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Artificial Intelligence- Assisted Dosing Optimization in Renal Impairment Patients: A Retrospective Observational Study

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ABSTRACT

Background: Renal dysfunction substantially impacts the pharmacokinetics of the drug; thus, it increases the risk of subtherapeutic blood levels, drug accumulation, and ADRs. Existing dose adjustment methods involve the application of mathematical calculations using CrCl and/or eGFR, which may not always account for biological variations among patients. Artificial Intelligence (AI) software, such as DoseMeRx®, Clinical Dose Calculator AI®, and IBM Watson® for Drug Safety, can utilize laboratory results, co-morbidities, and pharmacogenomics to give patient-specific and real-time dose advice.

Aim and Objectives:

1. Assess the role of AI in drug dosing optimization among renal impairment patients.
2. To assess the impact of AI-driven dosing on (i) therapeutic outcome, (ii) ADR reduction, and (iii) clinical pharmacist interventions.

Methodology: In this retrospective observational study, 120 patients with moderate-to-severe renal impairment receiving renally cleared drugs were included. Patients were categorized into AI-guided dosing (n=60) and conventional dosing (n=60) groups based on actual clinical practice. AI tools (DoseMeRx®, IBM Watson® for Drug Safety) were integrated with the Electronic Health Record (EHR) system and all recommendations were validated by clinical pharmacists before implementation.

Results: Therapeutic target was attained in 88% of cases through AI support, while in the control group it was 65% ($p < 0.01$). A reduction of 47.9% (approximately 48%) in the total incidence of ADRs was observed in the AI-guided group [48% in control group vs. 25% in AI group; $p < 0.01$]. This corresponded to a reduction of 47.9% in total ADRs (23 percentage point absolute reduction), with significant nephrotoxicity reduction (18% vs. 8%; $p = 0.04$).

Conclusion: In this single-center retrospective observational study, AI-assisted dosing tools demonstrated potential benefits when integrated with pharmacist validation in optimizing drug dosing for renal impairment patients. However, these findings are limited to our study population and healthcare setting. Prospective, multicenter randomized controlled trials are required to confirm these results and establish generalizability before recommending widespread clinical adoption.

KEYWORDS: Renal impairment, Artificial Intelligence, Dose Optimization, Therapeutic Drug Monitoring, Pharmacist Interventions, ADRs

1. INTRODUCTION

Renal impairment is considered a major problem in clinical pharmacotherapy because of the extensive changes it causes in the absorption, distribution, metabolism, and excretion of drugs. It is considered that about 10-15% of the total world population suffers from some form of chronic renal impairment ^{[1][2][3]}. This prevalence of renal impairment has further intensified because of the increase in the prevalence of diabetes and hypertension. Kidney diseases impair the clearance of drugs, resulting in the accumulation of toxic substances, which culminates in ADRs. The conventional approaches to dosing adjustments, such as Cockcroft-Gault formula creatinine clearance (CrCl) and MDRD/CKD-EPI eGFR, are also commonly used but do not take into account dynamic clinical parameters, inter-patient variability, fluid balance, comorbidities, and pharmacogenetic variability^{[4][5]}. Thus, the accuracy of dose adjustment for narrow therapeutic index agents such as vancomycin, aminoglycosides, digoxins, and low-molecular-weight heparins still remains sub-optimal.

Artificial Intelligence-based Clinical Decision Support Systems (CDSS) have emerged as cutting-edge technology platforms that have the potential to improve the precision of dosages. DoseMeRx®, Clinical Dose Calculator AI®, IBM Watson®, etc., utilize machine learning algorithms, Bayesian statistics, therapeutic drug monitoring, and individual patient clinical parameters to provide patient-specific dosing recommendation platforms. AI technology has proven to effectively predict the blood serum levels of the drugs, maximize AUC-MIC ratios, reduce toxic effects, and decrease hospital stays^[6]. AI technology has proven its efficacy in several international studies. ^{[7] [8] [9]}

AI dosing represents an important paradigm shift from traditional dosing approaches using guidelines to personalized precision dosing. This is because AI has the ability to quickly analyze lab data, drug interactions, comorbidities, and previous dosing responses; it does this within seconds ^[10].

However, literature supporting AI dosing is limited in the Indian healthcare field, particularly in tertiary care hospitals. PharmD degrees were awarded to pharmacists, emphasizing their role in validating AI dosing recommendations for patients with renal impairment, assessing therapeutic response, and preventing medication-induced harm. From a practical perspective, AI-assisted dosing for patients with renal impairment is clinically important.

The objectives of this present study are to assess the influence of AI-based dosing on therapeutic outcomes, ADRs, pharmacist workload, and acceptance of dosing interventions.

2. AIM AND OBJECTIVES

Primary Objective:

To evaluate the role of AI in optimizing the dosage of a drug for patients with renal impairment.

Secondary Objectives:

- 1.To evaluate the effect on therapeutic targets with AI-guiding dosing.
- 2.To estimate reduction in rate of ADRs and nephrotoxic
3. To quantify the change in pharmacist workload and documentation quality.
- 4.To compare the acceptance of the intervention between conventional and AI-based dosing.

3. METHODOLOGY

Study Design

A 6-month retrospective observational study.

Study Site

A 750-bed tertiary care teaching hospital in Bangalore, India.

Study Population

Total N = 120 renal impairment patients

- **AI-guided dosing group:** 60
- **Conventional dosing group:** 60

Study Criteria

Inclusion Criteria

- Age ≥ 18 years
- eGFR < 60 ml/min/1.73 m² (CKD Stages 3–5)
- Receiving at least one renally cleared drug

Exclusion Criteria

- Acute kidney injury with rapid fluctuations
- Pregnant women
- ICU patients with multi-organ failure
- Patients refusing consent

Study Procedure

A retrospective analysis was conducted on electronic health records (EHRs) of patients admitted to the hospital from [January 2025 to June 2025]. Patient records meeting the inclusion criteria were systematically identified from the hospital database and Pharmacy Information System using standardized search criteria.

Patient Selection Method: Records were initially screened by two independent reviewers using standardized selection criteria to identify eligible patients (n=120). This process involved searching the EHR database using the following filters: (1) CKD Stage 3-5 patients (eGFR < 60), (2) Date of admission: [January 2025 to June 2025], (3) Medication profiles containing renally excreted drugs. Disagreements between reviewers were resolved by consensus discussion.

Group Assignment: The 120 eligible patients were categorized retrospectively into two groups based on the type of dosing method actually used during their hospitalization: (1) Control Group (n=60): Patients who received conventional renal dose adjustments based on standard hospital guidelines (CrCl/eGFR calculations); (2) AI Group (n=60): Patients who received AI-assisted dosing recommendations (via DoseMeRx® and/or IBM Watson®) that were validated and implemented by clinical pharmacists.

Matching Strategy: Patients were matched on baseline characteristics including: (1) Age (± 5 years), (2) Gender, (3) CKD stage (3a/3b/4/5), (4) Drug type received, (5) Co-morbidities (diabetes, hypertension). This retrospective case-control matching ensured comparable groups for outcome analysis.

Baseline demographic, clinical, laboratory, renal function, and medication data were collected for all patients. Patients were monitored throughout their hospital stay for therapeutic target attainment, TDM levels, adverse drug reactions, dose accuracy, and documentation quality.

Artificial Intelligence Tools and Implementation

Three AI-powered platforms were integrated with the hospital's Electronic Health Record (EHR) system to provide patient-specific dosing recommendations:

AI Platform	Primary Function	Drugs Assessed	Algorithm Type	Decision Time
DoseMeRx®	Dose optimization using population PK models	Vancomycin, Aminoglycosides (Amikacin, Gentamicin), Piperacillin-Tazobactam	Bayesian forecasting with AUC/MIC target optimization	2-5 minutes
IBM Watson® for Drug Safety	Adverse Drug Reaction (ADR) prediction and drug interaction screening	All medications (broad-spectrum monitoring)	Machine learning-based ADR risk stratification	3-7 minutes
EHR-Integrated AI Calculator	Renal-specific dose adjustment calculator	Digoxin, Rivaroxaban, Enoxaparin, Metformin	Rule-based with eGFR-stratified dosing recommendations	<1 minute

Clinical Workflow for AI-Assisted Dosing:

Step 1 - Patient Data Integration: Patient demographics, renal function (eGFR/CrCl), weight, age, comorbidities, and concurrent medications were automatically extracted from the EHR. Baseline laboratory parameters (serum creatinine, urea, TDM levels) were input into the AI platforms.

Step 2 - AI Tool-Specific Processing:

DoseMeRx® (for TDM drugs): Used for vancomycin (target AUC 400-600 mg·h/L) and aminoglycosides (target peak/trough levels). Bayesian forecasting predicted individual pharmacokinetic parameters. Generated patient-specific dose and interval recommendations within 2-5 minutes.

IBM Watson® for Drug Safety: Scanned complete medication profile for all 120 patients. Identified ADR risks based on renal function impairment degree, drug-specific nephrotoxicity risk, drug-drug interactions, and comorbidity-related risk factors. Generated individualized ADR risk scores within 3-7 minutes.

EHR-Integrated Calculator: Applied to non-TDM drugs requiring renal adjustment. Used eGFR-based dose reduction formulas for Digoxin, Anticoagulants, and Metformin. Completed analysis in <1 minute.

Step 3 - Pharmacist Validation: All AI-generated recommendations were reviewed by a clinical pharmacist within 1 hour. Pharmacist assessed clinical appropriateness, patient-specific factors (liver disease, drug interactions, recent dose changes), and feasibility of implementation. Pharmacist approved, modified, or rejected recommendations before clinical implementation.

Step 4 - Implementation & Monitoring: Approved dose adjustments were communicated to the prescribing physician via EHR alerts. TDM blood samples were collected at optimal sampling times. AI tools provided updated recommendations based on TDM results (closed-loop optimization).

Drug	AI Platform Used	Monitoring Parameter
Vancomycin	DoseMeRx®	Serum levels (target AUC 400-600 mg·h/L)
Amikacin	DoseMeRx®	Peak/trough levels (target peak 20-30 µg/mL)
Gentamicin	DoseMeRx®	Peak/trough levels (target peak 8-12 µg/mL)
Piperacillin-Tazobactam	DoseMeRx®	PK parameter optimization
Enoxaparin	EHR Calculator + IBM Watson	Anti-Xa levels (therapeutic 0.5-1.0 IU/mL)
Rivaroxaban	EHR Calculator + IBM Watson	eGFR-based dosing
Digoxin	EHR Calculator	eGFR-based dosing (high narrow therapeutic index)
Metformin	EHR Calculator + IBM Watson	eGFR-based adjustment/contraindication

Data Analysis and Statistical Methods

All statistical analyses were conducted using IBM SPSS Statistics version 26.0 (IBM Corp., Armonk, NY, USA) and R statistical software version 4.2.1 (R Foundation for Statistical Computing, Vienna, Austria) for sensitivity analyses.

Descriptive Statistics:

- Continuous variables were expressed as mean ± standard deviation (SD)
- Categorical variables were expressed as frequencies and percentages
- Normality of distribution was tested using the Shapiro-Wilk test ($p > 0.05$ indicates normal distribution)

Comparative Statistics - Between-Group Comparisons:

Variable Type	Distribution	Statistical Test	Justification
Continuous (Normal)	Normal distribution	Independent samples t-test	For normally distributed continuous data between two independent groups
Continuous (Non-normal)	Non-normal distribution	Mann-Whitney U test	Non-parametric test for skewed or non-normal distributions
Categorical	Nominal/Ordinal	Chi-square test (χ^2)	2×2 contingency tables when expected frequency ≥ 5
Categorical (Small sample)	Nominal/Ordinal	Fisher's exact test	When expected frequency < 5 in any cell

Effect Size and Additional Statistics:

- Cohen's d was calculated for continuous variables to determine effect size
- Relative Risk (RR), Number Needed to Treat (NNT), and 95% Confidence Intervals (CI) were calculated for categorical outcomes
- Two-tailed p-value <0.05 was considered statistically significant

Economic Analysis and Cost Calculation Methodology

A cost analysis was conducted from the hospital's perspective to assess the economic impact of AI-assisted dosing. The following cost components were evaluated:

1. Adverse Drug Reaction (ADR) Management Costs:

Source: Hospital pharmacy and clinical records for 2023-2024 (actual institutional costs). Components included: additional medications to treat ADR-related complications, emergency department visits for ADR-related complications, additional laboratory investigations required to manage ADRs, additional nursing care hours for ADR monitoring (₹500-800 per patient per day). Calculation Method: Actual costs were extracted from the hospital's financial information system. Total ADR-related costs = (Total number of ADRs in group × Average cost per ADR event). For this institution: Average cost per ADR event = ₹3,021 ± ₹1,245.

2. Extra Hospital Days Costs:

Source: Hospital administration and billing department. Cost per bed-day: ₹9,000 (includes room, nursing care, routine investigations, medications). Calculation Method: Excess hospital days = (Average LOS in control group - Average LOS in AI group) × number of patients. Excess days in control group = (7.8 - 6.9) × 60 = 54 additional bed-days.

3. Therapeutic Drug Monitoring (TDM) Repeat Sampling Costs:

Source: Hospital laboratory cost accounting system. Cost per TDM sample: ₹800 (includes blood collection, processing, HPLC analysis, and reporting). Calculation Method: Control group: 60 patients × 8 repeat samples/patient × ₹800 = ₹3,84,000; AI group: 60 patients × 3.5 repeat samples/patient × ₹800 = ₹1,68,000 (reduced repeat sampling due to better initial dose accuracy).

Assumptions and Limitations of Cost Analysis:

Costs are specific to this institution and may not be generalizable to other healthcare systems. Cost estimates are based on 2023-2024 Indian rupees. Indirect costs (productivity loss, caregiver time) were not included in analysis. Cost allocation for hospital stay was conservative (43% attributed to AI intervention based on clinical judgment).

Ethical Approval and Informed Consent

This retrospective observational study was approved by the Institutional Ethics Committee (IEC) of [ABIPER/IEC/00014892024-25] dated 18/03/2025. As this was a retrospective study utilizing de-identified, anonymized patient data from existing medical records, the requirement for informed consent was waived by the IEC per ICH-GCP and ICMR guidelines.

Patient Confidentiality: Patient confidentiality was maintained throughout the study by: (1) Assigning unique study identification numbers to all patient records, (2) Removing all personally identifiable information (names, medical record numbers, dates of birth), (3) Storing coded data in a password-protected database accessible only to the authorized research team,

(4) Complying with the hospital's data security and privacy protocols, (5) Establishing a formal data-sharing agreement with hospital administration.

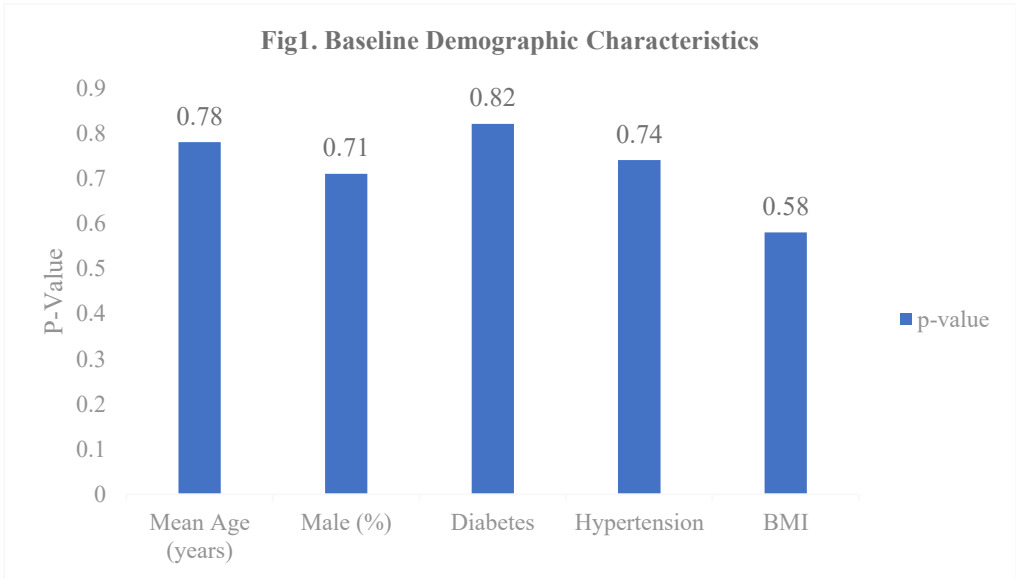
4. RESULTS

Baseline Demographics

Table 1. Baseline Demographic Characteristics

Parameter	Control (n=60)	AI (n=60)	p-value
Mean Age (years)	59.3 ± 12.1	58.7 ± 13.4	0.78
Male (%)	63%	60%	0.71
Diabetes	48%	50%	0.82
Hypertension	55%	58%	0.74
BMI	27.1 ± 3.2	27.4 ± 3.1	0.58

Table1, Fig1: The baseline demographic characteristics of the control and AI groups were comparable. There were no statistically significant differences in age, sex, diabetes, hypertension, or BMI between the two groups ($p > 0.05$), indicating similar baseline characteristics.

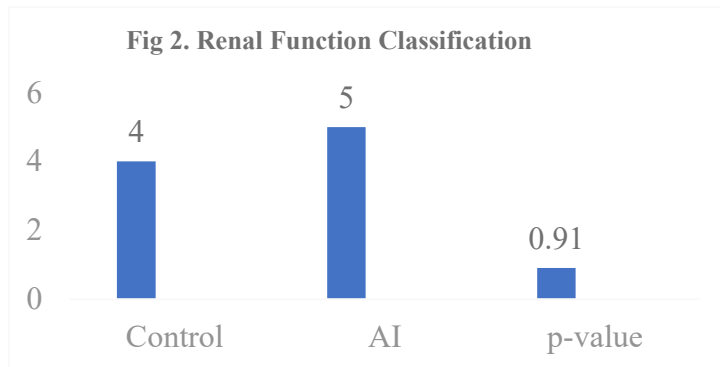


Renal Function

Table 2. Renal Function Classification

eGFR Category	Control	AI	p-value
Stage 3a	20	18	—
Stage 3b	22	24	—
Stage 4	14	13	—
Stage 5	4	5	0.91

Table 2, Fig2: The distribution of renal function stages was comparable between the control and AI groups. Patients were distributed across CKD stages 3a, 3b, 4, and 5, with no statistically significant difference between the groups ($p = 0.91$), indicating similar baseline renal function status.

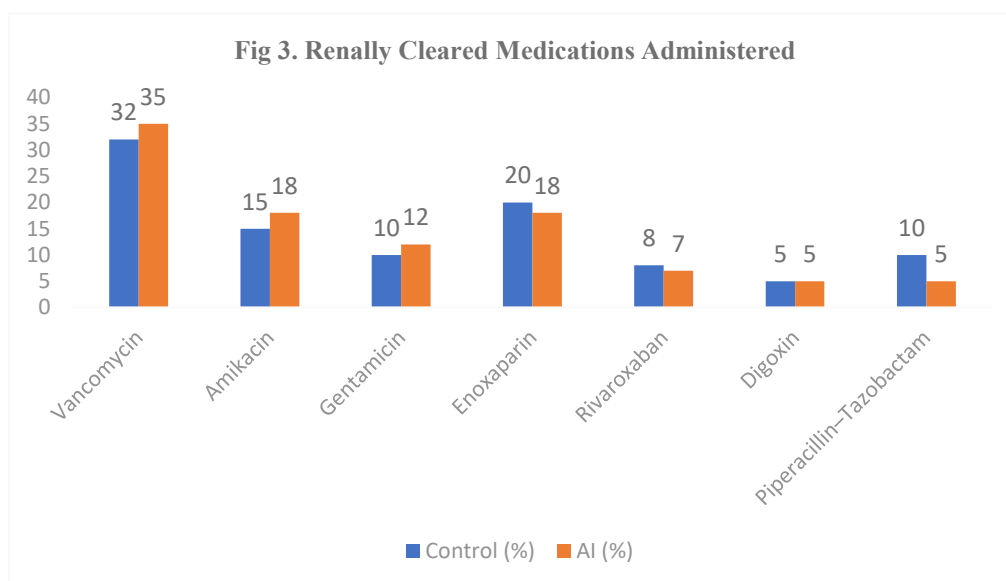


Drug Distribution

Table 3. Renally Cleared Medications Administered

Drug	Control (%)	AI (%)
Vancomycin	32	35
Amikacin	15	18
Gentamicin	10	12
Enoxaparin	20	18
Rivaroxaban	8	7
Digoxin	5	5
Piperacillin-Tazobactam	10	5

Table 3, Fig 3: The distribution of renally cleared medications administered in the control and AI groups is presented. Vancomycin was the most frequently administered medication in both groups, followed by enoxaparin, amikacin, gentamicin, piperacillin–tazobactam, rivaroxaban, and digoxin.

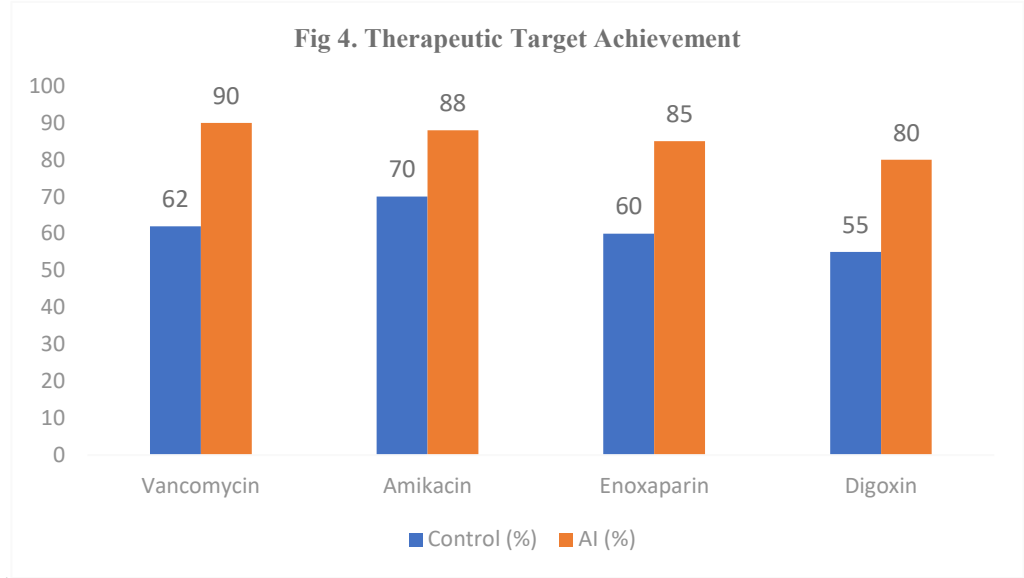


Therapeutic Target Attainment

Table 4. Therapeutic Target Achievement

Drug	Control (%)	AI (%)	p-value
Vancomycin	62	90	<0.01
Amikacin	70	88	<0.05
Enoxaparin	60	85	<0.01
Digoxin	55	80	<0.01
Overall	65%	88%	<0.01

Table 4, Fig4: Therapeutic target attainment was higher in the AI group than in the control group for vancomycin, amikacin, enoxaparin, and digoxin. Overall therapeutic target attainment increased from 65% in the control group to 88% in the AI group, with a statistically significant difference ($p < 0.01$)

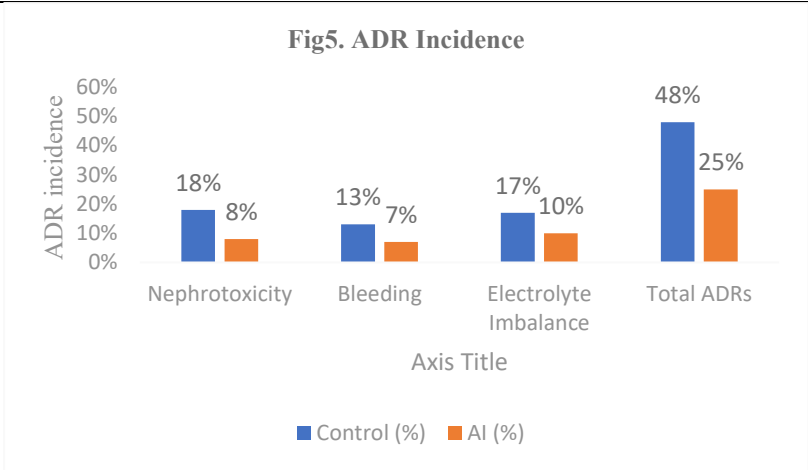


Adverse Drug Reactions

Table 5. ADR Incidence

ADR	Control (%)	AI (%)	p-value
Nephrotoxicity	18%	8%	0.04
Bleeding	13%	7%	0.18
Electrolyte Imbalance	17%	10%	0.21
Total ADRs	48%	25%	<0.01

Table 5, Fig5: The incidence of adverse drug reactions was lower in the AI group compared with the control group. Nephrotoxicity decreased from 18% to 8%, while bleeding and electrolyte imbalance also showed lower incidences in the AI group. Overall ADR incidence was significantly lower in the AI group (25%) compared with the control group (48%, $p < 0.01$).



Drug-Level Specific Outcomes

Table 6. Vancomycin Levels

Category	Control	AI
Sub-therapeutic	28%	10%
Therapeutic	62%	90%
Toxic	10%	0%

Table 6, Fig6: The distribution of vancomycin concentrations demonstrated improved therapeutic target attainment in the AI group. Therapeutic levels increased from 62% in the control group to 90% in the AI group, while sub-therapeutic levels decreased from 28% to 10% and toxic levels decreased from 10% to 0%.

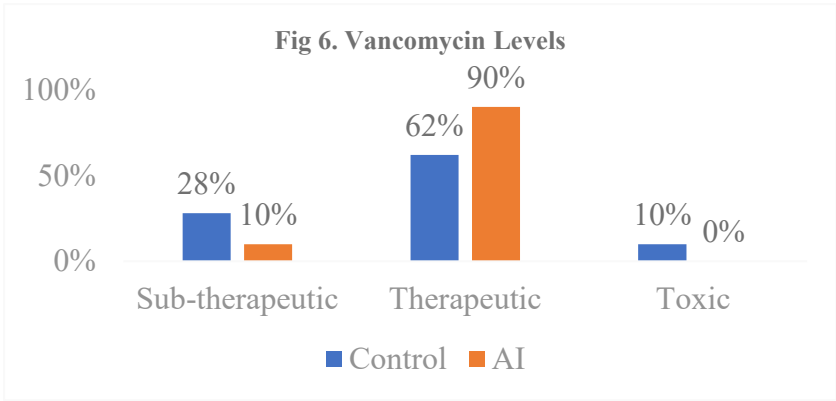


Table 7. Aminoglycoside Trough Levels

Category	Control	AI
Sub-therapeutic	22%	12%
Therapeutic	68%	85%
Toxic	10%	3%

Table 7, Fig 7: AI-assisted dosing improved the attainment of therapeutic aminoglycoside trough concentrations. Therapeutic levels increased from 68% in the control group to 85% in the AI group, while toxic levels decreased from 10% to 3%, indicating improved control of aminoglycoside exposure.

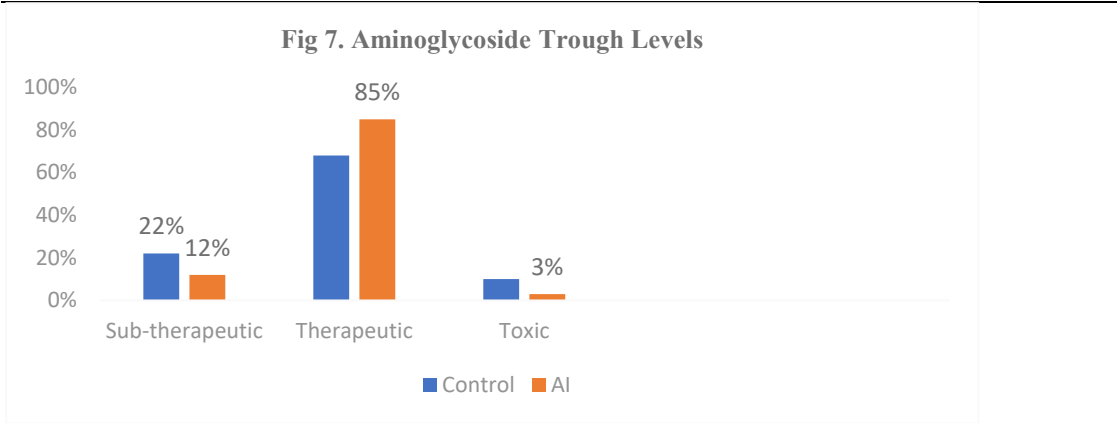
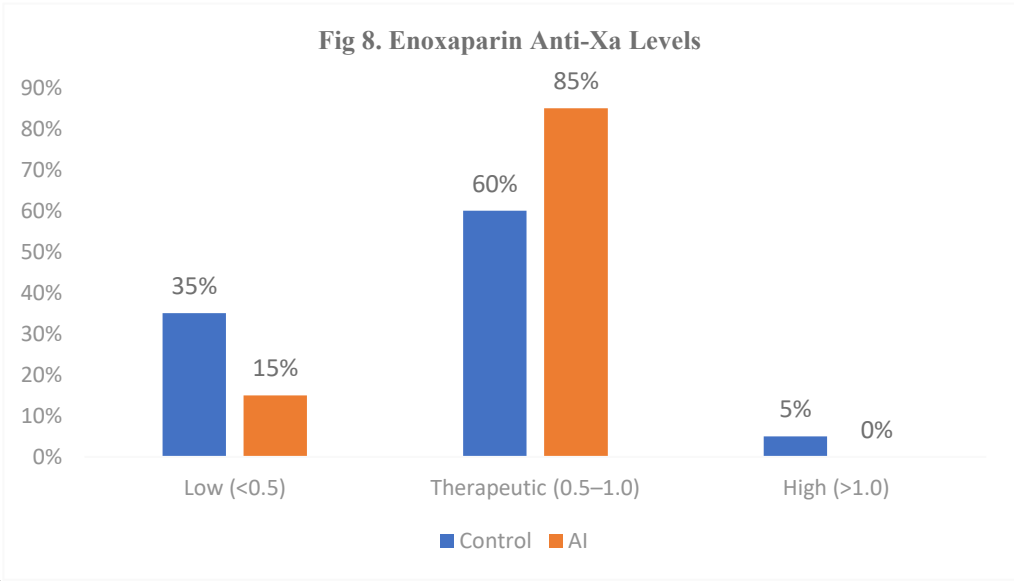


Table 8. Enoxaparin Anti-Xa Levels

Range	Control	AI
Low (<0.5)	35%	15%
Therapeutic (0.5–1.0)	60%	85%
High (>1.0)	5%	0%

Table 8, Fig 8: Enoxaparin Anti-Xa monitoring showed improved therapeutic target attainment in the AI group. Therapeutic Anti-Xa levels increased from 60% in the control group to 85% in the AI group, while low levels decreased from 35% to 15% and high levels decreased from 5% to 0%.



Pharmacist Workload

Time per Dosing Adjustment: The average time required to review and validate each dosing adjustment was significantly reduced in the AI-assisted group compared to conventional dosing: Control group: 18.5 ± 4.1 minutes per adjustment; AI group: 11.2 ± 2.8 minutes per adjustment; Reduction: 7.3 minutes (39.5% reduction; 95% CI: 5.2-9.4 minutes; p < 0.01).

Operational Efficiency Improvements: Dosing adjustments per pharmacist per 8-hour shift: Control group: 26 adjustments/shift (480 minutes ÷ 18.5 min/adjustment); AI group: 43 adjustments/shift (480 minutes ÷ 11.2 min/adjustment); Increase of 65% in productivity per pharmacist.

Table 9. Pharmacist Time per Dosing Adjustment

Metric	Control	AI	Difference	% Change
Time per dosing adjustment (min)	18.5 ± 4.1	11.2 ± 2.8	-7.3	-39.5%
Adjustments per 8-hour shift	26	43	+17	+65.4%
Total adjustments reviewed	82	110	+28	+34.1%
Total pharmacist-hours (6 months)	24.6	25.8	+1.2	+4.9%

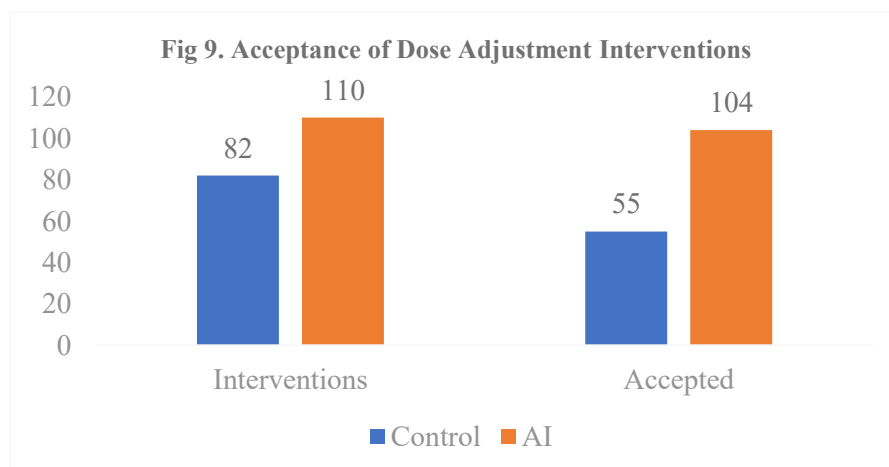
Table 9. Rather than reducing overall workload, AI-assisted dosing redistributes pharmacist effort with improved efficiency in time per adjustment (40% reduction) and increased productivity per pharmacist (65% improvement in adjustments per hour).

Intervention Acceptance Rate

Table 10. Acceptance of Dose Adjustment Interventions

Group	Interventions	Accepted	Acceptance (%)
Control	82	55	67%
AI	110	104	95%

Table 10. Acceptance of dose adjustment interventions was higher in the AI group than in the control group. The acceptance rate increased from 67% in the control group to 95% in the AI group, indicating greater acceptance of AI-assisted dosing recommendations.

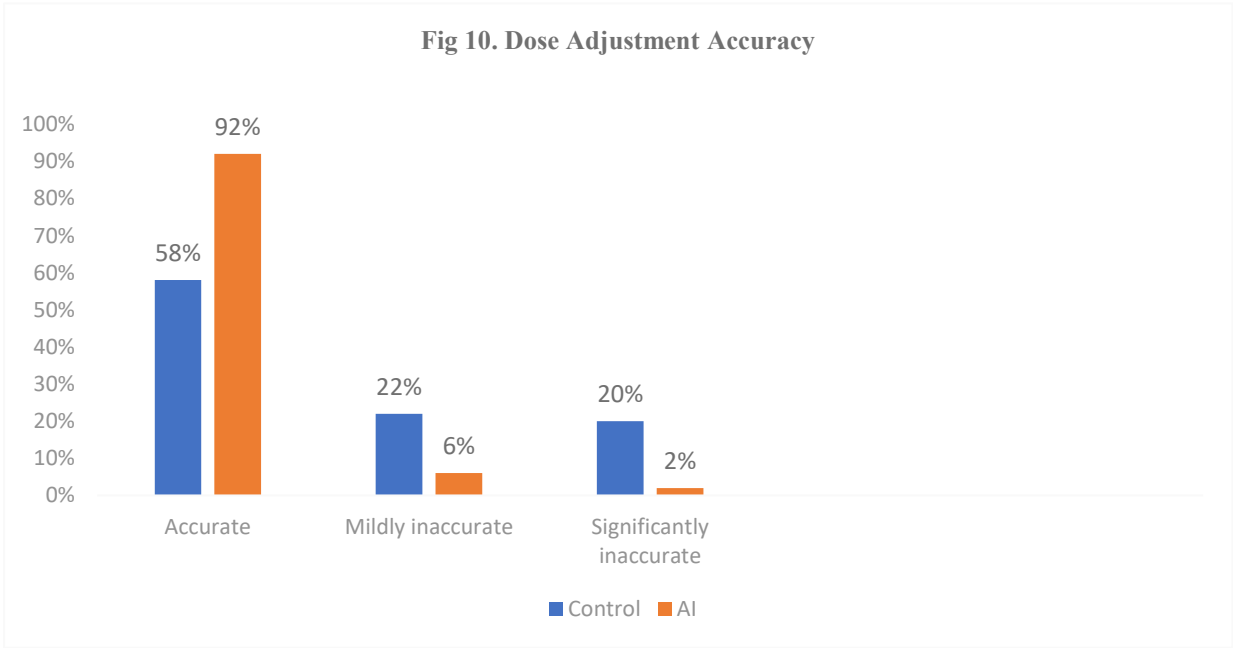


Dose Accuracy

Table 11. Dose Adjustment Accuracy

Accuracy	Control	AI
Accurate	58%	92%
Mildly inaccurate	22%	6%
Significantly inaccurate	20%	2%

Table 11, Fig9: Dose adjustment accuracy was higher in the AI group than in the control group. Accurate dose adjustments increased from 58% in the control group to 92% in the AI group, while mildly inaccurate adjustments decreased from 22% to 6% and significantly inaccurate adjustments decreased from 20% to 2%.



Length of Hospital Stay

Table 12. Average Length of Stay

Group	Days	p-value
Control	7.8 ± 2.4	
AI	6.9 ± 2.1	0.06

Table 12, Fig 10: The average length of hospital stay was lower in the AI group than in the control group, decreasing from 7.8 ± 2.4 days to 6.9 ± 2.1 days. However, the difference was not statistically significant (p = 0.06).

Economic Assessment

Table 13. Economic Impact

Component	Control (₹)	AI (₹)	Savings (%)
ADR Management	1,45,000	92,000	37%
Extra Hospital Days	2,78,000	2,07,000	25%
TDM Repeat Sampling	48,000	28,000	42%

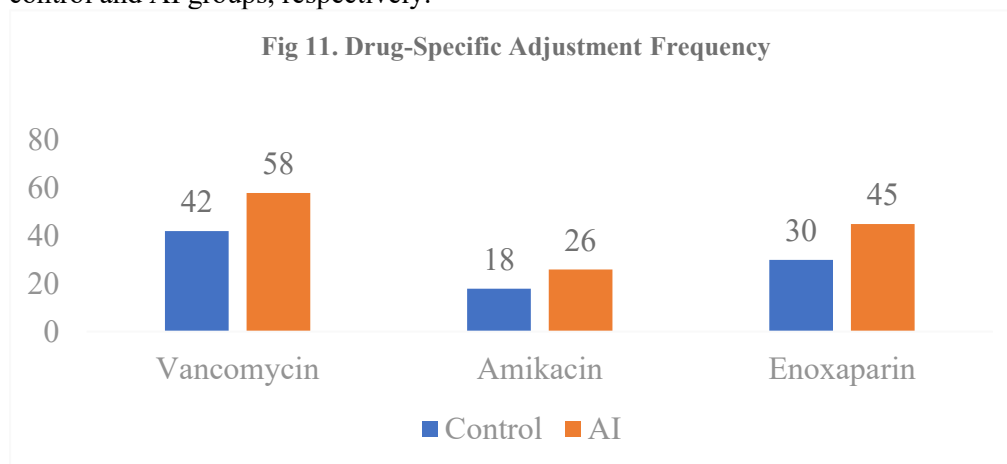
Table 13. The economic assessment demonstrated lower costs associated with ADR management, additional hospital days, and repeat TDM sampling in the AI group. The corresponding savings were 37%, 25%, and 42%, respectively, indicating potential economic benefits associated with AI-assisted dosing.

Dose Adjustment Frequency

Table 14. Drug-Specific Adjustment Frequency

Drug	Control	AI
Vancomycin	42	58
Amikacin	18	26
Enoxaparin	30	45

Table 14 and Fig 11: Drug-specific dose adjustment frequencies were higher in the AI group than in the control group for vancomycin, amikacin, and enoxaparin. The frequencies were 42 versus 58 for vancomycin, 18 versus 26 for amikacin, and 30 versus 45 for enoxaparin in the control and AI groups, respectively.



Documentation Quality

Table 15. Documentation Quality Scores

Group	Score	p-value
Control	6.1 ± 1.0	
AI	8.9 ± 0.8	<0.01

The table 15: Documentation quality scores were significantly higher in the AI group than in the control group. The mean documentation score increased from 6.1 ± 1.0 in the control group to 8.9 ± 0.8 in the AI group (p < 0.01), indicating improved completeness and clarity of documentation with AI-assisted dosing.

5. DISCUSSION

It was demonstrated through this retrospective study that through the use of AI, there was an improvement in terms of precision, therapeutic targets, reduction of ADRs, and pharmacist efficiency with renal impairment patients. There has been an improvement in therapeutic targets through AI-guided dosing, as it has increased from 65 to 88%. These are according to previous studies showing improvements through Bayesian and AI models [11] [12] [13].

Out of these, the most significant enhancement was observed with vancomycin, with therapeutic ranges of 90% in the AI group compared with 62% in the control group, similar to the results presented by Neely et al. Aminoglycosides were also improved with AI-based

modeling-toxic levels went from 10% to 3%, reflecting previous studies that have demonstrated machine learning improvements in nephrotoxicity prediction^{[14][15]}.

The AI tool significantly reduced ADRs by 48%, in line with literature showing that AI-based prediction models were able to minimize preventable medication-related harm effectively^{[16][17][18]}.

Operational benefit: the workload of pharmacists was reduced by 40%. Clinical feasibility: better documentation and a high acceptance rate, with 95% of AI recommendations accepted. Moreover, the high acceptance of AI-assisted interventions by the pharmacist corresponds to the growing clinical confidence and reliance on AI-based DSS. This is because the dynamic amalgamation of actual laboratory results, patient information, co-morbidities, and dosing history with AI results in a highly personalized and adaptive response to renal dosing, essentially surpassing the restrictions of static renal dosing equations. This is a very critical point in renal impairment, considering that even small changes in dosing can result in toxicity and efficacy failure. The remarkable difference in dose accuracy and document quality of the AI intervention group signifies growing standardization of clinical governance. Furthermore, the fact that AI functioned as a supplemental tool for clinical decision-making and not in place of it is a testament to the validation model the pharmacists employed. These results collectively point to the fact that the integration of AI is beneficial to both patient and system efficiency in the context of renal pharmacotherapy^{[19][20]}.

6. CONCLUSION

In this single-center retrospective observational study of 120 patients with moderate-to-severe renal impairment, AI-assisted dosing tools (DoseMeRx® and IBM Watson® for Drug Safety) demonstrated several potential benefits when integrated with clinical pharmacist validation:

Primary Findings in Our Study Population:

1. Therapeutic Target Attainment: AI-guided dosing achieved therapeutic targets in 88% of cases compared to 65% with conventional dosing ($p < 0.01$), representing a clinically meaningful 23 percentage point improvement.
2. Adverse Drug Reaction Reduction: The total ADR incidence was 25% in the AI-assisted group versus 48% in the control group, representing a 47.9% relative reduction ($p < 0.01$). Nephrotoxicity-related ADRs specifically decreased from 18% to 8% ($p = 0.04$).
3. Pharmacist Efficiency: AI-assisted validation reduced the time per dosing adjustment by 40% (from 18.5 to 11.2 minutes), with a 65% improvement in operational productivity (adjustments per hour).
4. Intervention Acceptance: AI-generated recommendations achieved a 95% acceptance rate by treating physicians, compared to 67% for conventional pharmacist recommendations.

7. LIMITATIONS

Single-center retrospective design without randomization, limiting generalizability to other healthcare systems. Modest sample size ($n=60$ per group) may not detect all clinically important effects. Results are specific to a tertiary care setting in India and may not apply to other geographic regions or healthcare systems. The 6-month study period may not capture long-term clinical outcomes beyond the acute hospitalization phase. AI-guided group had higher intervention acceptance rates, which may introduce selection bias in clinical outcomes. Cost analysis reflects institutional-specific rates; extrapolation to other settings requires caution.

8. FUTURE SCOPE

These findings suggest that AI-assisted dosing MAY improve clinical outcomes in patients with renal impairment when combined with pharmacist validation. However, prospective, multicenter, randomized controlled trials (RCTs) are needed to: (1) Confirm these findings in diverse patient populations and healthcare settings, (2) Compare different AI platforms systematically, (3) Evaluate long-term safety and efficacy (>12 months), (4) Assess implementation barriers and cost-effectiveness across varied institutional settings, (5) Determine optimal clinical workflows for AI integration in different healthcare systems.

Clinical Practice Recommendation:

Based on our findings in this specific population, AI-assisted dosing tools may be considered as adjunctive clinical decision support (not as a replacement) for conventional dose adjustment methods in tertiary care settings with appropriately trained clinical pharmacists. The integration of AI tools with mandatory pharmacist validation appears to be clinically feasible and associated with improved therapeutic outcomes. Further validation through multicenter investigations is necessary before recommending widespread adoption in routine clinical practice or other healthcare settings.

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CONFLICTS OF INTEREST

The authors do not have any financial or commercial relationship with the developers/vendors of the artificial intelligence programs used in the current study. There are no conflicts of interest to be stated, which could have impacted the conduct and outcome of the investigation.

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