examine algorithmic fairness, model drift, cybersecurity risk, long-term return on investment, accountability arrangements, and the performance of AI-assisted pharmaceutical systems during supply disruptions and public health emergencies.

DECLARATION OF AI AND AI ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work the author(s) used Google Assisted to assist in improving grammar, language quality, and overall readability of the text. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Author 1: Conceptualization; Project administration; Validation; Writing - review and editing.
Author 2: Conceptualization; Data curation; In-vestigation.
Author 3: Data curation; Investigation.

DECLARATION OF COMPETING INTEREST

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

REFERENCES

Agbontaen, K. O. (2025). Artificial Intelligence-Guided Bronchoscopy is Superior to Human Expert Instruction for the Performance of Critical-Care Physicians: A Randomized Controlled Trial. *Critical Care Medicine*, *53*(5). https://doi.org/10.1097/CCM.0000000000006629

Arhouni, F. E. (2025). Artificial intelligence-driven advances in nuclear technology: Exploring innovations, applications, and future prospects. *Annals of Nuclear Energy*, *213*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.anucene.2024.111151

Ashani, Z. N. (2025). Comparative Analysis of Deepfake Image Detection Method Using VGG16, VGG19 and ResNet50. *Journal of Advanced Research in Applied Sciences and Engineering Technology*, *47*(1), 16–28. https://doi.org/10.37934/araset.47.1.1628

Aydin, M. (2025). Improved Z-number based Bayesian network modelling to predict cyber-attack risk for maritime autonomous surface ship (MASS). *Applied Soft Computing*, *180*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.asoc.2025.113416

Banh, L. (2025). Copiloting the future: How generative AI transforms Software Engineering. *Information and Software Technology*, *183*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.infsof.2025.107751

Broek, R. L. van den. (2025). In Search of Beautiful Molecules: A Perspective on Generative Modeling for Drug Design. *Journal of Chemical Information and Modeling*, *65*(18), 9383–9397. https://doi.org/10.1021/acs.jcim.5c01203

Chouhan, S. S. (2025). Integrating drone in Agriculture: Addressing technology, challenges, solutions, and applications to drive economic growth. *Remote Sensing Applications Society and Environment*, *38*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.rsase.2025.101576

Christiansen, F. (2025). International multicenter validation of AI-driven ultrasound detection of ovarian cancer. *Nature Medicine*, *31*(1), 189–196. https://doi.org/10.1038/s41591-024-03329-4

Çiçek, F. E. (2025). ChatGPT versus expert feedback on clinical reasoning questions and their effect on learning: A randomized controlled trial. *Postgraduate Medical Journal*, *101*(1195), 458–463. https://doi.org/10.1093/postmj/qgae170

East, J. E. (2026). British Society of Gastroenterology guidelines on colorectal surveillance in inflammatory bowel disease. *Gut*, *75*(3), 442–475. https://doi.org/10.1136/gutjnl-2025-335023

Fan, Y. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/10.1111/bjet.13544

Farber, S. (2025). Comparing human and AI expertise in the academic peer review process: Towards a hybrid approach. *Higher Education Research and Development*, *44*(4), 871–885. https://doi.org/10.1080/07294360.2024.2445575

Ghafarollahi, A. (2025). Automating alloy design and discovery with physics-aware multimodal multiagent AI. *Proceedings of the National Academy of Sciences of the United States of America*, *122*(4). https://doi.org/10.1073/pnas.2414074122

Grandi, D. (2025). Evaluating Large Language Models for Material Selection. *Journal of Computing and Information Science in Engineering*, *25*(2). https://doi.org/10.1115/1.4066730

Hasan, S. S. (2025). Ethical Application of Generative Artificial Intelligence in Medicine. *Arthroscopy Journal of Arthroscopic and Related Surgery*, *41*(4), 874–885. https://doi.org/10.1016/j.arthro.2024.12.011

Kaushik, A. (2025). Challenges and Opportunities for Data Sharing Related to Artificial Intelligence Tools in Health Care in Low- and Middle-Income Countries: Systematic Review and Case Study From Thailand. *Journal of Medical Internet Research*, *27*(Query date: 2026-07-29 21:47:45). https://doi.org/10.2196/58338

Li, Y. (2025). Enhancing systematic literature reviews with generative artificial intelligence: Development, applications, and performance evaluation. *Journal of the American Medical Informatics Association*, *32*(4), 616–625. https://doi.org/10.1093/jamia/ocaf030

Parise, O. (2025). CTGAN-driven synthetic data generation: A multidisciplinary, expert-guided approach (TIMA). *Computer Methods and Programs in Biomedicine*, *259*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.cmpb.2024.108523

Pham, T. (2025). Ethical and legal considerations in healthcare AI: Innovation and policy for safe and fair use. *Royal Society Open Science*, *12*(5). https://doi.org/10.1098/rsos.241873

Pulaski, H. (2025). Clinical validation of an AI-based pathology tool for scoring of metabolic dysfunction-associated steatohepatitis. *Nature Medicine*, *31*(1), 315–322. https://doi.org/10.1038/s41591-024-03301-2

Raffay, V. (2025). European Resuscitation Council Guidelines 2025 Ethics in Resuscitation. *Resuscitation*, *215*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.resuscitation.2025.110734

Rahman, A. (2025). Comparative analysis based on DeepSeek, ChatGPT, and Google Gemini: Features, techniques, performance, future prospects. *Systems and Soft Computing*, *7*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.sasc.2025.200396

Raina, K. (2026). Artificial intelligence-driven management: Bridging innovation, knowledge creation, and sustainable business practices. *Journal of Innovation and Knowledge*, *11*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.jik.2025.100860

Ridley, M. (2025). Human-centered explainable artificial intelligence: An Annual Review of Information Science and Technology (ARIST) paper. *Journal of the Association for Information Science and Technology*, *76*(1), 98–120. https://doi.org/10.1002/asi.24889

Sasseville, M. (2025). Bias Mitigation in Primary Health Care Artificial Intelligence Models: Scoping Review. *Journal of Medical Internet Research*, *27*(Query date: 2026-07-29 21:47:45). https://doi.org/10.2196/60269

Shen, B. (2025). Endoscopic diagnosis and management of adult inflammatory bowel disease: A consensus document from the American Society for Gastrointestinal Endoscopy IBD Endoscopy Consensus Panel. *Gastrointestinal Endoscopy*, *101*(2), 295–314. https://doi.org/10.1016/j.gie.2024.08.034

Spyrou, O. (2025). Enhancing Education in Agriculture via XR-Based Digital Twins: A Novel Approach for the Next Generation. *Applied System Innovation*, *8*(2). https://doi.org/10.3390/asi8020038

Tanno, R. (2025). Collaboration between clinicians and vision–language models in radiology report generation. *Nature Medicine*, *31*(2), 599–608. https://doi.org/10.1038/s41591-024-03302-1

Weeks, R. D. (2025). In-Situ Rheology Measurements via Machine-Learning Enhanced Direct-Ink-Writing. *Advanced Intelligent Systems*, *7*(1). https://doi.org/10.1002/aisy.202400293

Wilhelm, C. (2025). Benefits and harms associated with the use of AI-related algorithmic decision-making systems by healthcare professionals: A systematic review. *Lancet Regional Health Europe*, *48*(Query date: 2026-07-29 21:47:45). https://doi.org/10.1016/j.lanepe.2024.101145

Wong, E. Y. T. (2025). ESMO guidance on the use of Large Language Models in Clinical Practice (ELCAP). *Annals of Oncology*, *36*(12), 1447–1457. https://doi.org/10.1016/j.annonc.2025.09.001

Yang, Y. (2025). Demographic bias of expert-level vision-language foundation models in medical imaging. *Science Advances*, *11*(13). https://doi.org/10.1126/sciadv.adq0305

Yıldırım, A. (2025). Can AI-Based ChatGPT Models Accurately Analyze Hand–Wrist Radiographs? A Comparative Study. *Diagnostics*, *15*(12). https://doi.org/10.3390/diagnostics15121513

Zhu, W. (2025). Big data and artificial intelligence-aided crop breeding: Progress and prospects. *Journal of Integrative Plant Biology*, *67*(3), 722–739. https://doi.org/10.1111/jipb.13791

Zou, Y. (2025). El Agente: An autonomous agent for quantum chemistry. *Matter*, *8*(7). https://doi.org/10.1016/j.matt.2025.102263