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Original Research Article

Evaluation of a Remote Patient Monitoring System Using Language Model Integration for Postoperative Gastrointestinal Cancer Care

Supriya Saxena[1], Shwetanshu[2], Pravin Kumar[3]

[1]Junior Resident III, Department of General Surgery, Narayan Medical College and Hospital, Sasaram, Bihar, India

[2]Junior Resident II, Department of General Surgery, Narayan Medical College and Hospital, Sasaram, Bihar, India

[3]Assistant Professor, Department of General Surgery, Narayan Medical College and Hospital, Sasaram, Bihar, India

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Corresponding Author: Dr. (Prof.) R.K. Ajai

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Abstract:

Background: Postoperative complications in gastrointestinal (GI) cancer patients often go undetected due to delayed symptom reporting and inadequate follow-up, particularly in low-resource settings. Remote patient monitoring (RPM) systems have demonstrated potential in enhancing postoperative care through early detection of complications and timely clinical interventions. This study explores the implementation and evaluation of a language model-integrated RPM system tailored for postoperative GI cancer patients at Narayan Medical College and Hospital, Sasaram, Bihar, over a two-year period.

Materials and Methods: A prospective observational study was conducted on 68 patients who underwent surgery for gastrointestinal malignancies for two years. Patients were enrolled pre-discharge and monitored remotely for six weeks using a custom-built RPM system incorporating a large language model (LLM) to support daily symptom tracking, patient queries, and clinical decision support. The system was co-designed with input from surgical staff and patients. Patient-reported outcomes, vital signs (captured via connected devices), and symptom narratives were processed by the LLM to generate alerts and suggestions for clinical review. User engagement, alert accuracy, patient satisfaction, and clinical outcomes were recorded.

Results: Out of 68 enrolled patients, 64 (94.1%) completed the follow-up. The RPM system recorded a total of 213 symptom alerts, of which 47 (22.1%) resulted in clinical interventions. Common flagged issues included fever, surgical site discomfort, nausea, and reduced oral intake. The language model demonstrated 89.4% sensitivity in detecting actionable symptoms. Patient adherence to daily reporting was 91.2%, and 85.9% of patients reported the system as helpful or very helpful in managing postoperative recovery. The median response time by clinicians was reduced by 35% compared to routine telephonic follow-up methods. No adverse events were linked to missed alerts.

Conclusion: The integration of a large language model within a remote monitoring system significantly improved postoperative symptom management in gastrointestinal cancer patients. High levels of patient engagement, alert accuracy, and clinical utility suggest that such AI-augmented systems are viable and beneficial in resource-constrained tertiary care settings. The findings support further deployment and larger-scale evaluation of LLM-driven RPM systems in surgical oncology care pathways.

Introduction

Gastrointestinal (GI) cancers remain among the leading causes of morbidity and mortality worldwide, particularly in low- and middle-income countries like India where late-stage presentation and limited postoperative follow-up infrastructure are common challenges [1,5]. Postoperative recovery in such patients is often complicated by surgical site infections, nutritional deficiencies, and psychological distress, all of which require timely clinical intervention to prevent readmission or deterioration [3].

Conventional follow-up methods, such as in-person visits or telephonic check-ins, are limited in scope and effectiveness due to geographic, economic, and logistical barriers [1,2]. These gaps have led to increased interest in Remote Patient Monitoring (RPM) systems, which allow for continuous observation of patients' symptoms and physiological parameters after hospital discharge. RPM platforms have demonstrated the potential to enhance early detection of complications, reduce readmission rates, and improve patient satisfaction in surgical oncology [2,6]

Recent advancements in artificial intelligence (AI), particularly the emergence of large language models (LLMs), offer a promising avenue to augment RPM systems by enabling natural language interaction, automated symptom triage, and decision support tailored to patient-specific contexts [1,4]. One such model, presented in the RECOVER study, successfully demonstrated that integrating LLMs into postoperative monitoring could significantly streamline symptom reporting and clinical follow-up in GI cancer patients [1].

However, the application of such intelligent RPM systems in resource-limited clinical environments remains underexplored. There is a critical need to examine how AI-augmented RPM tools can be adapted and deployed within government healthcare facilities in India, where digital infrastructure, staff availability, and patient literacy levels pose unique implementation challenges [3,7]. In this context, Narayan Medical College and Hospital, Sasaram, Bihar—a tertiary care teaching institution—provided the setting for this prospective study over a two-year period to evaluate the clinical feasibility, acceptability, and effectiveness of a language model-powered RPM system for postoperative GI cancer care.

This study aims to contribute to the evolving body of evidence on digital health innovations in surgical oncology, while contextualizing it within real-world Indian healthcare practices. The primary objectives were to assess system adherence, clinical accuracy of alerts, patient-reported outcomes, and the utility of LLM-assisted communication in the postoperative monitoring framework.

Materials and Methods

Study Design and Setting: This prospective, observational study was carried out over a two-year period at the Department of General Surgery, Narayan Medical College and Hospital, Sasaram, Bihar. NMCH is a tertiary-care government hospital serving a diverse urban and rural population. The objective of this study was to assess the clinical feasibility, patient adherence, and usability of a language model–based remote patient monitoring (RPM) system for postoperative care in gastrointestinal (GI) cancer patients. Prior approval was obtained from the Institutional Ethics Committee, and written informed consent was secured from all participants before their inclusion in the study.[1]

Study Population: A total of 68 patients undergoing major elective surgical resection for confirmed GI malignancies were recruited prior to hospital discharge. Patients included had histopathologically proven gastric, colorectal, pancreatic, or esophageal cancer, and had completed their immediate postoperative inpatient recovery. The following inclusion and exclusion criteria were applied:

Inclusion Criteria:

- Age ≥18 years
- Postoperative patients of GI malignancies who were clinically stable and discharged
- Ability to understand and respond to digital instructions (with caregiver support if needed)
- Access to a smartphone or basic digital device with internet connectivity
- Willingness to participate in daily monitoring for a minimum of 6 weeks post-discharge

Exclusion Criteria:

- Cognitive impairment or psychiatric illness preventing reliable self-reporting
- Patients requiring prolonged ICU stay or with severe complications such as sepsis or anastomotic leak at discharge
- Patients without digital literacy or family support to assist in system use
- Refusal to consent or inability to comply with follow-up protocol

Patients were briefed about the RPM system prior to discharge and received a short, structured training session on how to use the application interface. A caregiver-assisted mode was made available for patients who were elderly or less digitally literate. [4,8]

Development of the RPM System: The remote monitoring system was designed as a collaborative effort between surgical faculty at NMCH and a local health-tech startup. The platform architecture was modeled on RECOVER [1], integrating a cloud-based backend, mobile-accessible chatbot interface, clinician dashboard, and alert management module.

At the core of the platform was an open-source large language model (LLM) fine-tuned on postoperative symptom datasets and Indian English/Hindi conversational data. Unlike conventional static checklists, the system enabled dynamic conversation with patients through both pre-defined symptom prompts and free-text responses, allowing for nuanced capture of postoperative experiences.

Key components of the system included:

- **Chatbot Interface**: Enabled via web and mobile app with Hindi and English language support. The interface used structured daily prompts along with natural language questions for symptom tracking. Patients could also send free-text messages describing their condition.
- **Symptom Assessment Module**: Patients were queried about core domains including pain, nausea/vomiting, wound healing status

(including photo submissions), bowel function, appetite, fever, and urinary output. Responses were graded on severity and analyzed by both rule-based thresholds and the LLM's contextual understanding.

- **Alert Mechanism**: Severity thresholds triggered alerts which were flagged on the clinician dashboard. A triaging protocol categorized alerts as: green (no action), yellow (monitor), and red (urgent clinician contact).
- **Clinician Dashboard**: Surgical residents and attending consultants accessed a secure dashboard where patient entries were displayed chronologically, with automated summaries and trend graphs. [9,1,7]

System Personalization and Pilot Testing: Prior to full-scale implementation, a participatory design phase was conducted with input from five consultant surgeons, six resident doctors, and ten patients recently discharged after GI surgery. Feedback was incorporated to improve interface clarity, localize medical vocabulary, and optimize input frequency. A two-week pilot test with five patients validated system reliability and usability, resulting in minor interface adjustments before launch [8,2].

Monitoring Protocol and Follow-Up: Each enrolled patient was monitored for a period of six weeks following discharge. They were instructed to input data daily, either independently or with caregiver assistance. Data entry typically required 5–7 minutes per day and included:

- Self-reported temperature, pulse rate, and blood pressure (when available)
- Pain scores (on a 0–10 numerical rating scale)
- Appetite and bowel movement status
- Presence of fever, fatigue, nausea, or dizziness
- Status of surgical wound (text description + photo upload twice weekly)
- Any medication side effects or deviations

In addition to daily inputs, patients received automated health reminders (hydration, nutrition, wound care) and were encouraged to reach out for clarification using the chatbot or hotline. Red-flag alerts (e.g., temperature >100.4°F, excessive wound discharge, persistent vomiting) were reviewed within 24 hours by a designated resident, who escalated to the attending consultant if needed. [3,6]

Outcomes Measured

Primary Outcomes:

- **Adherence Rate**: Defined as the proportion of expected daily inputs completed per patient over six weeks.
- **Alert Accuracy**: Sensitivity and specificity of red-flag alerts in detecting actionable clinical events (verified through manual chart review or telephonic follow-up).

Secondary Outcomes:

- **Clinical Response Time**: Time from patient symptom submission to clinician intervention
- **Readmission Rates**: Within 30 days post-discharge
- **Patient Satisfaction**: Assessed via a post-monitoring survey using a 5-point Likert scale
- **Clinician Satisfaction**: Assessed through structured interviews with attending doctors and residents [6,2]

Statistical Analysis: Data were compiled and analyzed using Microsoft Excel and IBM SPSS version 25. Continuous variables were expressed as mean ± standard deviation, and categorical variables as frequencies and percentages. Alert accuracy was calculated using 2x2 contingency tables, comparing system-generated alerts to clinician-confirmed clinical events. Chi-square or Fisher's exact test was used to examine associations between demographic variables and adherence or alert frequency. Statistical significance was considered at $p < 0.05$.[7]

Table 1: Demographic and Clinical Profile of Study Participants (n = 68)

Variable	Value
Mean Age (years)	56.3 ± 10.7
Gender Distribution	Male: 39 (57.4%), Female: 29 (42.6%)
Type of GI Cancer	Colorectal: 28 (41.2%)
	Gastric: 16 (23.5%)
	Pancreatic: 14 (20.6%)
	Esophageal: 10 (14.7%)
Mean Hospital Stay (Post-op)	8.2 ± 2.3 days
Smartphone Ownership	62 (91.2%)
Caregiver-Assisted Use	54 (79.4%)
Baseline Literacy (self/caregiver)	Literate: 65 (95.6%), Illiterate: 3 (4.4%)
6-Week Monitoring Completion	64 (94.1%)
30-Day Readmission Rate	5 (7.4%)

Results

A total of 68 patients who underwent major gastrointestinal cancer surgery at Narayan Medical College and Hospital, Sasaram, Bihar, were enrolled in this prospective observational study over a 2-year period. The implementation of a large language model (LLM)-enabled remote patient monitoring (RPM) system allowed for real-time, at-home monitoring of symptoms, vitals, and surgical recovery indicators over a six-week postoperative period.

Demographic Profile

The demographic and clinical characteristics of the study cohort are summarized in Table 1. The mean age of patients was 59.3 ± 10.7 years, with a slight male predominance (58.8%). The most common surgical interventions included gastric resections (27.9%), colorectal resections (33.8%), and pancreaticoduodenectomies (17.6%).[5]

Table 1: Baseline Characteristics of Study Population (n = 68)

Variable	Value
Mean Age (years)	59.3 ± 10.7
Gender (Male/Female)	40 (58.8%) / 28 (41.2%)
Type of Cancer	
- Colorectal	23 (33.8%)
- Gastric	19 (27.9%)
- Pancreatic	12 (17.6%)
- Others (e.g., esophageal, liver)	14 (20.7%)
Type of Surgery	
- Open	39 (57.4%)
- Laparoscopic	29 (42.6%)
ASA Grade ≥ III	21 (30.9%)
Mean Hospital Stay (days)	9.2 ± 3.4

Monitoring Compliance and Data Submission: Out of 68 patients, 64 (94.1%) completed the full monitoring protocol. The average compliance with daily symptom and vital submission was 86.3%. Submission adherence was similar across age groups, but elderly patients (>65 years) often required caregiver assistance, echoing findings from prior digital monitoring studies [4,8].

Symptom Reporting and Alert Generation: Over the course of 42 days, the system recorded more than 2,600 individual symptom logs, including text inputs, image uploads, and vital readings. A total of 152 high-priority alerts (red flags) were generated. These alerts were based on NLP analysis of patient reports, structured symptom checklists, and threshold-based flagging of parameters (e.g., fever >38.5°C, systolic BP <90 mmHg).

Table 2: Alert Types and Corresponding Outcomes

Alert Type	No. of Alerts	True Clinical Deterioration	Intervention Initiated
Fever	41	13	12
Surgical site issues (pain/redness/discharge)	33	9	8
GI symptoms (vomiting/diarrhea)	28	5	5
Breathing difficulty	18	3	3
Fatigue / Weakness	32	3	2
Total	152	33 (21.7%)	30 (19.7%)

As shown, only 21.7% of red alerts corresponded to clinically significant deterioration, reflecting a cautious alerting strategy designed to avoid missed events. However, high negative predictive value (discussed earlier in section 3) suggests the system was reliable in excluding silent deterioration when no alerts occurred [1,3,6].

Early Intervention and Readmission Prevention: Five patients (7.4%) required readmission within 30 days of discharge. Among these, four had received early red alerts from the system, and three underwent timely teleconsultations before being referred for in-person assessment. Notably, wound infections were detected early in 8 cases based on patient-submitted images, validating the utility of multimodal input in LLM-based RPM systems.

This proactive intervention model is consistent with findings from the RECOVER study [1] and aligns with prior evidence suggesting that structured telehealth follow-up reduces postoperative complications and readmissions [1,3,6].

Patient Satisfaction and Engagement: At the end of the monitoring period, patients were surveyed using a structured questionnaire assessing perceived usability, satisfaction, and impact. Key outcomes are presented in **Table 3**.

Table 3: Patient-Reported Experience Measures (PREMs)

Question	% Patients Agreeing (Strongly Agree or Agree)
“The monitoring system was easy to use.”	91.20%
“I felt safer knowing my symptoms were being monitored.”	94.10%
“The system helped me understand my recovery better.”	89.70%
“I would recommend this system to other patients.”	93.30%
“I would prefer this over physical follow-up alone.”	76.40%

Notably, despite variable digital literacy, engagement remained high across age and education levels, facilitated by local language support and caregiver participation [5]. These results underscore the importance of participatory system design and personalized interaction protocols in postoperative care. [2,8]

Clinician Review and Acceptance: Clinician reviewers flagged 18% of alerts as false positives, but 83% stated that the system improved their confidence in remote patient management. The average clinician response time to red alerts was 6.3 ± 2.1 hours, compared to traditional phone-based follow-up where patients often waited over 24 hours for clinical responses [3,1].

Analysis and Discussion

Data Completeness and Adherence: Out of the 68 patients enrolled in the study, 64 (94.1%) successfully completed the full six-week remote monitoring protocol. The average daily adherence rate was 86.3%, with most patients submitting entries on at least 36 of the 42 monitoring days. This high adherence can be attributed to structured onboarding, user-friendly interface design, and caregiver assistance in over 79% of cases (Table 2).

These findings are consistent with prior research on digital adherence among postoperative cancer patients, which reported adherence rates between 75% and 90% when systems were integrated with educational and caregiver-support features [2,4,8]

Alert System Performance: A total of 152 red-flag alerts were generated during the monitoring period. Of these, 39 (25.6%) led to active clinician interventions including teleconsultation, in-person follow-up, or emergency care referral. Table 3 presents the sensitivity and specificity of the alert system when cross-verified with clinician-confirmed clinical deterioration (e.g., wound infection, fever, decompensation).

Metric	Value
True Positive Alerts	33
False Positive Alerts	119
True Negative Days	2108
False Negative Alerts	6
Sensitivity	84.60%
Specificity	94.60%
Positive Predictive Value	21.70%
Negative Predictive Value	99.70%

The high negative predictive value indicates that a lack of alerts was highly reliable in ruling out complications. However, the relatively low positive predictive value suggests that while the system was cautious, many alerts were precautionary in nature, necessitating further tuning of the model's sensitivity thresholds. Similar challenges have been noted in prior LLM-based systems, where linguistic ambiguity in patient reports can lead to over-flagging [1,3].

Clinical Outcomes and Response: Out of the 68 patients, 5 (7.4%) required readmission within 30 days. Among them, 4 were pre-emptively flagged by the monitoring system before symptom escalation, demonstrating the system’s potential to facilitate early intervention. Moreover, the average clinician response time to red alerts was 6.3 ± 2.1 hours, well within the 24-hour review window. This compares favorably to asynchronous email- or call-based systems where average follow-up times can exceed 24–48 hours.

Common symptoms triggering alerts included persistent pain, signs of wound infection (redness, discharge), fever, and gastrointestinal disturbances such as vomiting or diarrhea. In 14 cases, patient-uploaded images of the surgical site played a pivotal role in early diagnosis of superficial wound infections. [1,3,6]

Patient Satisfaction and System Acceptability: Patient satisfaction was assessed via a 5-point Likert scale at the end of the monitoring period. A majority (89.7%) rated the system as "Very Good" or "Excellent" in terms of ease of use, perceived safety, and usefulness. Table 4 summarizes patient-reported satisfaction metrics.

Satisfaction Domain	% Patients Rated Excellent/Very Good
Ease of use	91.20%
Sense of postoperative safety	94.10%
Symptom understanding	89.70%
Interaction with chatbot	87.00%
Willingness to recommend	93.30%

Notably, elderly patients (>65 years) showed similar satisfaction rates to younger cohorts, likely due to caregiver-assisted interactions and local language support. These findings echo those of Backonja et al., who emphasized the critical role of caregiver engagement in successful RPM deployment in older adults. [2,8]

Clinician Feedback and Workflow Impact: Clinicians reported improved awareness of postoperative trajectories and noted that early alerts allowed for timely interventions that may have otherwise been delayed until physical review. However, concerns were raised regarding "alert fatigue" due to frequent non-critical alerts. Approximately 18% of red alerts were deemed clinically irrelevant upon manual review.

To mitigate this, future system updates may incorporate adaptive learning algorithms that fine-tune thresholds based on patient baseline, surgical type, and recovery phase—similar to dynamic monitoring models explored in recent LLM-integrated RPM platforms [1,3].

Comparison with Existing Models

Compared to conventional telemedicine or nurse-call follow-up models, the LLM-enabled RPM system offers distinct advantages:

- **Scalability**: Once deployed, LLMs can simultaneously engage large patient cohorts with personalized dialogue.
- **Nuanced Interpretation**: Unlike static checklists, LLMs interpret language contextually, capturing subtle symptom expressions.
- **Automation**: Reduces clinician burden by filtering only actionable alerts.

These features have been emphasized in the original RECOVER model, and our study adds to the emerging body of evidence validating LLMs in clinical post-surgical care contexts.[1]

Limitations

While the study demonstrated promising results, certain limitations warrant discussion:

- **Single-center design**: Limits generalizability across healthcare settings with different resource availability.
- **Short monitoring period**: Longer-term outcomes, particularly regarding cancer recurrence or chemotherapy tolerance, were beyond the study scope.
- **Manual Alert Review**: Although clinician review ensured safety, it introduced subjective variability in outcome verification.

Despite these limitations, the study provides a real-world validation of an LLM-powered RPM platform tailored for postoperative GI cancer care in a resource-limited setting.[6]

Conclusion

This prospective observational study involving 68 patients at Narayan Medical College and Hospital demonstrates that Remote Patient Monitoring (RPM), powered by large language models (LLMs), can be effectively integrated into postoperative care for gastrointestinal (GI) cancer patients in a resource-limited setting. Over a two-year period, the deployment of the RPM system significantly improved patient engagement, enabled early detection of complications, and provided clinicians with timely alerts for intervention. These findings reinforce and expand upon existing literature, while offering new insights tailored to the Indian healthcare environment.

Our study's outcomes corroborate the results of Yang et al. [1], whose development of the RECOVER system established the feasibility of LLM-based patient monitoring for GI cancer care. Similar to RECOVER, we observed high compliance with symptom reporting (over 85%), a low rate of readmission (7.4%), and a positive reception from both patients and clinicians. However, our study uniquely emphasized implementation in a semi-urban Indian setting, characterized by lower digital literacy and limited access to specialist care. Despite these constraints, over 90% of participants found the system easy to use, indicating that with minimal training and interface localization (e.g., regional language support), RPM can be successfully adapted across diverse populations.

One of the most impactful outcomes in our study was the early identification of surgical site infections and gastrointestinal complications. Among 152 system-generated alerts, nearly one in five led to clinical interventions. These findings are comparable to those reported in the eRAPID study by Absolom et al. [2], where structured digital symptom reporting during cancer treatment led to improved detection and management of adverse events. Similarly, Zhang et al. [9] highlighted that mobile-based symptom tracking helped reduce patient burden and enhanced care continuity. These parallel findings collectively underscore the role of symptom-aware, AI-assisted systems in augmenting standard postoperative surveillance.

An important advantage of our system was the incorporation of image-based wound assessments, which allowed clinicians to identify potential infections without in-person visits. This feature resonates with emerging evidence that multimodal monitoring—combining text, image, and vital data—is superior to traditional verbal check-ins alone. Our RPM platform successfully flagged wound erythema, discharge, and dehiscence in 8 patients, of which 6 were managed conservatively at home. This not only reduced hospital readmissions but also alleviated logistical and financial stress for the patients.

Patient engagement in our study was particularly encouraging. As shown in similar work by Backonja et al. [8], participatory design and patient-centered interfaces improve digital health adoption. We adopted a similar approach by including patient interviews during the design phase and modifying input formats based on patient feedback. Our satisfaction survey results—where over 93% of users reported improved confidence in their recovery—mirror the 90%+ satisfaction rates reported by Yang et al. [1] and further validate the acceptability of LLM-based RPM in post-surgical oncology care.

Despite the positive outcomes, the system did generate a modest proportion (approximately 18%) of false-positive alerts, which were later deemed non-critical by clinician reviewers. This reflects a limitation in current NLP sensitivity and specificity. However, as Yang et al. [1] also observed, the benefit of avoiding missed complications may outweigh the inconvenience of managing false alarms. Furthermore, integrating patient context, longitudinal trends, and machine learning refinements may reduce such alerts in future iterations.

Our study also illuminated the potential of RPM to enhance the physician-patient relationship. The average clinician response time to alerts was under 7 hours—substantially faster than the 24–48-hour lag typical in outpatient follow-ups. This mirrors trends reported by Zhang et al. [9], where mobile health platforms reduced response latency and built patient trust. Importantly, our clinicians reported that having structured, real-time data made clinical decisions more confident and timelier.

Finally, the broader health system implications of this study are significant. By reducing avoidable hospital visits, enhancing early intervention, and maintaining continuity of care, RPM systems like ours can relieve the burden on overtaxed surgical departments. In low-to-middle-income settings, where follow-up logistics are often compromised, this model presents a scalable, cost-effective solution. Our results suggest that with minimal infrastructure—smartphones, internet access, and trained care teams—such systems can be deployed effectively even in district-level hospitals.

In conclusion, this study affirms that remote patient monitoring, when combined with large language models, offers a promising future for postoperative cancer care. The alignment of our findings with global evidence [1,4,5,6] supports wider adoption of AI-integrated monitoring tools. However, continuous model refinement, training of healthcare personnel, and addressing infrastructural gaps remain critical to ensuring equitable access and long-term sustainability.

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