ARTIFICIAL INTELLIGENCE–BASED PREDICTION OF MORTALITY AND MORBIDITY IN PERFORATION PERITONITIS: A COMPARATIVE STUDY WITH MANNHEIM PERITONITIS INDEX (MPI) AND JABALPUR PROGNOSTIC INDEX (JPI)

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ABSTRACT

Background: Perforation peritonitis is a common surgical emergency in developing countries with high postoperative morbidity and mortality. Early identification of high-risk patients is crucial for improving outcomes and optimizing resource utilization. Although conventional scoring systems such as the Mannheim Peritonitis Index (MPI) and Jabalpur Prognostic Index (JPI) are widely used for risk stratification, their predictive accuracy may be limited. Artificial intelligence (AI)-based models can integrate multiple clinical variables, offering the potential for more accurate outcome prediction.

Aim: To evaluate the diagnostic accuracy of an AI-based model for predicting morbidity and mortality in perforation peritonitis and compare it with the MPI and JPI.

Materials and Methods: An observational comparative study was conducted in the Department of General Surgery of a tertiary care teaching hospital over 18 months. Adult patients with perforation peritonitis undergoing emergency laparotomy were included. Demographic, clinical, laboratory, operative, and postoperative data were prospectively collected. MPI and JPI scores were calculated, and an AI-based predictive model was developed using routinely available perioperative variables. Model performance was evaluated using sensitivity, specificity, positive and negative predictive values, diagnostic accuracy, and the area under the ROC curve

Results: A total of 150 patients were included in the study. Postoperative morbidity occurred in 51 (34%) patients, while 22 (14.7%) patients died during hospitalization. The AI-based predictive model demonstrated superior performance compared with the Mannheim Peritonitis Index and Jabalpur Prognostic Index, achieving a sensitivity of 95.5%, specificity of 89.8%, positive predictive value of 60%, negative predictive value of 99.1%, diagnostic accuracy of 90.7%, and an area under the receiver operating characteristic curve (AUC) of 0.94 for predicting postoperative mortality.

Conclusion: Artificial intelligence–based predictive modelling provides more accurate risk stratification than conventional prognostic scoring systems in patients with perforation peritonitis. Integration of AI-assisted decision

support into routine surgical practice may facilitate early recognition of high-risk patients, optimize perioperative management, and improve clinical outcomes.
Keywords: Artificial intelligence; Perforation peritonitis; Mannheim Peritonitis Index; Jabalpur Prognostic Index; Mortality prediction; Surgical outcomes.
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INTRODUCTION

Perforation peritonitis is one of the most common surgical emergencies worldwide and is associated with high postoperative morbidity and mortality despite advances in antimicrobial therapy, critical care, anaesthesia, and surgical techniques. Perforation of a hollow viscus leads to contamination of the peritoneal cavity, resulting in sepsis, multiorgan dysfunction, and prolonged hospitalization if not managed promptly. Patient outcomes are influenced by factors such as age, comorbidities, delay in presentation, physiological status, extent of peritoneal contamination, and adequacy of surgical source control [1, 2].

Early and accurate risk stratification is essential for identifying high-risk patients, guiding perioperative management, optimizing intensive care utilization, and facilitating patient counselling. The Mannheim Peritonitis Index (MPI) and Jabalpur Prognostic Index (JPI) are widely used prognostic scoring systems for perforation peritonitis. Although both have demonstrated clinical utility, their predictive performance may vary across different patient populations because they rely on predefined weighted variables and conventional statistical models [3–5].

Recent advances in artificial intelligence (AI) have enabled the development of predictive models capable of analyzing complex interactions among multiple clinical, laboratory, and operative variables. AI-based models have shown promising results in predicting postoperative complications and mortality across various surgical conditions, offering the potential for more accurate and individualized risk assessment than conventional scoring systems [6].

Therefore, the present study aimed to evaluate the diagnostic performance of an AI-based prediction model for postoperative mortality and morbidity in patients with perforation peritonitis and compare its predictive accuracy with the Mannheim Peritonitis Index and the Jabalpur Prognostic Index. This study may provide evidence regarding the role of AI-assisted risk prediction in improving clinical decision-making and patient outcomes in emergency general surgery.

MATERIALS AND METHODS

This prospective observational comparative study was conducted in the Department of General Surgery at a tertiary care teaching hospital over a period of 18 months. A total of 150 consecutive adult patients presenting with clinically and radiologically confirmed perforation peritonitis and undergoing emergency exploratory laparotomy were enrolled.

Inclusion Criteria

- Patients aged 18 years or older.
- Patients with clinically and radiologically confirmed perforation peritonitis.
- Patients undergoing emergency exploratory laparotomy.
- Patients who provide written informed consent.
- Patients with complete clinical, laboratory, and operative records.

Exclusion Criteria

- Patients younger than 18 years.
- Patients with primary peritonitis or postoperative peritonitis.
- Patients managed conservatively without surgery.
- Pregnant women.
- Patients with incomplete clinical records or missing essential data.
- Patients who declined participation.

Data Collection: Demographic characteristics, clinical presentation, comorbidities, duration of symptoms, vital signs, laboratory investigations, radiological findings, operative findings, site and etiology of perforation, degree of peritoneal contamination, operative procedure, postoperative complications, intensive care unit admission, duration of hospital stay, and in-hospital mortality were recorded using a predesigned case record form. All patients underwent routine preoperative evaluation and received standard perioperative management according to institutional protocols.

Assessment of Prognostic Scores: The MPI was calculated for each patient using established parameters, including age, organ failure, malignancy, duration of peritonitis, origin of sepsis, extent of peritonitis, and nature of peritoneal exudate. Similarly, the JPI was calculated using clinical and laboratory variables such as age, pulse rate, serum creatinine level, delay before surgery, and extent of peritoneal contamination. Patients were categorized into different risk groups according to their respective MPI and JPI scores.

Artificial Intelligence–Based Prediction Model: An AI-based predictive model was developed using routinely available demographic, clinical, laboratory, and intraoperative variables to predict postoperative mortality and major morbidity. The predictive performance of the model was compared with the MPI and JPI. Model performance was evaluated using sensitivity, specificity, positive predictive value, negative predictive value, diagnostic accuracy, and the area under the ROC curve.

Outcome Measures: The primary outcome was in-hospital mortality. Secondary outcomes included postoperative morbidity, surgical site infection, intra-abdominal abscess, septic shock, need for intensive care unit admission, reoperation, and duration of hospital stay.

Statistical Analysis: Data were analyzed using IBM SPSS Statistics version 26.0. Continuous variables were expressed as mean ± standard deviation (SD), while categorical variables were presented as frequencies and percentages. Continuous variables were compared using the Independent Student's t-test or Mann–Whitney U test, whereas categorical variables were analyzed using the Chi-square test or Fisher's exact test, as appropriate. Receiver operating characteristic (ROC) curve analysis was performed to compare the predictive performance of the AI model, MPI, and JPI. A p-value of <0.05 was considered statistically significant.

RESULTS

A total of 150 patients with perforation peritonitis who underwent emergency exploratory laparotomy were included in the study. The mean age of the study population was 46.8 ± 15.2 years, with a predominance of male patients. Duodenal perforation was the most common etiology, followed by ileal and gastric perforations. The overall postoperative morbidity was 34.0%, while the in-hospital mortality rate was 14.7%.

Table 1: Baseline Demographic and Clinical Characteristics of the Study Population

Variable		Number (n = 150)	Percentage
Age Group (years)	18–30	28	18.7%
	31–45	47	31.3%
	46–60	43	28.7%
	>60	32	21.3%
Gender	Male	108	72%
	Female	42	28%
Diabetes Mellitus		39	26%
Hypertension		46	30.7%
Smoking History		57	38%
Symptom Duration >24 hours		69	46%

Most patients belonged to the 31–45 years age group (31.3%), and males constituted nearly three-fourths of the study population (72.0%). Delayed presentation (>24 hours) was observed in 46.0% of patients, while diabetes mellitus and hypertension were present in 26.0% and 30.7% of cases, respectively.

Table 2: Clinical and Operative Characteristics of Patients with Perforation Peritonitis

Variable		Number (n = 150)	Percentage
Site of Perforation	Duodenum	58	38.7%
	Ileum	36	24%
	Stomach	25	16.7%
	Jejunum	12	8%
	Colon	10	6.7%
	Appendix	9	6%
Generalized Peritonitis		94	62.7%
Purulent/Fecal Contamination		61	40.7%
ICU Admission		37	24.7%

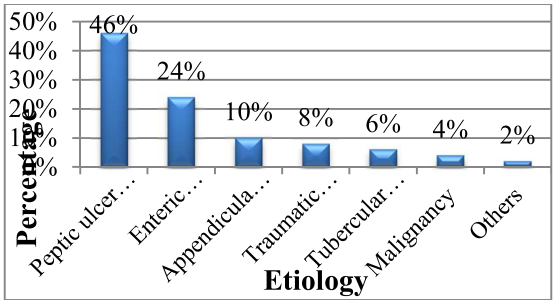
Duodenal perforation was the most common site (38.7%), followed by ileal perforation (24.0%). Generalized peritonitis was present in nearly two-thirds of patients, and approximately one-fourth required postoperative ICU admission.

Table 3: Distribution of MPI and JPI Scores with Clinical Outcomes

Risk Category	Total Patients	Morbidity n (%)	Mortality n (%)
MPI <21	48	6 (12.5%)	1 (2.1%)
MPI 21–29	61	22 (36.1%)	7 (11.5%)
MPI >29	41	23 (56.1%)	14 (34.1%)
JPI Low Risk	52	7 (13.5%)	1 (1.9%)
JPI Moderate Risk	63	24 (38.1%)	8 (12.7%)
JPI High Risk	35	20 (57.1%)	13 (37.1%)

Both MPI and JPI demonstrated a progressive increase in postoperative morbidity and mortality with increasing risk scores. Patients categorized as high risk had substantially greater mortality than those in the low-risk groups, indicating the clinical usefulness of both scoring systems for risk stratification.

Figure 1: Distribution of Etiology of Perforation Peritonitis



Peptic ulcer disease was the leading cause of perforation peritonitis, accounting for nearly half of all cases, followed by enteric perforation. Traumatic, tubercular, and malignant perforations were comparatively less frequent.

Table 4: Diagnostic Performance of the Artificial Intelligence (AI) Model for Predicting Postoperative Mortality

Performance Parameter	Value (%)
Sensitivity	95.5%
Specificity	89.8%
Positive Predictive Value (PPV)	60%
Negative Predictive Value (NPV)	99.1%
Overall Diagnostic Accuracy	90.7%
Area Under ROC Curve (AUC)	0.94%

The AI-based prediction model demonstrated excellent predictive performance for postoperative mortality. The model achieved a high sensitivity (95.5%) and specificity (89.8%), with an overall diagnostic accuracy of 90.7%. The AUC of 0.94 indicated outstanding discrimination between survivors and non-survivors.

Table 5: Comparative Performance of AI, Mannheim Peritonitis Index (MPI), and Jabalpur Prognostic Index (JPI) for Mortality Prediction

Parameter	AI Model	MPI	JPI
Sensitivity (%)	95.5	81.8	77.3
Specificity (%)	89.8	78.1	75.8
Diagnostic Accuracy (%)	90.7	78.7	76
AUC	0.94	0.84	0.81
p-value	<0.001	-	-

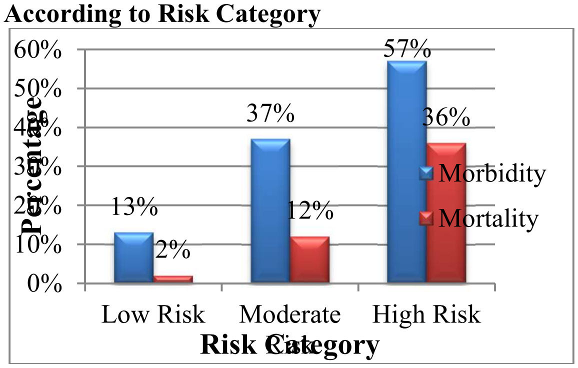
The AI model outperformed both conventional prognostic scoring systems in predicting postoperative mortality. It showed higher sensitivity, specificity, diagnostic accuracy, and AUC compared with MPI and JPI, indicating superior predictive capability.

Table 6: Multivariate Logistic Regression Analysis for Independent Predictors of In-Hospital Mortality

Variable	Adjusted Odds Ratio (AOR)	95% Confidence Interval	p-value
Age >60 years	2.61	1.12 – 6.08	0.026
Delay in surgery >24 hours	3.47	1.49 – 8.10	0.004
Generalized peritonitis	3.86	1.52 – 9.81	0.005
Serum Creatinine >1.5 mg/dL	2.95	1.27 – 6.84	0.012
AI Predicted High Risk	6.72	2.68 – 16.82	<0.001

Multivariate analysis identified delayed surgery, generalized peritonitis, elevated serum creatinine, advanced age, and AI-predicted high-risk status as significant independent predictors of in-hospital mortality. Among these, the AI model demonstrated the strongest association with mortality.

Figure 2: Postoperative Morbidity and Mortality According to Risk Category



Postoperative morbidity and mortality increased progressively across risk categories. Patients classified as high risk experienced substantially higher complication and mortality rates than those in the low- and moderate-risk groups, supporting the clinical value of accurate preoperative risk stratification.

DISCUSSION

Compared with the conventional scoring systems, the AI model demonstrated higher sensitivity, specificity, diagnostic accuracy, and area under the receiver operating characteristic curve (AUC), suggesting superior discriminatory ability. These observations support the emerging role of AI-assisted risk prediction as a valuable adjunct to clinical decision-making in emergency general surgery and highlight its potential to improve perioperative risk stratification [7].

In the present study, the majority of patients were middle-aged males, and duodenal perforation was the most common etiology. These observations are consistent with previous studies from South Asia, where peptic ulcer disease continues to account for a substantial proportion of gastrointestinal perforations. Delayed hospital presentation and generalized peritonitis were frequently observed among patients who subsequently developed postoperative complications, highlighting the importance of early diagnosis and prompt surgical intervention [8].

In our study, increasing MPI scores were associated with progressively higher rates of postoperative morbidity and mortality, confirming its usefulness for clinical risk stratification. However, its overall predictive performance remained inferior to that of the AI model. Conventional scoring systems rely on predetermined weighted variables and may not adequately account for complex interactions among clinical, laboratory, and intraoperative factors. Similar limitations of fixed prognostic scores have been reported in recent validation study evaluating patients with complicated intra-abdominal infections [9].

The Jabalpur Prognostic Index also demonstrated satisfactory discrimination of patient outcomes, with higher mortality observed among patients in the high-risk category. Because JPI incorporates variables that are readily available in emergency surgical practice, it remains a useful bedside tool, particularly in resource-limited settings. Nevertheless, the comparatively lower diagnostic accuracy observed in the present study suggests that conventional scoring systems may underestimate risk in certain patients with severe physiological derangements. AI-based models overcome many of these limitations by integrating multiple variables simultaneously and recognizing nonlinear relationships that cannot be captured by traditional statistical scoring systems [10].

The findings of the present study are in agreement with recent evidence demonstrating the increasing utility of artificial intelligence in surgical risk prediction. Machine learning algorithms have consistently shown better predictive performance than conventional statistical models because they can simultaneously evaluate numerous clinical variables and identify complex interactions that influence patient outcomes. Such models have been successfully applied in predicting postoperative complications, intensive care unit admission, and mortality across several surgical specialties. These observations support the growing integration of AI-based decision-support systems into perioperative care [11].

Early identification of patients at increased risk of adverse outcomes is particularly important in perforation peritonitis, where delays in diagnosis and treatment may rapidly lead to sepsis, multiple organ dysfunction, and death. In the present study, advanced age, delayed surgery, generalized peritonitis, elevated serum creatinine, and AI-predicted high-risk status were independently associated with mortality. These findings emphasize that timely surgical intervention and appropriate perioperative optimization remain essential for improving survival. Incorporating AI-based risk prediction into routine clinical assessment may assist surgeons in prioritizing high-risk patients for intensive monitoring and aggressive postoperative management [12, 13].

CONCLUSION

The findings of this study suggest that an Artificial Intelligence–based predictive model offers better overall performance than the Mannheim Peritonitis Index and Jabalpur Prognostic Index for predicting postoperative mortality and morbidity in patients with perforation peritonitis. The AI model achieved higher sensitivity, specificity, diagnostic accuracy, and overall discriminatory ability, enabling more accurate identification of high-risk patients. While MPI and JPI remain useful bedside prognostic tools, AI-assisted risk prediction offers a promising complementary approach for improving perioperative decision-making and optimizing patient outcomes. Further multicenter prospective studies with larger sample sizes are recommended to validate these findings and facilitate the integration of artificial intelligence into routine emergency surgical practice.

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