A Comprehensive Review of Gauze and Mop Counting Automation Systems for Orthopedic Surgical Safety

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Abstract— *Retained surgical items (RSIs), particularly gauze pieces and mops, remain a preventable yet persistent threat to patient safety in orthopedic operations. Manual counting protocols, though standardized worldwide, are vulnerable to human fatigue, distraction, and workflow complexity conditions frequently intensified in lengthy orthopedic procedures that involve multiple instruments, draping layers, and substantial blood loss. To address these challenges, diverse automation systems have been developed using bar-coding, radio-frequency identification (RFID), radiofrequency detection (RFD) wands, computer vision (CV), and sensor-fusion architectures. This paper presents a comprehensive review of gauze and mop counting automation systems with a specific focus on orthopedic surgical safety. A systematic literature search was conducted across Scopus, PubMed, IEEE Xplore, and ScienceDirect databases for the period January 2010 to May 2025 using PRISMA based screening criteria. Each study was analyzed for detection accuracy, workflow integration, sterility, human factors, and compliance with international standards (ISO 13485, 14971, IEC 60601).*

The review identifies that while RFID and RFD technologies achieve high detection sensitivity, they face interference and sterilization constraints; computer vision approaches offer real-time potential but remain limited by dataset variability and occlusion. Few studies report on orthopedic specific validation or multimodal fusion strategies. The synthesis highlights critical research gaps in interoperability, calibration, regulatory validation, and human-automation collaboration.

Building upon these findings, the paper proposes a robotics oriented framework integrating RFID and CV within a closed-loop counting ecosystem capable of edge-level decision making and standardized audit trails. Such an approach could substantially enhance count accuracy, reduce intra-operative delays, and strengthen traceability. The review thus provides a consolidated evidence base and future roadmap toward intelligent, standards-compliant counting automation for safer orthopedic surgery. This review identifies critical pathways for future research in robotics-assisted surgical safety systems.

Keywords— Surgical Safety; RFID; Computer Vision; Retained Surgical Items; Orthopedic Surgery; Automation Framework.

I. INTRODUCTION

Retained surgical items (RSIs) primarily gauze pieces and mops inadvertently left inside the patient's body remain a serious but preventable source of postoperative complications. The issue persists across surgical specialties despite stringent manual counting and verification protocols. The frequency of RSIs is estimated at one per 1,000 - 1,500 intra-abdominal surgeries, with underreporting masking the true burden (Steelman et al., 2018). RSIs lead to foreign body reactions, infections, reoperations, and legal actions, posing direct threats to both patient safety and hospital credibility (Rupp et al., 2012).

In orthopedic surgery, the risk is significantly magnified. These procedures are often long, involve deep cavities, heavy draping, use of metal implants, and multiple team handovers all of which compound the cognitive load on the surgical team (Zejnullahu et al., 2017). Gauze and mop counts are conventionally conducted manually by scrub and circulating nurses, but studies show that up to 80% of RSI cases occur even when manual counts are reportedly correct (Cima et al., 2011). Fatigue, interruptions, multitasking, and environmental distractions remain unavoidable in real-world operation theatres, limiting human reliability (Steelman & Petersen, 2012).

Recent advances in automation and robotics have introduced new paradigms to enhance surgical safety. Technologies such as RFID tags, radiofrequency detection (RFD) mats, barcode tracking systems, and AI-driven computer vision algorithms have demonstrated potential to detect, track, and verify surgical consumables in real time (Cima et al., 2011; Steelman et al., 2011; Abo-Zahhad et al., 2024). From a robotics and automation viewpoint, these solutions exemplify sensor integration, real-time control, and human-machine interaction, domains central to modern intelligent healthcare systems.

However, despite multiple innovations, no single system yet achieves universal adoption. RFID tags may be hindered by metallic interference from orthopedic implants (Inaba et al., 2016); RFD devices may produce false alarms due to proximity artifacts; and vision-based systems often underperform in cluttered, blood-contaminated fields (Lázaro-Andreu et al., 2022). Furthermore, most commercial and academic efforts have generalized surgical use cases, overlooking orthopedic-specific environmental and ergonomic challenges.

Therefore, a systematic, robotics-oriented review is required to consolidate existing evidence, evaluate technology readiness, identify performance and regulatory gaps, and propose a coherent framework for next-generation automation in orthopedic operation theatres. This paper aims to fill that gap by analyzing current gauze and mop counting technologies and highlighting pathways toward standardized, intelligent, and safe surgical ecosystems.

II. LITERATURE REVIEW

2.1 Manual Counting Systems:

Despite nearly two decades of standardized counting protocols, retained surgical items (RSIs) persist as a major source of morbidity and litigation. Manual count accuracy is compromised by fatigue, interruptions, multitasking, and environmental distractions (Steelman et al., 2018; Cochran, 2022). Orthopedic operating rooms are particularly vulnerable due to longer procedure durations, heavy draping, and the use of multiple mops and gauze packs (Zejnullahu et al., 2017; Puvanesarajah et al., 2019). Process-aided methods such as sponge holders, whiteboards, and count bags minimize cognitive load but rely entirely on human compliance (Fencl, 2016). De Vries et al. (2010) and Urbach et al. (2014) observed that even with WHO surgical-safety checklists, residual errors occur when workflow stress is high. These limitations motivated development of automation-assisted systems to enhance verification integrity.

2.2 Barcode and Data-Matrix Technologies:

Early automation focused on optical identification. Cima et al. (2011) demonstrated that bar-coded or data-matrix-tagged sponges improve traceability and reconciliation accuracy by >98 %. Subsequent multi-center studies confirmed sustained elimination of unreconciled counts over 18 months of continuous use (Cima et al., 2011). However, the requirement for line-of-sight scanning and additional handling introduces workflow interruptions, especially in high-throughput orthopedic theatres (Grant & Lin, 2020). Comparative analyses by Sirihorachai et al. (2021) and Peng et al. (2023) classified optical codes as cost-effective but limited to “surface verification” tasks, unsuitable for deep-field detection once sponges are saturated or obscured.

2.3 RFID-Based Systems:

Radio-frequency identification (RFID) has emerged as the most intensively studied technology for RSI prevention since 2010. Clinical and bench investigations reported detection sensitivities of 99–100 % for passive tags positioned within the surgical cavity (Steelman, Cullen, & Anderson, 2011; Steelman, Alasagheirin, & Petersen, 2012; Rupp et al., 2012; Kranzfelder et al., 2012). Wiederkehr et al. (2014) validated performance in porcine models, while Inaba et al. (2016) confirmed effectiveness

during emergency surgeries. RFID advantages include non-line-of-sight detection, rapid scanning, and electronic audit trails (Schnock et al., 2017; Hendricks et al., 2022). Nevertheless, tag cost, sterilization tolerance, antenna placement, and metal interference remain barriers to orthopedic deployment where implants and instruments dominate the field (Parlak, Marsic, & Burd, 2012). Cost benefit models (Cima et al., 2011) indicate positive returns only at high surgical volumes.

Recent RF engineering efforts address these challenges through miniaturized antennas, multi-band readers, and anti-collision protocols (Hendricks et al., 2022). Yet, most validations remain small-scale; large orthopedic-specific trials are absent, underscoring a translational gap.

2.4 RFD Systems:

RFD systems employ passive tags activated by external readers at closure. Steelman et al. (2011) and Rupp et al. (2012) showed that RFD scanning detects sponges through tissue up to 9 cm deep. Inaba et al. (2016) demonstrated reliable performance in live surgical settings, significantly reducing search times and unreconciled counts. However, false alarms can occur due to orientation, saline pooling, or proximity to metal (Steelman et al., 2012). Comparative reviews categorize RFD as an adjunctive safeguard effective at final closure but unable to track items throughout the operation (Peng et al., 2023). Integration of RFD mats with OR tables offer hands-free detection yet raises electromagnetic-compatibility and sterilization concerns (Rupp et al., 2012).

2.5 Computer Vision and AI Approaches:

Parallel advances in medical imaging and machine learning have enabled vision-based counting. Early image processing systems tracked gauze on instrument tables (de la Fuente López, Borras, & Vidal, 2020), later extended to deep learning architectures capable of object segmentation under occlusion (Chávez, Naranjo, & Albiol, 2020; Lázaro-Andreu et al., 2022). Recent work leverages YOLOv7/v8 detectors and transformer networks for real-time instrument and gauze recognition with >95 % mAP (Ran et al., 2023; Xu, Li, & Hu, 2025). Multi-camera and depth-sensor systems enhance robustness against illumination variation (Weidert, Gruetzner, & Mutschler, 2023; Haider et al., 2025).

AI-driven methods show promise for closed loop verification but face hurdles in dataset representativeness, annotation effort, and generalization across specialties (Deol et al., 2024; Abo-Zahhad, Elhoseny, & Abd-Elkader, 2024). Orthopedic workflows introduce additional complexity like blood contamination, metallic reflections, and layered draping impair visual cues (Puvanesarajah et al., 2019). Consequently, CV systems require multimodal redundancy or domain-adaptation strategies to reach clinical reliability (Chávez et al., 2020).

Beyond intra-operative detection, AI also aiding diagnostic identification of retained items in postoperative imaging. Yamaguchi et al. (2022) reported computer-aided diagnosis for sponge visualization on CT, demonstrating the complementary role of AI in both prevention and detection phases.

2.6 Sensor Fusion and IOT Integration:

Emerging research proposes combining RF and vision modalities to exploit complementary strengths. Multi-sensor prototypes integrate RFID for non-line-of-sight detection and CV for visual confirmation, reducing false positives (Hendricks et al., 2022; Deol et al., 2024). IoT architectures with edge computing enable low-latency analytics and cloud-based audit trails (Haider et al., 2025). These frameworks align with the trend toward smart operating rooms, where robotic subsystems and hospital information systems communicate through interoperable standards such as HL7 and FHIR (Parlak et al., 2012; Kooijmans et al., 2024).

Nevertheless, most sensor-fusion studies remain at simulation or prototype level, with limited orthopedic-specific evidence. Reported accuracy ranges from 93 % to 99 %, but testing conditions seldom replicate blood contamination, metallic implants, or prolonged operative time typical of orthopedic procedures (Sirihorachai et al., 2021). Furthermore, heterogeneous performance metrics and absence of standardized evaluation protocols impede cross-study comparison (Chávez et al., 2020; Lázaro-Andreu et al., 2022).

2.7 Human Factors and Regulatory Considerations:

All automation systems must coexist with human workflow. AORN and ISO/IEC standards emphasize usability engineering and alarm management (AORN Guidelines Advisory Board, 2022; Steelman et al., 2018). Human-machine interaction studies highlight the need for intuitive interfaces, graded alarm priorities, and minimal additional steps to avoid non-adherence (Cochran, 2022; Kooijmans et al., 2024). Cost analyses reveal that RFID/RFD systems become cost effective when institutional RSI rates exceed 1 per 5,000 cases or when litigation costs are included (Regenbogen et al., 2009; Grant & Lin, 2020).

From an automation standpoint, the literature converges on several design imperatives: (i) multimodal sensing for redundancy, (ii) edge-AI inference to maintain low latency, (iii) adherence to ISO 14971 risk-management and IEC 60601-1 safety standards, (iv) traceability through interoperable OR-IoT infrastructure, and (v) validation through multicenter, orthopedic-specific trials.

Between 2010 and 2025, gauze- and mop-counting automation evolved from optical identifiers to intelligent, connected systems integrating sensors, algorithms, and hospital data streams. Yet no single technology fully satisfies the orthopedic domain's demands for robustness, sterility, usability, and regulatory compliance.

Collectively, the reviewed studies reveal that while detection accuracy has improved significantly, orthopedic-specific validation and regulatory readiness remain underdeveloped.

Research Gap:

Based on the literature synthesis, the following research gaps were identified, guiding the aims and objectives of this review.

1) Lack of integrated multimodal sensing frameworks that combine RFID and CV under orthopedic conditions.
2) Limited validation protocols addressing sterility, occlusion, and metallic interference.
3) Insufficient regulatory and interoperability alignment in most published prototypes.
4) Underexplored human factors, engineering and workflow integration.
5) Minimal cross-validation of AI models on orthopedic-specific datasets.
6) Absence of an open, reproducible framework for Ph.D. level extension and validation.

Aims and Objectives:

The primary aim of this review is to critically evaluate, classify, and synthesize existing gauze and mop counting automation systems, with a focused lens on orthopedic surgical safety, and to propose a robotics-oriented, multimodal framework that enhances accuracy, usability, and regulatory compliance through intelligent sensing and automation.

1) Conduct a systematic review (2010–2025) of RFID, barcode, and CV-based RSI prevention systems.
2) Develop a unified taxonomy of sensing, decision-making, and usability parameters.
3) Identify and classify existing technological and regulatory limitations.
4) Align proposed systems with international standards (ISO 13485, ISO 14971, IEC 60601, IEC 62366, HL7/FHIR).
5) Propose a conceptual RFID–CV hybrid framework with edge-AI integration.
6) Outline a research roadmap for future doctoral validation.

III. PROPOSED METHODOLOGY

3.1 Concept Overview:

In response to the identified research gaps, this study conceptually proposes a robotics oriented, multimodal counting framework that integrates Radio Frequency Identification (RFID) and Computer Vision (CV) technologies to enable intelligent, real time gauze and mop tracking during orthopedic surgeries.

The proposed model is presented as a conceptual framework for future development serving as a blueprint for research scholars and engineers aiming to implement, validate, and clinically translate such systems.

Its novelty lies in merging sensing, automation, and safety regulation principles into a unified workflow that aligns with orthopedic surgical realities as shown in Figure 1.

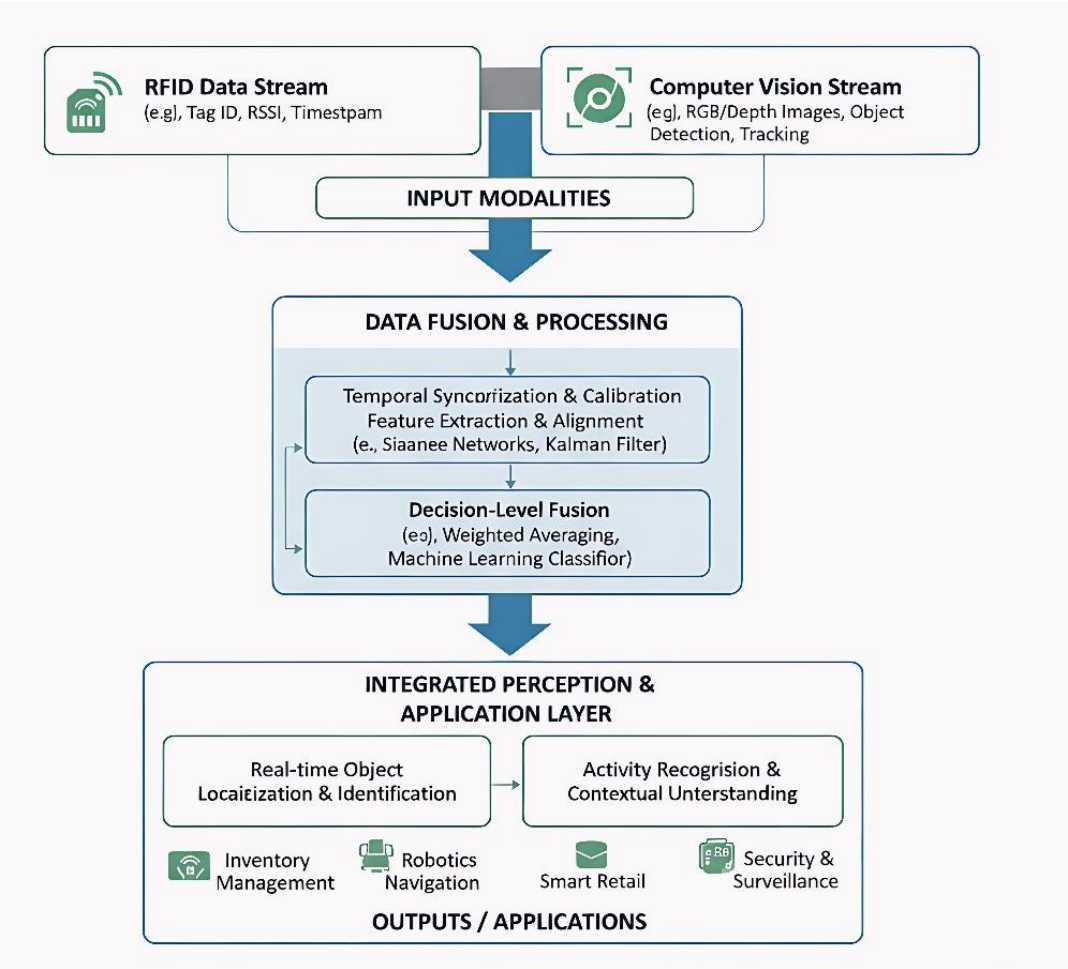

FIGURE 1: Conceptual architecture of the proposed RFID–CV multimodal framework

3.2 Conceptual System Architecture:

The framework is designed with four conceptual layers, representing the operational flow of an automated counting ecosystem as tabulated in Table 1:

3.2.1 Sensing Layer (Perception):

- Passive sterilizable RFID tags embedded in gauze/mops provide nonvisual identification.
- Overhead or side-mounted cameras use deep learning based CV algorithms for object detection and count tracking.
- Together, these systems provide redundant sensing under diverse operating conditions, improving reliability.

3.2.2 Data Fusion and Edge Processing Layer:

- Both RFID and CV data streams are processed in parallel.
- Fusion logic integrates results using a weighted-confidence algorithm or Bayesian inference model to confirm gauze/mop presence.
- Edge-AI hardware (e.g., Jetson or equivalent) is conceptually proposed for near real time processing, ensuring minimal latency.

3.2.3 Decision Support and Alerting Layer:

- The system performs automatic reconciliation between initial and final counts.

- Any mismatch triggers a graded alert sequence (visual/auditory), prompting staff verification before wound closure.
- Decision outcomes and timestamps are logged digitally for audit purposes.

3.2.4 Integration and Compliance Layer:

- Conceptually integrates with hospital information systems via standard communication protocols such as HL7 and FHIR.
- Aligns with ISO 14971 (risk management), IEC 60601 (electrical safety), and IEC 62366 (usability) to ensure regulatory readiness.

TABLE 1
FUNCTIONAL MAPPING OF PROPOSED FRAMEWORK LAYERS, OBJECTIVES, AND COMPLIANCE REFERENCES

Framework Layer	Primary Objective	Key Functional Components	Regulatory/Compliance References
1. Sensing Layer (Perception)	Provide redundant, high reliability tracking of gauze and mops.	Passive sterilizable RFID tags and readers; Deep-learning based Computer Vision (CV) algorithms (object detection/tracking) via overhead/side-mounted cameras.	ISO 13485 (Quality Management System for Medical Devices) related to sensor reliability.
2. Data Fusion and Edge Processing Layer	Confirm object presence and location in near-real-time with minimal latency.	Parallel processing of RFID and CV streams; Weighted-confidence algorithm or Bayesian Inference for data fusion; Edge-AI hardware (e.g., NVIDIA Jetson or equivalent).	IEC 60601-1 (Electrical Safety) and related standards for hardware integration in the surgical environment.
3. Decision Support and Alerting Layer	Ensure automatic and accurate reconciliation of surgical counts and prompt staff action upon discrepancy.	Automatic count reconciliation logic (Initial vs. Final count); Graded alert sequence (visual/auditory); Digital logging of decision outcomes and timestamps for audit.	ISO 14971 (Risk Management) for defining and mitigating risks associated with count errors; IEC 62366 (Usability) for alert design.
4. Integration and Compliance Layer	Facilitate seamless operational workflow and ensure regulatory readiness for clinical translation.	Integration with Hospital Information Systems (HIS); Standard protocols like HL7 and FHIR for data exchange; Alignment with safety and usability standards.	HL7/FHIR (Interoperability); ISO 14971 (Risk Management); IEC 60601 (Electrical Safety); IEC 62366 (Usability/Human Factors).

3.3 Conceptual Workflow in Orthopedic Surgery:

The proposed model as evidenced in Figure 2 can be embedded at three critical surgical checkpoints:

- **Preoperative (Initial Count):** Each gauze/mop is RFID-scanned and visually registered in the system inventory.
- **Intraoperative (Active Tracking):** Continuous sensing monitors item transitions between the sterile field, wound cavity, and waste zones. The system conceptually maintains an active count database through multimodal confirmation.
- **Postoperative (Final Verification):** Before closure, the fusion algorithm reconciles total detected items with the initial registry. Any unverified count triggers a system-generated critical alert requiring manual resolution. This workflow ensures closed-loop traceability without disrupting existing surgical roles or responsibilities.

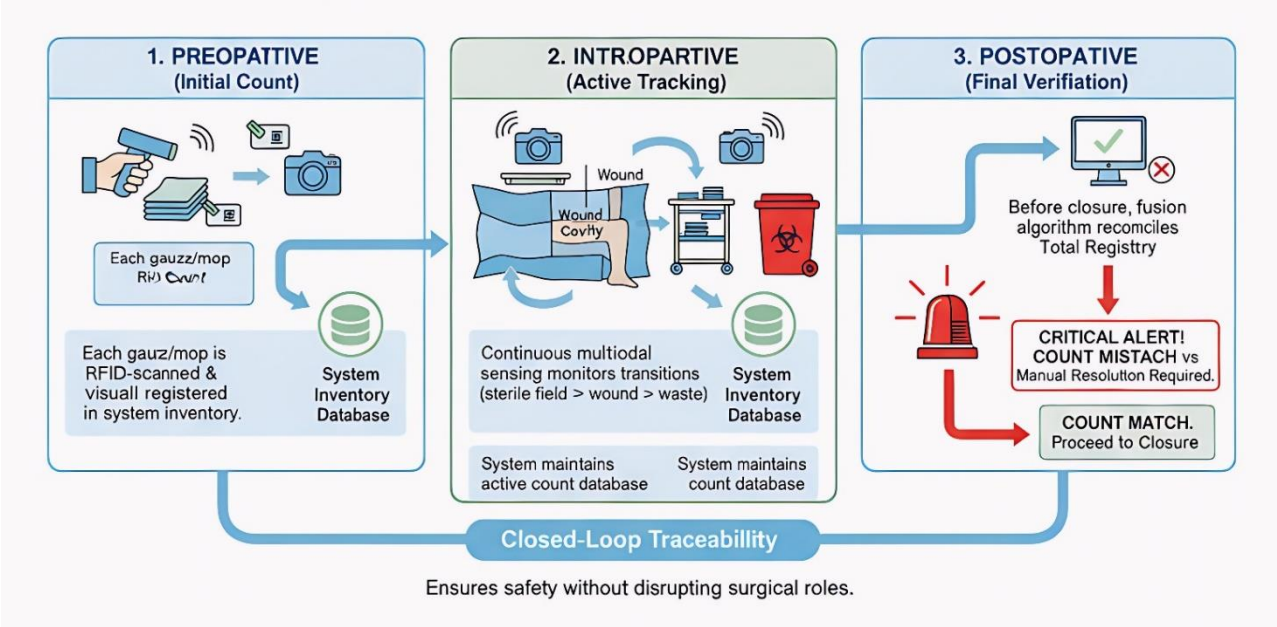

FIGURE 2: Proposed integration of the multimodal counting framework within orthopedic surgical workflow

3.4 Research Implementation Roadmap:

While this review does not perform experimental validation, it provides a conceptual implementation roadmap for future doctoral or research projects as shown in Figure 3:

1) **Phase 1 – Algorithm Development:**
   Development of modular AI models for visual recognition and RFID event handling, with simulated data fusion for proof of concept.

2) **Phase 2 – Prototype Design:**
   Construction of a benchtop prototype integrating RFID readers and camera modules for controlled testing in a laboratory environment.

3) **Phase 3 – Validation and Optimization:**
   Future researchers can extend this framework for clinical evaluation under ethical approval, focusing on orthopaedic-specific constraints (metallic interference, draping, blood contamination).

This roadmap defines how the framework may be realized, without implying direct execution in the current study.

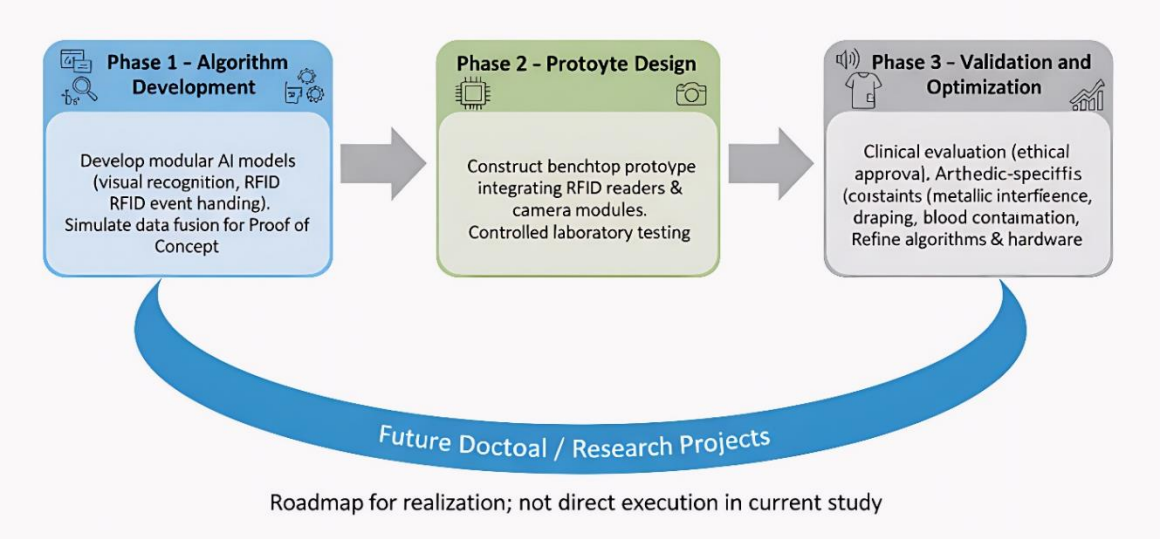

FIGURE 3: Conceptual three phase roadmap for future research and validation of the proposed system

3.5 Anticipated Benefits and Research Contributions:

The conceptual framework aims to provide the following academic and practical contributions as summarized in Table 2:

- **Multimodal redundancy:** Combining RFID and CV ensure high detection confidence, even under occlusion or electromagnetic noise.
- **Human–machine synergy:** Designed for minimal cognitive load and alignment with surgical counting checkpoints.
- **Regulatory readiness:** Framework integrates standard compliance considerations early in design, enabling smoother translation.
- **Scalability and adaptability:** Modular architecture allows easy expansion to instrument tracking and robotic surgical platforms.
- **Research utility:** Offers a structured roadmap for postgraduate and doctoral scholars to implement, refine, and validate multimodal OR automation systems.

TABLE 2
PROJECTED BENEFITS AND RESEARCH CONTRIBUTIONS OF THE PROPOSED FRAMEWORK

Contribution/Benefit	Description/Impact
Multimodal Redundancy	Combines RFID and CV to ensure high detection confidence, even under common surgical challenges like occlusion or electromagnetic noise.
Human–Machine Synergy	Designed for minimal cognitive load on surgical staff and aligns directly with existing surgical counting checkpoints.
Regulatory Readiness	Integrates standard compliance considerations (e.g., ISO, IEC) early in the design process, enabling smoother clinical translation and adoption.
Scalability and Adaptability	Features a modular architecture that allows for easy expansion to other critical tracking needs, such as surgical instrument tracking and integration with robotic surgical platforms.
Research Utility	Offers a structured roadmap and conceptual blueprint for postgraduate and doctoral scholars to implement, refine, and validate multimodal Operating Room (OR) automation systems.

IV. CONCLUSION

Automation in surgical safety has progressed substantially, yet orthopedic RSIs remain a challenge due to human error and environmental complexity. Reviewing RFID, RFD, and AI-based approaches reveals strong potential but limited clinical translation. This paper proposes a conceptual multimodal framework combining RFID and computer vision, grounded in robotics and automation principles. The system architecture emphasizes multimodal redundancy, regulatory compliance, and human–machine synergy. While implementation is beyond current scope, this work provides a research blueprint for doctoral scholars aiming to achieve verifiable, deployable, and standard-compliant automation systems for surgical safety. Ultimately, this review bridges engineering and medicine laying a path toward data-driven, intelligent operating rooms capable of achieving zero retained surgical items. The proposed review contributes a conceptual roadmap that robotics researchers and healthcare engineers can extend into experimental validation, thereby strengthening surgical safety automation frameworks.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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