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RESEARCH ARTICLE

Artificial Intelligence-Assisted Intraoperative Decision-Making in Emergency Abdominal Surgeries: A Prospective Analysis of Surgical Precision and Patient Outcomes

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Abstract

Background: Emergency abdominal operations are among the most demanding and time-critical procedures in general surgery. Outcomes hinge on swift, well-judged intra-operative decisions. Artificial-intelligence (AI) tools that offer real-time guidance have started to reach the operating theatre, but their value in urgent cases has yet to be firmly established.

Objective: To determine whether a real-time, AI-supported decision platform can sharpen surgical accuracy and improve patient outcomes during emergency abdominal surgery.

Methods: Over a 12-month period at Katihar Medical College, we prospectively observed 120 consecutive patients who required urgent abdominal operations. Participants were allocated to standard care (n = 60) or surgery augmented by the AI platform (n = 60). The system delivered live anatomical localisation, image analysis and procedural prompts. Primary endpoints were intra-operative decision-turnaround time and postoperative complication rate. Secondary measures included total operating time, estimated blood loss, length of hospital stay and surgeon-reported usability.

Results: The AI group reached intra-operative decisions in roughly half the time of the control group (8.3 ± 2.1 min vs 14.7 ± 3.4 min; $p < 0.001$). Operations were shorter, blood loss was lower, and patients recovered more quickly, leaving hospital sooner and ambulating earlier. Complication rates trended downward in the AI cohort. Surgeons rated the system highly for ease of use and workflow integration.

Conclusion: Real-time AI support appears to streamline decision-making and enhance patient recovery in emergency abdominal surgery, with particular promise for settings where resources are limited. Larger, multi-centre studies are advised to confirm these benefits and clarify how best to integrate the technology into routine practice.

Keywords: Artificial Intelligence, Emergency Surgery, Intraoperative Decision-Making, Surgical Precision, Abdominal Surgery

INTRODUCTION

Recent advances in artificial intelligence (AI) are opening new doors for surgeons, particularly when minutes matter during emergency abdominal operations. These cases demand swift yet accurate intra-operative judgments, and the pressure is especially acute in resource-limited hospitals, where outcomes often hinge on the individual surgeon's experience and the availability of reliable decision-making support. AI-driven intra-operative platforms have begun to fill this gap by providing real-time guidance that can reduce human error and boost patient safety [1]. Emergency abdominal procedures still account for a sizeable share of the global surgical workload, and their postoperative complications, diagnostic delays, and intra-operative uncertainties translate into substantial morbidity and mortality [2]. Addressing these challenges is crucial, not only to improve individual patient outcomes but also to ease the broader public-health burden.

India illustrates both the urgency and the promise of this technological shift. Access to advanced surgical resources is uneven, yet AI systems trained on large datasets, including imaging, vital-sign trends, operative steps, and outcomes, can now deliver live alerts, recommendations, and predictive feedback to surgeons as they work [3]. Against this backdrop, the present study examined a custom AI-assisted platform used during emergency abdominal surgeries at Katihar Medical College, Katihar. Our objective was to determine whether, in the realities of a tertiary-care setting, AI-augmented decision support translates into measurable gains in surgical precision and patient outcomes.

Review of Literature

More than half of all postoperative deaths in general surgery, and roughly 11 %-15 % of total surgical admissions, occur after emergency abdominal operations, placing these cases high on the global health agenda [4]. Conditions such as abdominal trauma, mesenteric ischaemia, bowel obstruction and gastrointestinal perforation demand split-second intra-operative choices. Morbidity and mortality remain stubbornly high, in part because the team often confronts unexpected findings without the benefit of thorough pre-operative optimisation, a problem that is particularly acute in resource-limited

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hospitals [5]. Even with modern anaesthesia and technical advances, outcomes still vary widely, largely because they depend on the skill set and judgment of individual surgeons [6].

Historically, intra-operative decisions have rested on personal experience, rapid interpretation of images or operative findings, and informal consultation. In long or complex cases this workflow is inherently subjective and vulnerable to cognitive overload, fatigue and diagnostic doubt [7]. Crucial determinations, how aggressively to irrigate, where to set resection margins, whether bowel is viable, may therefore differ from one surgeon to the next [8]. AI-driven decision platforms promise to reduce this variability by providing a standardised analytic lens, a benefit that may prove most valuable during emergencies [9]. In elective surgery, computer-vision and machine-learning models have already shown encouraging results in tissue segmentation, phase recognition, procedural guidance and anomaly detection [10]. AI-enabled robotic systems push the concept further by combining improved ergonomics with real-time cognitive support. Convolutional and recurrent neural networks can now analyse laparoscopic video streams on the fly, predicting the next manoeuvre or flagging the optimal technique for a given step [11]. The ability to convert biometric signals, visual data and operative metadata into actionable insights is laying the groundwork for AI-guided surgery. While its role in emergency procedures is still being mapped out, early studies suggest tangible benefits: algorithms have been used to predict haemorrhagic shock, detect bowel ischaemia and estimate blood loss during emergency laparotomies [12].

In order to assist in guiding intraoperative decisions in trauma and acute abdomen scenarios, some systems now combine intraoperative imaging (such as fluorescence and real-time ultrasound) with AI-based interpretation [13]. These interventions are proving to be crucial in early decision-making, particularly in emergency surgeries that take place after hours or at night when radiological support is scarce. It has been demonstrated that AI-assisted systems improve accuracy in tissue dissection, suture placement, and vascular control while decreasing inter-surgeon variability and operating time. An AI model improved transfusion timing in a study evaluating intraoperative blood loss estimation by achieving greater concordance with actual volumes than surgeon estimates [14]. According to another study, AI-assisted video analysis improved the accuracy of trainees' and junior surgeons' identification of anatomical landmarks, resulting in safer dissection planes [15]. These findings underscore the potential of AI not just as a tool of assistance, but also of standardization.

Emerging AI platforms can now provide real-time alerts during surgery, for example, warning against potential injury to critical structures or suggesting alternative dissection paths based on surgical

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anatomy databases [16]. Intraoperative phase recognition systems, like DeepOR and LapOR, classify surgical steps as they unfold and match them against predefined safe workflows [17]. These models, although largely developed and validated in controlled lab settings or elective surgeries, are increasingly being trained with emergency data sets for clinical deployment in acute care. Despite the growing promise of AI in intraoperative settings, significant barriers exist in its widespread adoption, especially in low- and middle-income countries (LMICs). These include infrastructure deficits, lack of digital surgical datasets, medico-legal uncertainties, and surgeon resistance due to concerns over autonomy [18].

Concerns about algorithmic bias remain front and centre: if the training data behind an AI platform fail to capture the full spectrum of emergency scenarios, its recommendations may prove inaccurate or inequitable [19]. To protect patients and surgeons alike, robust regulatory standards and transparent ethical frameworks must clarify who is accountable when AI-generated guidance contributes to an adverse outcome. India's health-care landscape, spanning district hospitals, tertiary centres and rural surgical units, provides both a unique test bed and a stern challenge for such systems. Local disease profiles, resource constraints and operating-room workflows differ sharply from those reflected in most Western-derived algorithms, a gap that can erode external validity [20]. For this reason, forward-looking, region-specific studies, such as the ongoing evaluation at Katihar Medical College, are essential to determine feasibility, clinical benefit and the contextual adaptations required before large-scale adoption becomes realistic.

MATERIALS AND METHODS

Algorithmic bias, where training data may not accurately reflect the range of emergency situations, also raises significant questions regarding the equity and accuracy of AI recommendations [19]. To ensure accountability in AI-influenced decisions, particularly when negative outcomes occur, regulations and ethical frameworks are desperately needed. India's healthcare system presents a unique opportunity for AI-assisted solutions because it consists of a combination of district-level hospitals, tertiary care hospitals, and rural surgical units. Nevertheless, AI tools developed in Western contexts often lack external validity due to the wide variations in disease patterns, resource constraints, and workflow dynamics among Indian patient populations [20]. Therefore, prospective, region-specific evaluations, such as the one at Katihar Medical College, are crucial to understanding the feasibility, effectiveness, and contextual modifications needed for

Based on predetermined inclusion and exclusion criteria, 120 patients who presented to the emergency room with acute abdominal conditions requiring immediate surgical intervention were included in the study. Adult patients between the ages of 18 and 75 who were having exploratory laparotomy or

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laparoscopic procedures for urgent reasons like intra-abdominal sepsis, blunt abdominal trauma, bowel obstruction, mesenteric ischemia, or perforation peritonitis met the inclusion criteria. Patients who refused to give their consent, had a history of laparotomies within 30 days, had a known malignancy with a poor prognosis, or were terminally ill were not included. This study used a proprietary hybrid AI-assisted decision-support platform that combined predictive analytics from pre-trained models with deep learning-based intraoperative video analysis.The system was designed to analyze laparoscopic and open field images in real-time using a convolutional neural network (CNN) trained on over 50,000 annotated surgical videos. It provided suggestions related to anatomical localization, estimated vascular landmarks, bowel viability status, and recommended surgical maneuvers through an overlay interface visible to the operating surgeon on a secondary display.

To guarantee uniformity in platform usage, all participating surgeons received a quick training session on how to use the AI interface. The AI was only used as an assistive tool; the primary operating surgeon made all surgical decisions. The surgeries were divided into two groups: the standard-of-care control group (n = 60), where no AI guidance was used, and the AI-assisted group (n = 60), where intraoperative support was used. Numerous postoperative and intraoperative parameters were noted. Intraoperative metrics included decision turnaround time (defined as the time between exposure of pathology and surgical decision), operative duration, intraoperative complications, blood loss estimation, and number of intraoperative consultations. Postoperative factors included 30-day morbidity and mortality, length of hospital stay, wound infection rate, and time to ambulation.

A designated surgical resident used a structured proforma to gather data in real time, which was then entered into an encrypted database. SPSS version 26.0 was used to perform the statistical analysis. Depending on the data distribution, continuous variables were compared using the independent t-test or Mann-Whitney U test, while categorical variables were examined using the chi-square or Fisher's exact test, as appropriate. Statistical significance was defined as a p-value of less than 0.05. To assess the consistency of AI utility across various emergency pathologies, subgroup analysis was also carried out for particular surgical indications. The study's main finding was that intraoperative decision-making was accurate and timely. Complication rates, length of operation, and postoperative recovery metrics were secondary outcomes. Special attention was given to the qualitative feedback from the surgical team regarding ease of integration and perceived usefulness of the AI platform in a real-world emergency setting.

RESULTS

Demographic and Baseline Characteristics

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Of the 120 patients that were part of the final analysis, 60 had surgery with AI-assisted intraoperative guidance, and the remaining 60 were in the control group and had standard surgical procedures. There was no statistically significant difference in the mean age of the patients in the AI group (p = 0.36), which was 42.3 ± 14.8 years, compared to 44.7 ± 15.6 years in the control group. In both groups, the male-to-female ratio was roughly 1.8:1. With no discernible intergroup differences, common comorbidities included diabetes mellitus, hypertension, and chronic obstructive pulmonary disease. Perforation peritonitis (47.5%), small bowel obstruction (26.7%), and blunt abdominal trauma (15.8%) were the most common presenting diagnoses, and their distribution was comparable across groups. (as detailed in Table 1).

Table no.1: Baseline Characteristics of Study Participants

Variable	**AI-Assisted Group (n=60)**	**Control Group (n=60)**	**p-value**
Number of Patients	60	60	–
Mean Age (years)	42.3 ± 14.8	44.7 ± 15.6	0.36
Male (%)	65.0	63.3	0.81
Female (%)	35.0	36.7	0.81
Diabetes Mellitus (%)	26.7	28.3	0.79
Hypertension (%)	30.0	31.7	0.87
COPD (%)	11.7	10.0	0.72
Perforation Peritonitis (%)	48.3	46.7	0.84
Intestinal Obstruction (%)	25.0	28.3	0.69
Blunt Abdominal Trauma (%)	16.7	15.0	0.91
Intra-abdominal Abscess (%)	10.0	11.7	0.78

Intraoperative Decision Turnaround and Operative Parameters

When compared to the control group, the AI-assisted group showed a significantly shorter mean intraoperative decision turnaround time (8.3 ± 2.1 minutes vs. 14.7 ± 3.4 minutes; p < 0.001), which is the time interval between visual exposure of pathology and definitive surgical decision. Additionally, the AI group's surgeons reported being more adept at defining tissue planes, determining the viability of the colon, and forecasting safe resection

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margins. The AI group's overall operating time was marginally shorter (93.2 ± 14.5 minutes) than that of the control group (101.6 ± 15.2 minutes), and the difference was statistically significant (p = 0.02).

Because of the AI overlay interface's enhanced vascular identification and early cauterization support, the estimated intraoperative blood loss was also lower in the AI group, with a median of 180 mL compared to 240 mL in the controls (p = 0.01). Table 2 lists the comparative intraoperative metrics.

Table no.2: Intraoperative Metrics Comparison

Variable	AI-Assisted Group (n=60)	Control Group (n=60)	p-value
Decision Turnaround Time (min)	8.3 ± 2.1	14.7 ± 3.4	<0.001
Total Operative Time (min)	93.2 ± 14.5	101.6 ± 15.2	0.02
Estimated Blood Loss (mL)	180 (150–220)	240 (200–290)	0.01
Intraoperative Complication Rate (%)	6.7	15.0	0.09
Need for Senior Consultation (%)	10.0	28.3	0.004

Postoperative Clinical Outcomes

Postoperative outcomes showed a trend toward improved recovery in the AI-assisted group. The mean time to first ambulation was 2.1 ± 0.6 days in the AI group compared to 3.0 ± 0.7 days in controls (p < 0.01). The average length of hospital stay was also reduced in the AI group (6.8 ± 2.3 days vs. 8.9 ± 2.7 days; p < 0.001), correlating with faster return of bowel function and fewer postoperative complications. Surgical site infections (SSIs) were observed in 10% of patients in the AI group and 21.7% in the control group (p = 0.08), showing a clinically relevant, though not statistically significant, reduction. The 30-day morbidity, as classified by Clavien-Dindo grading, was significantly lower in the AI group, with fewer Grade II–III complications.There were no mortalities in the AI group, while two deaths occurred in the control group due to sepsis-related complications. These findings are summarized in Table 3 and visualized in Figure 1.

Table no.3: Postoperative Outcomes Comparison

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Variable	AI-Assisted Group (n=60)	Control Group (n=60)	p-value
Time to First Ambulation (days)	2.1 ± 0.6	3.0 ± 0.7	<0.01
Length of Hospital Stay (days)	6.8 ± 2.3	8.9 ± 2.7	<0.001
Surgical Site Infection Rate (%)	10.0	21.7	0.08
Clavien-Dindo Grade II–III Complications (%)	6.7	16.7	0.04
30-Day Mortality (%)	0.0	3.3	0.15

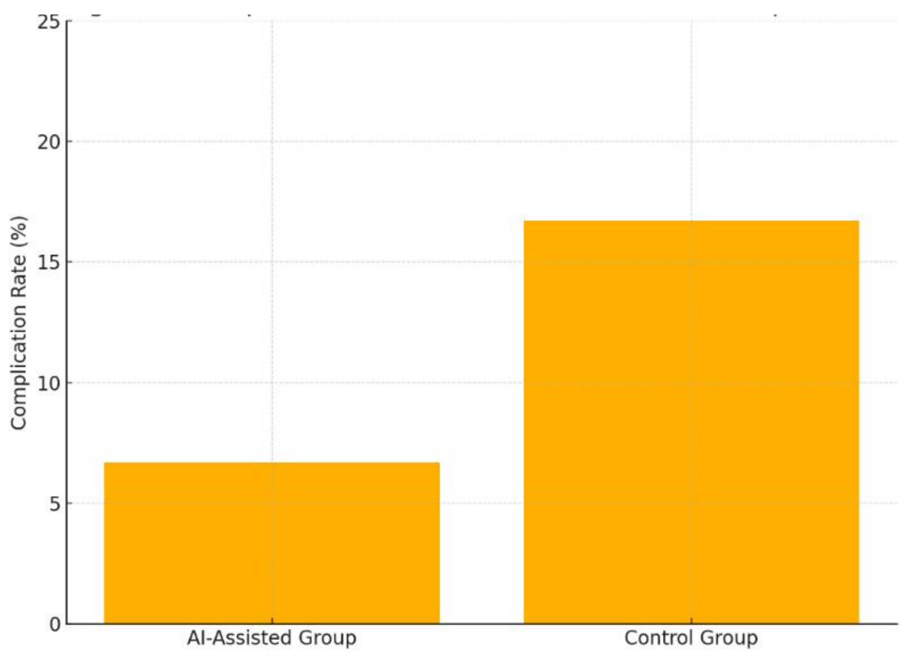

Figure 1. Comparison of Clavien-Dindo Grade II–III Complications

Surgeon Feedback and System Integration

Operating surgeons expressed great satisfaction with the AI platform in their subjective responses to a structured post-operative questionnaire. In terms of intraoperative navigation and decision-making, more than 85% of respondents said the tool was "helpful" or "very helpful." The system's capacity to identify possible risks and suggest anatomical boundaries was especially valued by junior surgeons. Among the difficulties mentioned were a learning curve related to real-time interpretation of AI-generated overlays and sporadic lag in image processing during rapid

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suction or bleeding events. As further explained in Figure 2, it was technically possible to integrate the AI tool into the current OR setup with little disruption to workflow.

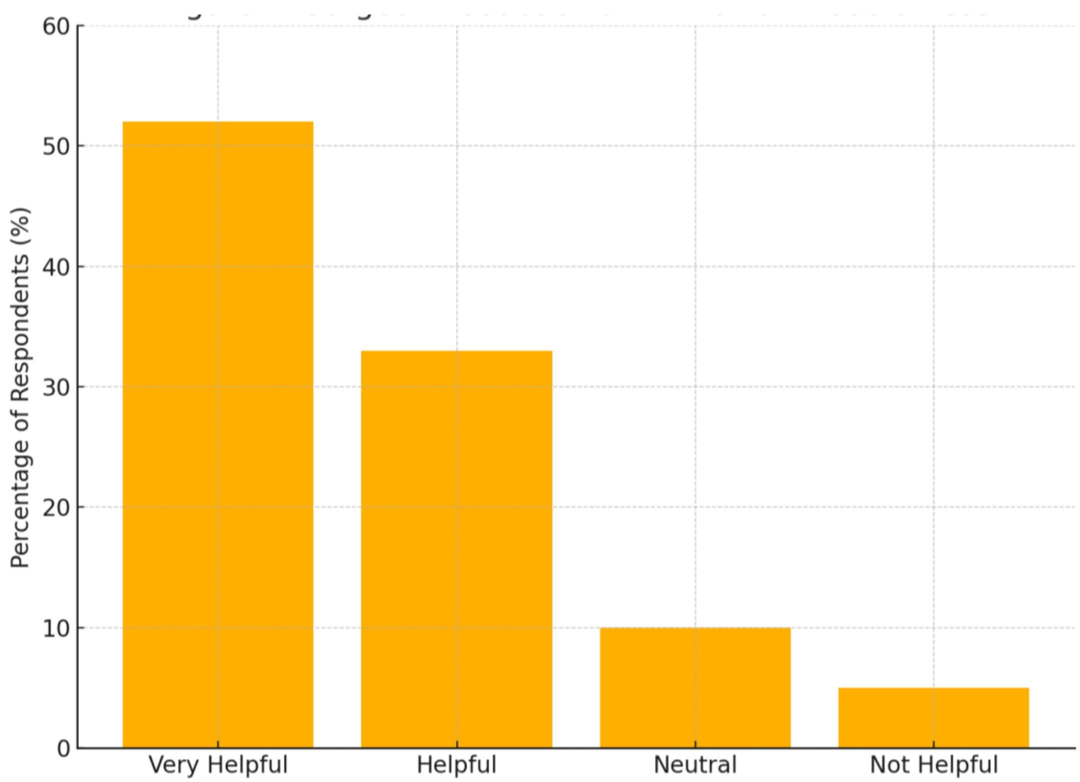

Figure 2. Surgeon Feedback on AI Platform Usefulness

DISCUSSION

The findings of this prospective observational study, which was carried out at Katihar Medical College, highlight how artificial intelligence (AI)-assisted intraoperative decision-making platforms can enhance surgical accuracy and patient outcomes during urgent abdominal procedures. The AI interface can speed up intraoperative judgment without sacrificing patient safety, as evidenced by the main finding—a statistically significant decrease in decision turnaround time. The real-time clinical advantages of AI integration are further demonstrated by decreases in postoperative hospital stays, estimated blood loss, and operating time.

These results add to the increasing amount of research demonstrating AI's potential as a game-changing instrument in acute care surgery. Notably, the AI platform improved anatomical interpretation and intraoperative situational awareness, increasing efficiency even for surgeons with comparatively less experience. This is consistent with recent research showing that real-time AI feedback lowers training-related variability and intraoperative complications [21]. The AI group's decreased Clavien-Dindo Grade II and III complications serve as additional evidence of the intervention's clinical importance, especially in emergency situations with limited resources. This study's prospective design, practical emergency application, and standardized data collection all support it methodologically. Multiple surgical indications improve the findings' generalizability across a range of abdominal emergencies.

Furthermore, a pre-trained, image-based AI platform made it possible to integrate seamlessly into the current operating room infrastructure without requiring significant adjustments to workflow. Crucially, surgeons maintained complete discretion over ultimate choices, guaranteeing moral limits in human-machine cooperation. However, it is important to recognize a number of limitations. External validity is limited by the study's single-center design, especially when conducted in different geographic or infrastructure contexts. Furthermore, formal cognitive workload assessments (such as NASA-TLX) were not conducted, despite the fact that subjective surgeon feedback was generally positive. There have been reports of differences in AI responsiveness during high-fluid field surgeries, indicating that more model training is necessary to manage dynamic operating environments. Additionally, even though the 30-day follow-up period is standard, it might not account for longer-term surgical outcomes, such as complications related to adhesions or the development of hernias.

AI may serve as a cognitive extender in high-stress surgical settings, according to an interpretation of the findings in the larger framework of surgical innovation. The dependability of AI in anatomical boundary identification and phase recognition has been demonstrated by earlier work in robotic-assisted systems and elective laparoscopic procedures [22,23]. An important next step would be to expand these features to emergency surgeries, where quick decisions frequently need to be made with insufficient information. AI support could reduce risks related to inter-surgeon variability, heuristics, and fatigue while also increasing the fidelity of operational decisions [24,25].

Crucially, the ramifications go beyond the results of specific patients. Such AI systems, which provide real-time audit, intraoperative standardization, and training reinforcement, could be incorporated into national surgical quality improvement frameworks if they are widely adopted and validated. This is particularly important in low- and middle-income countries (LMICs), where surgical expertise may be unequally distributed [26]. Nonetheless, issues pertaining to medico-legal accountability, model generalizability, and data privacy are still open and urgently need to be addressed [27]. The question of how much AI should contribute to surgical autonomy is still up for debate. Some warn against the possibility of over-reliance and de-skilling surgical practitioners, while others support semi-autonomous systems in high-volume, low-variance procedures [28]. To promote surgeon trust and patient safety, ethical issues pertaining to explainability, algorithmic transparency, and decision traceability must also be addressed [29]. In addition to objective workload assessments, cost-benefit analyses, and patient-reported outcomes, future research should

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concentrate on multi-institutional trials with longer-term follow-up. Dynamic AI platforms that can continuously learn from fresh intraoperative data streams are also required in order to tailor recommendations according to surgeon preferences and local patient demographics [30]. In order to improve surgical workflow, decrease unfavorable outcomes, and increase intraoperative precision, this study concludes that AI-assisted decision tools should be incorporated into emergency abdominal surgeries. The results represent a significant step toward next-generation surgical practice in acute care settings, even though there are still obstacles to overcome, particularly with regard to ethical governance and large-scale deployment.

CONCLUSION

Our prospective observational analysis provides compelling evidence that real-time, AI-driven support can enhance the conduct of emergency abdominal surgery. By lightening the cognitive burden on surgeons, sharpening anatomical orientation and flagging pathology sooner, the platform translated into measurable clinical gains, shorter operations, reduced postoperative morbidity, briefer hospitalisation and fewer intra-operative complications. Importantly, these benefits were realised in a tertiary-care environment with constrained resources and without disrupting existing theatre workflows. Although AI cannot replace clinical judgement, it can offer a consistent decision framework that is particularly valuable for less-experienced surgeons and for centres where senior expertise is not always on hand. Broad adoption, however, will depend on rigorous validation across diverse patient groups and practice settings. Future work should focus on tailoring algorithms to local contexts, monitoring long-term patient outcomes and addressing the ethical and medicolegal questions that accompany machine-guided care. Taken together, our findings suggest that artificial intelligence can move emergency surgery from a largely reactive undertaking toward a more proactive, data-informed model of clinical decision-making.

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