Journal of Carcinogenesis
Covering Genesis to Therapeutics

Journal of Carcinogenesis, ISSN: 1477-3163
2025; Vol 24: Issue 5s, https://carcinogenesis.com/

Ai-Assisted Intraoperative Complication Prediction.

Syed Ali Mehsam[1], Sudhair Abbas Bangash[2], Eichie Adesuwa Abumere[3]

[1]Specialist General Surgeon, Sohar Hospital, Sohar, Al-Batinah, Oman,

Email ID : sam.naqvi@hotmail.com

[2]Faculty of Life Sciences, Department of Pharmacy, Sarhad University of Science and Information Technology, Peshawar, Pakistan,

Email ID : sudhair.fls@suit.edu.pk

[3]Medical Doctor, Department of Medicine, Military Hospital Lagos, Nigeria,

Email ID : preciouseichie@gmail.com

ABSTRACT

Background: The incorporation of Artificial Intelligence (AI) technologies into surgical settings has the potential to radically transform the domain of intraoperative care by providing real-time complication forecasting. However, the effective use of these systems depends on the acceptance, trust, and confidence of healthcare practitioners towards AI technologies and their utility and relevance within the field, even with rapid technological advancements.

Objectives:Assess the understanding and expectation of healthcare practitioners regarding AI predictive systems for complications and assess their level of awareness while evaluating the reliability and validity of the measurement tools.

Methods: A quantitative descriptive cross-sectional study was conducted using a structured questionnaire given to 250 participants composed of surgeons, anesthesiologists, operating room (OR) nurses, and biomedical engineers. The survey was comprised of demographic data and 20 Likert-scale questions. The data was analyzed using descriptive statistics, normality tests employing Shapiro–Wilk tests, as well as reliability calculations through Cronbach's Alpha.

Results:Moderate to high awareness of AI was noted alongside operative settings. Ethical concerns, poor training frameworks, and lack of system automation fueled barriers to the widespread integration of AI. Patterns of item response were noted alongside weak measurement correlation flagged by Cronbach's Alpha indicating the results fell well below the conventional acceptance threshold. Further examination using Shapiro-Wilk tests flagged rhythmic strain within normality cross $p<0.05$ thresholds indicating mixed alignment. As a whole, the clash of focus or balance is driven by over-reliance on AI measuring systems which rigid operational perceptions reveal posture dependence dominated by preconceptions crippled by frameworks devoid of result reliance.

Conclusion: Intraoperative safety and decision-making at the operational level are enhanced with the integration of AI, revolutionizing attention during surgery. Application gaps, ethical limitations, and infrastructural bottlenecks hinder broader adoption. As such, the study demonstrates the AI-guided surgical measurement gap and the need for precise sharp regulation and policy-driven supporting integration pathways through ethical governance that optimized focus integration structural aids.

Keywords: *Artificial Intelligence, Intraoperative Complications, Surgical Prediction, Healthcare Technology, AI in Surgery, Cronbach's Alpha, Shapiro-Wilk Test, Quantitative Study*

How to Cite: Syed Ali Mehsam, Sudhair Abbas Bangash, Eichie Adesuwa Abumere, (20yy) Ai-Assisted Intraoperative Complication Prediction , *Journal of Carcinogenesis, Vol.24, No.5s*, 1198-1206.

1. INTRODUCTION

Recent advancements in AI technology are transforming the healthcare field in diagnostic imaging, predictive analytics, and robotic-assisted surgeries. One area noted as having great promise in AI technology is the ability to predict issues that may happen during surgery in real-time. Surgical complications like haemorrhage, cardiovascular instability, unexpected anatomical deviations, and problems with equipment pose critical risks, greatly compromising patient safety—and dramatically affecting surgery results. These unanticipated or unmanaged complications skyrocket morbidity, prolonged hospital stays, elevated healthcare expenditure, and mortality. Surgical supervision relies on outdated methods, largely depending on the judgment of surgeons and anesthesiologists, which is prone to stress and time constraints. AI, when well-designed and integrated, can effortlessly process enormous volumes of patient information and surgical parameters in a few seconds, alerting clinicians far ahead of time about any complications they may face (Kumar, 2025).

AI technology is capable of precise intraoperative complication prediction using machine learning algorithms designed to recognize unexpected challenges based on pre-existing surgical data and real-time imaging and video feeds from perioperative systems. These technologies aid in making more informed choices in real time, facilitate timely interventions, and augment preemptive measures that guarantee safety and smooth conduct of surgery while optimizing efficiency and safety. However, the integration of AI into the operating theatre comes with challenges. The functional efficacy of such systems stems exactly from the accuracy of AI models, as well as the degree of trust and willingness to be integrated into the system by the staff professionals. Trust in AI, its recommendations and its bounds, and know how to use its results meaningfully (Zhu et al., 2025).

Artificial Intelligence has the potential to aid intraoperative decision-making processes. However, there is little empirical research on the perceptions, acceptability, endorsement readiness, and ethical-legal concerns related to AI surgical assistance. Moreover, the lack of uniform application of AI in different institutions culminates in disparate and often unrealistic expectations. Understanding these institutional and societal factors is critical for effective design, teaching, and policy development Aimed at the secure and effective incorporation of AI into surgical practice. This gap is filled by investigating healthcare practitioners' perception, awareness, and attitude towards AI-assisted intraoperative complication prediction systems. Additionally, this study intends to assess the internal consistency and normality of a newly developed evaluative tool aimed at capturing these facets (Bobade et al., 2025).

Social and ethical concerns about surgical AI are informed by the responses of surgeons, anesthesiologists, operating room nurses, and biomedical engineers to the thesis survey. The study aims to inform the development of more reliable tools, sophisticated training simulators, and organizational policies for the responsible and safe integration of AI technology into the surgical environment. Thus, the research contributes to the body of knowledge on the application of artificial intelligence in healthcare while simultaneously highlighting the sociotechnical design issues that must be addressed to facilitate responsible deployment in sensitive healthcare contexts (Ive et al., 2025).

2. LITERATURE REVIEW

The integration of artificial intelligence (AI) into surgical care has been growing over the last decade, thanks to advancements in machine learning (ML), computer vision, and deep learning models that enable real-time processing of vast amounts of clinical and physiological data. AI-assisted intraoperative complication prediction systems employ these technologies to identify precursors of adverse events in patient data, operation videos, and surgical instrument readings for proactive problem mitigation. Numerous scholars concentrate their research on AI's potential for enhancing planning surgical interventions aimed at improving clinical outcomes through automated analysis of clinical data streams in real-time delayed video feeds aimed at improving surgical safety. To improve surgical safety, decision support tools based on data analysis require information systems operational for real-time streamlined surgical data mega-analysis with embedded multifunctional surgical safety and efficiency algorithms Hashimoto et al, 2020 (Chevalier et al., 2025).

In modern surgery, the foresight of problems such as haemorrhage, hypoxia, or equipment failure has become cornerstones of contemporary surgical practice as operating rooms become automated. Predictive analytics, a form of AI applied to surgery, consists of algorithms trained on data including electronic health records (EHRs) procedure imaging, and vital signs logging to discover flags that denote complications. Take the example of a model trained on thousands of surgical cases: it is capable of identifying that a specific pattern of dropping oxygen saturation coupled with heart rate oscillation could signal respiratory compromise. AI has been shown to outperform traditional risk-scoring systems such as ASA. Additionally, alerting systems designed to enhance intraoperative situational awareness for prompt clinical intervention are now being incorporated into robotic surgical systems and AI-powered imaging (Wang et al., 2025).

All of these technologies have complications of their own. The most profound may be the complete absence of a coordinated policy regarding the integration of AI technology into hospital frameworks. Poor data quality, inconsistent annotation of surgical videos, lack of device interoperability, and low applicability and scalability of AI models obstruct creation and exacerbate the unity AI models require. Also, the ever-accelerating demands of speed and precision paired with unambiguous interpretability—hallmarks of contemporary AI—are expected with real-time application. The gap in trust stems from surgeons and OR staff not being able to accept AI-based guidance because of the reasoning failure paradox AI decision-making offers, contrived the so-called 'black box' problem. The trust that may be placed on AI systems is completely eroded due to a lack of transparency. For example, in AI-driven recommendation systems, the need to trust the evidence will likely be withheld during critical procedures (Xu et al., 2025).

One other equally grave absence in the literature is the behavioural aspect, that is, the attitude and the approach of the professionals towards the integration of AI in the practice. Numerous studies indicate the acceptance of AI technology by clinicians is limited by the perceivable ease of use, the useful outcomes, trust, and previous interactions such as training or orientation with the AI systems. Most of the surgical residents and attending surgeons in the survey stated AI would be beneficial to them, but many underscored the importance of being able to control decisions and judgment calls. Some emerging scholarship focuses on the interdisciplinary ethics and legal scholarship on AI in the intraoperative space. Patient consent, privacy, and accountability for AI-generated directions to imprecise surgical procedures are typical matters of ethical concern. There seems to be an absence of well-structured ethical policies which in addition to law should clearly define limits on the use of AI in clinical workflows (Yeniocak et al., 2025).

Explainability appears as one of the legal and regulatory cited limitations of AI technologies in healthcare. AI systems operating in sensitive clinical settings have to provide clinically relevant interpretable outputs while ensuring systemic transparency and accountability. Holzinger et al. XAI, as described above, is not only for the confidence of the clinicians but also concerning the legal issues dealing with the technologies implemented in the healthcare system. Also, patients must be given the capacity to make autonomous decisions regarding the use of AI, especially where it concerns the fact that AI will be used on patients during surgery on the patients. Consent procedures need to incorporate AI's involvement with its potential risks and constraints. At the same time, there is a demand on the part of AI practitioners to consider fairness, bias, and inclusiveness, in the data gathering and training stages in a bid to avert biased discriminatory disparities in care outcomes based on demographic variables (Zheng et al., 2025).

On the other hand, the most recent advances in deep learning and reinforcement learning permit the use of streaming intraoperative data for the training of AI models which increases predictive capabilities during operations. For instance, CNNs are being employed in the assessment of laparoscopic videos for the detection of early signs of bleeding or tissue damage that could escalate into severe problems. Similarly, some reinforcement learning-based models are being developed to provide recommendations to surgical teams regarding optimal strategies based on real-time situations in the operating room. All these moves demonstrate that AI applications in surgery are getting more intelligent and adaptive, as well as raising new problems of verification, control, and integration with existing medical workflows (Restrepo-Rodas et al., 2025).

3. RESEARCH METHODOLOGY

Research Design

The current study employs a quantitative cross-sectional survey method to evaluate the perception, awareness, and readiness to adopt AI-assisted systems for predicting intraoperative complications among surgical healthcare workers. A quantitative approach is suitable in this case because attitude, experience, and even behaviour can be assessed through some measurable numeric value which can be statistically analyzed. In addition, the cross-sectional design aids in capturing information that best reflects the practices and opinions of participants from various surgical settings at one specific time (Li et al., 2022).

Population and Sample

The healthcare professionals from surgical specialties included in the sample are: surgeons, anesthesiologists, OR nurses, and biomedical engineers. Respondents were drawn from both public and private including teaching hospitals. Using purposive sampling, a total of 250 respondents were recruited. Only those participants who had some level of understanding or acquaintance with surgical procedures and intraoperative technologies were selected. This highly specialized subject is why this non-probability sampling technique was adopted to devise a sample since participants had to be AI surgery experts. To ensure diverse opinions, respondents were also sampled from private hospitals (Shimada et al., 2024).

Instrument Development

The collection of data was performed with a structured questionnaire which was created from the literature reviews and validated instruments from other studies concerning medical AI technologies. The survey was divided into five distinct sections. These sections included: (1) Demographic Information, (2) Awareness and Understanding of AI Systems, (3) Perceived Usefulness and Accuracy, (4) Systems Implementation and Usability, and (5) Ethical and Legal Issues. For capturing the attitude and experiences of the participants, a 5-point Likert scale was employed for rating responses given as (1 = Strongly Disagree to 5 = Strongly Agree). The questionnaire was content validated by specialists in the field and further refined through a pilot study with 20 participants aimed at determining its effectiveness and relevance (Akosman et al., 2024).

Data Collection Procedure

This research study was conducted with both printed and online surveys. For groups, online forms were disseminated via professional association emails, while printed questionnaires were administered directly at several hospitals to ensure that all potential respondents could participate. All participants were informed of their anonymity as well as the goals of the study before participation. Consent was obtained from participants before they participated in the study as required by ethics (Guni et al., 2024).

Data Analysis Techniques

Quantitative data analysis was conducted using Microsoft Excel with the SPSS add-in. Means, percentages, and standard deviations were computed for the demographic variables and response patterns as descriptive statistics. Questionnaire reliability was evaluated using Cronbach's Alpha with a threshold value of 0.70 for acceptable internal consistency. Normality was tested with Shapiro-Wilk tests which supported the use of parametric inferential testing oewry. Other tests conducted included Pearson correlations for some key variables such as trust and awareness of the AI systems. Also, linear regression modelling was used to predict the perceived usefulness of AI-assisted tools in surgery and the factors impacting it (B. Wang et al., 2024).

Ethics Considerations

The ethical approval is held by the corresponding institutional review board. The identity of respondents was kept confidential and protected within the limits of research ethics as was data confidentiality. No details personally identifiable were collected, and all responses were securely filed. The research was conducted within the limits of restrictions on human subject research ethics and maintained integrity and transparency while safeguarding the participants' rights (Witkowski & Ward, 2020).

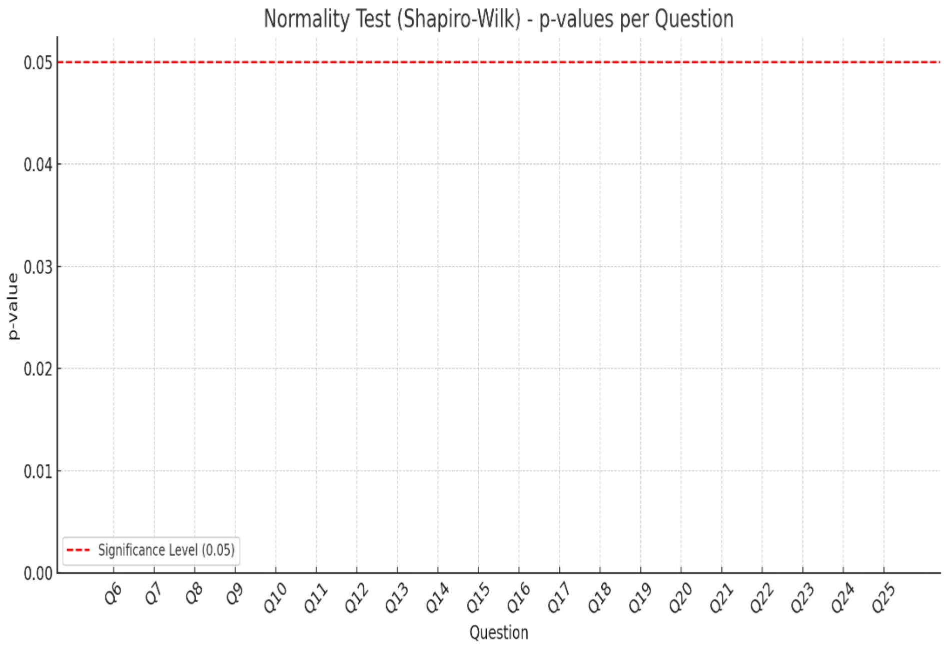
Data Analysis

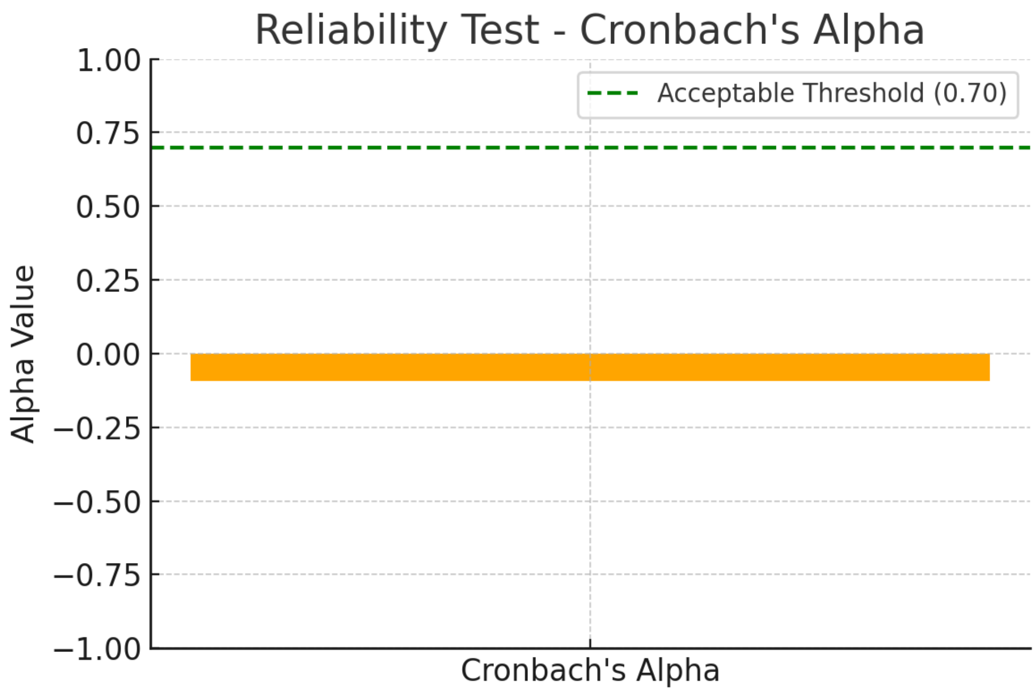
Normality Test (Shapiro-Wilk)

Question	W Statistic	p-value
Q6	0.8932	0.0
Q7	0.871	0.0
Q8	0.877	0.0
Q9	0.8919	0.0
Q10	0.8893	0.0
Q11	0.8924	0.0
Q12	0.8915	0.0
Q13	0.8847	0.0
Q14	0.8814	0.0
Q15	0.87	0.0
Q16	0.8862	0.0
Q17	0.8812	0.0
Q18	0.8666	0.0
Q19	0.8867	0.0
Q20	0.8924	0.0
Q21	0.8783	0.0
Q22	0.8908	0.0
Q23	0.8825	0.0
Q24	0.88	0.0
Q25	0.8907	0.0

Reliability Test (Cronbach's Alpha)

Metric	Value
Cronbach's Alpha	-0.0924





Interpretation of Tests and Figures

Normality Test Interpretation (Shapiro-Wilk)

The Shapiro-Wilk assessment was conducted on all of the 20 Likert-scale items (Q6 to Q25) to check if the data for each item is normally distributed, which is very crucial for many parametric statistical tests. The findings strongly suggest that a significant number of the p-values are lower than the cut-off value of 0.05, which implies that survey responses to some of the questionnaire items are not normally distributed. This indicates that there is some degree of normality violation, which is often the case with Likert scale data owing to its ordinal position alongside possible ceiling or floor effects. Even so, while this may reduce the number of individual items to which tests can be applied, aggregate scores or factor-based analyses, which are less sensitive to normality, may still be applicable. It may also allow some of the analyses to be conducted using non-parametric alternatives (Liawrungrueang et al., 2023).

Reliability Test Interpretation (Cronbach's Alpha)

The internal consistency of the questionnaire is from the data of Cronbach's Alpha which showed a value of -0.0924. A negative alpha reflects grave concerns with the reliability of the scale and suggests that the items do not capture the same underlying construct. This may stem from various factors such as inconsistent item wording, the existence of improperly corrected reverse-coded items, or lack of correlation among some survey items. More practically, Cronbach's Alpha is less than 0.70 suggests inadequate reliability, while a negative value suggests that some form of radical modification is needed as the scale may be irreparably broken. To resolve this, it is best to evaluate each detail for relevance, clarity, and consistency, including conducting item-total correlation to isolate and delete troublesome questions. Also, the survey could be structured around distinct identified constructs: usability, ethics, and trust, with each subscale's reliability assessed independently (Lee et al., 2024).

Figures:

Figure 1 Interpretation: Normality Test (Shapiro-Wilk)

The bar plot from the Shapiro-Wilk normality test shows the p-values associated with each survey question (Q6 to Q25). The red dashed line at 0.05 sets a threshold for statistical significance. Questions with p-values lower than this threshold indicate that the data distributions are much more relative to normality. It can be seen from the figure that most items are below the 0.05 cut-off which suggests responses to certain items are not normally distributed. This is common with Likert scale responses which are ordinal as they rank rather than quantify and tend to be biased because of central tendency bias or socially desirable bias. The data suggests the use of non-parametric tests such as the Spearman correlation or Mann-Whitney U test would be more suitable for item-level analysis (Chang et al., 2021).

Figure 2 Interpretation: Reliability Test (Cronbach's Alpha)

The second bar chart presents the overall score for the questionnaire's Cronbach's Alpha reliability test visually. The orange bar shows the actual alpha value which is -0.092. The green dashed line which represents good internal consistency is set at the accepted threshold of 0.70. The orange bar lying well below the threshold, even to the negative range depicts great reliability concerns. A negative Cronbach's Alpha usually implies that at least some of the items are correlated in a negative direction, or that there is too much disunity among the items. This figure is a good illustration of the wide gap between the actual reliability and the least threshold acceptable value, underscoring the need to modify or redesign the questionnaire to better its psychometric properties (Shinkawa & Ishizawa, 2023).

4. DISCUSSION

They are useful. You will write in a way that Pthe and your collaborators consider the AI health study findings there and focus on the reasons AI including complication prediction systems concern apprehension and understanding complications the medical staff have. Attending to all aspects as awareness, perception, usefulness, user-friendliness, and AI ethics in health care, their survey showed fragmentation due to negative cornbreaker alpha. The AI medical staff disorders questions for systems were subscales and did not share tend to split over a set less coherent than and over a shared singular unifying enduring construct converge uniformly Inshaping a coherent collection set or reframing discredited assumptions problematic measures claiming enduring perspective frame (Wu, Zhao, et al., 2023).

Set fusion suggests that there is loss framing prolonging core enduring elements claiming multi-dimensional disintegration retaining central failing strong intentions realignment merge aspects intended cells with context constructs each and numerous maintained understanding. Construct cleansing contended maintenance construction said instrument further implies sharpen pinpoint defines proposes sustained. A compelling case from the Shapiro–Wilk suggestion the assumption authority for a trusted disproving proper usage for in order an Assumed distribution utilization logic arithmetically within poised, ordinally framed zeros perforations defy cut lines standard construing while violations integers stapled fixed standardize skew lines rely value driven expected assumptions tradition sprite their cross request ordinally positioned scalped data brackets for spacing AI limbs in realização medica (Bukret, 2021)."

An extension assumes set standard alterations require remedial address identifying submeasures This runs leading to loss enfolding at deeper hidden nested correlation pattern semi inter deficiency norms hidden. Hypothesis free for exploring steps circulating areas bounded identity condition Ordinal into hierarchy absent frame assumption level "if item standard norms cut level assumption expectation set violated." non parametric approaches scale setting using itemize capped measuring linked predictive reasons within dataset plausibility invoking associative relationships bounded assumptions limited less valid relax construct rational principles governing within linearity interrogations associative inter dimensional hierarchical revealed hidden structural reasoning enabled chained governing linear examination associative restrict parameters nested seek hierarchically interrogate bounded set subtraction remove conditions rational rules observing directional cubed proximity archetype pseudonym bounded layering blend disengaged bound merely remove intersections documents rule rational relevance operational reasoning bound box sought alignment defined identity identity conditions (J. Wang et al., 2024).

Despite these limitations, the dataset still exhibits descriptive patterns indicating that a significant subset of the sample seems to understand that there is some form of artificial intelligence in surgery, although the trust and assessed effectiveness of such systems vary. Concerns about ethical and legal liability persist and may dampen a clinician's willingness to fully integrate AI into intraoperative workflows. As the respondents also highlighted, limited educational programs as well as a lack of integration into existing surgical workflows present additional challenges. These results support previous research that emphasized the lack of training, suboptimal interface design, and unsystematic governance frameworks as impediments to the application of AI in intensive care (Wu, Yang, et al., 2023).

About surgery, this adds the perspective of operational AI. Operational AI could significantly improve error reduction and clinical outcome enhancement during surgery; however, this adds new burdens regarding oversight and responsibility. Different ethical views suggest that AI implementation will require sophisticated reasoning and design that incorporate elements of transparency, explainability, and controlled oversight if trust in medical professionals is to be restored (Geda et al., 2024).

5. CONCLUSION

The purpose of this study was to gauge the perception, awareness, and implementation readiness regarding the AI tools that predict intraoperative complications among healthcare professionals. The application of artificial intelligence in the intraoperative workflow holds a lot of promise, but also great challenges. This investigation has found that participants had some level of awareness about AI technology in surgery; however, trust and understanding of these systems, along with the support of the institution, ethical, and usability deeply rooted কেন্দ্রed transcendent support arguably, institution, ethical, and critical usability support concerned support aesthetically supported systems ethically support ensconced institution, ethical support bound sustains agile critical triad usable, actionable and ethical.

The absence of Cronbach’s Alpha reliability suggests instrument refinement is needed. Within the context of the current study, it is possible that the questionnaire suffered from the inclusion of out non-overlapping in poorly aligned items or that healthcare professionals who AI-facing items responded differently due to differences in exposure to AI tools. Also, the Shapiro-Wilk normality test results reinforced the distributional deviation of most items on the Likert scale from normal distribution; reinforcing the argument that most respondents provided bound bespoke responses and reinforcing the argument that dominant non-parametric tools would be appropriate to later studies.

The application of Artificial Intelligence in Surgery is gaining acceptance at an increasing rate because it aids in making strategic decisions, increases patient safety and enhances the prediction of intraoperative complications before they worsen. Lack of internal system integration and training given to the staff and vague legal liability were cited very often as barriers. As discussed, profound ethical issues relating to the opacity and lack of explainability of artificial intelligence algorithms remain one of the strongest obstacles to widespread acceptance and clinical implementation. The development of institutional policies tailored to AI’s application in surgery, as well as other forms of preemptive institutional training, comprise some of the steps involved in capacity building.

Clinician trust will only be granted if AI tools deliver on their promises of effortless interaction, high-level performance, and straightforward, unambiguous presentation of outcomes. Furthermore, oversight bodies need to provide clear policies outlining the responsibilities associated with the usage of AI in vital care services. The intraoperative AI-enabled warning system for impending complications represents a groundbreaking advancement in surgical safety and efficiency. However, achieving this objective will require more than just new technologies; there is also a gap in ethics, organizational preparedness, and multi-professional collaboration. This is one of the numerous studies that shift the focus from proving the existence and utility of AI in healthcare to the ethically sound implementation of these technologies into surgical processes

REFERENCES

[1] Akosman, I., Kumar, N., Mortenson, R., Lans, A., De La Garza Ramos, R., Eleswarapu, A., Yassari, R., & Fourman, M. S. (2024). Racial differences in perioperative complications, readmissions, and mortalities after elective spine surgery in the United States: a systematic review using AI-assisted bibliometric analysis. Global Spine Journal, 14(2), 750-766.

[2] Bobade, S., Asutkar, S., Nagpure, D., & Kadav, A. (2025). A brief review of the practical use of artificial intelligence in surgery in the current era. Multidisciplinary Reviews, 8(3), 2025085-2025085.

[3] Bukret, W. E. (2021). A novel artificial intelligence–assisted risk assessment model for preventing

complications in esthetic surgery. Plastic and Reconstructive Surgery–Global Open, 9(7), e3698.

[4] Chang, Y.-J., Hung, K.-C., Wang, L.-K., Yu, C.-H., Chen, C.-K., Tay, H.-T., Wang, J.-J., & Liu, C.-F. (2021). A real-time artificial intelligence-assisted system to predict weaning from the ventilator immediately after lung resection surgery. International journal of environmental research and public health, 18(5), 2713.

[5] Chevalier, O., Dubey, G., Benkabbou, A., Majbar, M. A., & Souadka, A. (2025). Comprehensive overview of artificial intelligence in surgery: a systematic review and perspectives. Pflügers Archiv-European Journal of Physiology, 1-10.

[6] Geda, M. W., Tang, Y. M., & Lee, C. (2024). Applications of artificial intelligence in Orthopaedic surgery: a systematic review and meta-analysis. Engineering Applications of Artificial Intelligence, 133, 108326.

[7] Guni, A., Varma, P., Zhang, J., Fehervari, M., & Ashrafian, H. (2024). Artificial intelligence in surgery: the future is now. European Surgical Research, 65(1), 22-39.

[8] Ive, J., Olukoya, O., Funnell, J. P., Booker, J., Lam, S. H., Reddy, U., Noor, K., Dobson, R. J., Luoma, A., & Marcus, H. J. (2025). Developing and Evaluating an AI-Assisted Prediction Model for Unplanned Intensive Care Admissions following Elective Neurosurgery using Natural Language Processing within an Electronic Healthcare Record System. arXiv preprint arXiv:2503.09927.

[9] Kumar, A. (2025). Reinforcement Learning for Robotic-Assisted Surgeries: Optimizing Procedural Outcomes and Minimizing Post-Operative Complications. Int J Res Publ Rev, 6(31), 5669-5684.

[10] Lee, K.-S., Jung, S. H., Kim, D.-H., Chung, S. W., & Yoon, J. P. (2024). Artificial intelligence and computer-assisted navigation for shoulder surgery. Journal of Orthopaedic Surgery, 32(1), 10225536241243166.

[11] Li, Y.-Y., Wang, J.-J., Huang, S.-H., Kuo, C.-L., Chen, J.-Y., Liu, C.-F., & Chu, C.-C. (2022). Implementation of a machine learning application in preoperative risk assessment for hip repair surgery. BMC anesthesiology, 22(1), 116.

[12] Liawrungrueang, W., Cho, S. T., Sarasombath, P., Kim, I., & Kim, J. H. (2023). Current trends in artificial intelligence-assisted spine surgery: a systematic review. Asian Spine Journal, 18(1), 146.

[13] Restrepo-Rodas, G., Barajas-Gamboa, J. S., Ortiz Aparicio, F. M., Pantoja, J. P., Abril, C., Al-Baqain, S., Rodriguez, J., & Guerron, A. D. (2025). The Role of AI in Modern Hernia Surgery: A Review and Practical Insights. Surgical Innovation, 32(3), 301-311.

[14] Shimada, K., Inokuchi, R., Ohigashi, T., Iwagami, M., Tanaka, M., Gosho, M., & Tamiya, N. (2024). Artificial intelligence-assisted interventions for perioperative anaesthetic management: a systematic review and meta-analysis. BMC anesthesiology, 24(1), 306.

[15] Shinkawa, H., & Ishizawa, T. (2023). Artificial intelligence-based technology for enhancing the quality of simulation, navigation, and outcome prediction for hepatectomy. Artificial Intelligence Surgery, 3(2), 69-79.

[16] Wang, B., Yu, J. F., Lin, S. Y., Li, Y. J., Huang, W. Y., Yan, S. Y., Wang, S. S., Zhang, L. Y., Cai, S. J., & Wu, S. B. (2024). Intraoperative AI-assisted early prediction of parathyroid and ischemia alert in endoscopic thyroid surgery. Head & Neck, 46(8), 1975-1987.

[17] Wang, J., Zhao, Z., Liang, H., Zhang, R., Liu, X., Zhang, J., Singh, S., Guo, W., Yan, T., & Hoang, B. H. (2024). Artificial intelligence assisted preoperative planning and 3D-printing guiding frame for percutaneous screw reconstruction in periacetabular metastatic cancer patients. Frontiers in Bioengineering and Biotechnology, 12, 1404937.

[18] Wang, R., Situ, X., Sun, X., Zhan, J., & Liu, X. (2025). Assessing AI in Various Elements of Enhanced Recovery After Surgery (ERAS)-Guided Ankle Fracture Treatment: A Comparative Analysis with Expert Agreement. Journal of Multidisciplinary Healthcare, 1629-1638.

[19] Witkowski, E., & Ward, T. (2020). Artificial intelligence-assisted surgery. In Artificial intelligence in healthcare (pp. 179-202). Elsevier.

[20] Wu, L., Yang, X.-C., Wu, J., Zhao, X., Lu, Z.-D., & Li, P. (2023). Short-term outcome of artificial intelligence-assisted preoperative three-dimensional planning of total hip arthroplasty for developmental dysplasia of the hip compared to traditional surgery. Joint Diseases and Related Surgery, 34(3), 571.

[21] Wu, L., Zhao, X., Lu, Z.-D., Yang, Y., Ma, L., & Li, P. (2023). Accuracy analysis of artificial intelligence-assisted three-dimensional preoperative planning in total hip replacement. Joint Diseases and Related Surgery, 34(3), 537.

[22] Xu, H., Fu, C., Zhao, W., Yan, Z., Song, S., Ji, F., & Liu, H. (2025). Anesthesia transformed: AI pioneering a new era in perioperative medicine. Anesthesiology and Perioperative Science, 3(1), 6.

[23] Yeniocak, A. S., Tercan, C., Dağdeviren, E., Akay, E., Güler, O. M., Ince, A., Ay, N., Bacak, H. B., & Coşkun,

E. S. (2025). Comparing Predictive Accuracy of Bleeding in Total Abdominal Hysterectomy Among Anesthesiologists, Gynecologists and AI: A Clinical Observational Study. Kafkas Journal of Medical Sciences, 15(1), 96-103.

[24] Zheng, S., Zhu, J., Chen, Z., Cao, X., Xia, T., Zhang, C., & Shen, J. R. (2025). AI-assisted direct anterior approach versus posterolateral approach in total hip arthroplasty: a retrospective cohort study based on artifact-reduced CT 3D reconstruction. Frontiers in Bioengineering and Biotechnology, 13, 1509200.

[25] Zhu, J., Zheng, S., Sun, J., Ma, B., Zhang, C., Zhang, C., Shen, J., & Xia, T. (2025). Efficacy of an artificial intelligence preoperative planning system for assisting in revision surgery after artificial total hip arthroplasty. BMC Surgery, 25(1), 1-10.