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Artificial intelligence (AI)-assisted full-course case management for primary liver cancer: System design, preliminary implementation, and practical considerations

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Abstract: Primary liver cancer presents substantial management challenges across the surgical trajectory, including high recurrence rates, prolonged rehabilitation, and fragmented post-discharge care. This correspondence presents a multidisciplinary physician–nurse co-led, artificial intelligence (AI)-assisted full-course case management model grounded in just-in-time adaptive intervention (JITAI) theory. The model spans four phases—peri-admission, perioperative, post-discharge home-based care, and long-term follow-up—supported by an intelligent platform enabling automated decision triggering, symptom monitoring, tailored health education, and intervention matching. A pilot study with 25 patients was conducted from March to May 2026 at a tertiary cancer hospital in Tianjin, China. Preliminary results revealed improvements in antiviral medication adherence (80–96%), targeted therapy adherence (96–100%), and satisfaction (99.8%), with reductions in missed follow-ups and symptom reporting delays. Multicenter controlled studies need to be conducted to evaluate this model's effectiveness, cost-effectiveness, and long-term sustainability.

***Keywords*:** artificial intelligence, case management, just-in-time adaptive intervention, primary liver cancer, full-course management

1. Introduction

According to data from the National Cancer Center of China, an estimated 367,700 new cases of primary liver cancer were reported in 2022, representing 42.5% of global cases and ranking fourth among new cancer diagnoses nationally (*1*). Primary liver cancer accounted for 316,500 deaths that year, making it the second leading cause of cancer death in China. The overall 5-year relative survival rate remains at 14.4%, with over half of patients diagnosed in intermediate or advanced stages (*1*). For patients who are eligible for surgery, hepatectomy is a crucial curative treatment modality (*2*), and patients who undergo resection require continuous management spanning preoperative preparation, perioperative care, post-discharge rehabilitation, and long-term surveillance (*3*).

There are major gaps in the full-course management of surgically treated liver cancer patients. Current care pathways often place greater emphasis on in-hospital treatment decisions, whereas preoperative preparation, post-discharge rehabilitation, and recurrence monitoring may receive less systematic attention (*4*). Nurse-led follow-up may also be insufficiently integrated with clinical workflows, which may contribute to delayed symptom reporting, missed appointments, declining medication adherence, and delayed detection of complications (*5*). Full-course management models that integrate multidisciplinary collaboration with health information technology are evolving toward data-driven, personalized, and continuous care delivery (*6-8*).

Artificial intelligence (AI) offers promising tools for long-term cancer care, including remote monitoring, intelligent follow-up, risk stratification, tailored health education, and clinical decision-making support (*9,10*). Just-in-time adaptive intervention (JITAI) theory provides a framework for designing dynamic interventions based on tailoring variables, decision points, decision rules, intervention options, and proximal and distal outcomes (*11*). Integrating JITAI with AI platforms may help operationalize the delivery of the right intervention to the right patient at the right time (*12*).

Guided by JITAI theory, we developed an AI-assisted full-course case management model for patients undergoing surgery for primary liver cancer. In this correspondence, we describe the system design and AI-enabled functions, and we present preliminary feasibility findings from a single-center pilot study.

2. An AI-assisted full-course case management model for primary liver cancer based on JITAI theory

From December 2025 to February 2026, our team developed a multidisciplinary physician–nurse co-led, AI-enabled, multidisciplinary full-course case management program for patients undergoing surgery for primary liver cancer, grounded in JITAI theory. The development team consisted of three hepatobiliary oncologists, one head nurse with 18 years of liver cancer nursing experience, three specialist oncology nurses, and one software engineer; of these members, two oncology nurses served as case managers. The program was informed by our previous work on liver cancer perioperative and follow-up management needs, a comprehensive literature review, group discussion, and two rounds of Delphi expert consultation.

The final program spans four phases—peri-admission, perioperative care, post-discharge home-based care, and long-term follow-up—and is structured around key management nodes, including admission preparations, preoperative assessment, postoperative rehabilitation, discharge planning, medication management, symptom monitoring, appointment scheduling, and long-term surveillance. These are operationalized into 19 decision nodes supporting continuous, stratified, and individualized care.

The program's distinguishing feature is the systematic translation of JITAI's core components—tailoring variables, decision points, decision rules, and intervention options—into a platform-based workflow. Baseline tailoring variables include demographics, disease etiology, nutritional risk scores, Child–Pugh classification, family history, and medical history. Process tailoring variables encompass dynamic data generated across the care trajectory, including high-risk screening results (nutritional, fall, and pressure injury risk), laboratory and imaging findings, patient-reported symptoms, and medication adherence. Decision points correspond to clinically significant time points across all four phases. At each decision point, the platform automatically generates reminders, risk alerts, and intervention recommendations by integrating preset rules, risk tags, and AI-assisted analysis functions, which are then reviewed by specialized nurses and a multidisciplinary team.

3. Platform architecture and AI-enabled functions

The final program was deployed on the Full-Course Case Management Platform operating within our institution's Internet hospital network.

The intelligent information-based management platform and the final program are presented in Figure 1. The platform's functional modules and information infrastructure include AI-driven analytics, knowledge graphs, automated response engines, semantic processing, intelligent interaction interfaces, patient stratification algorithms, and Internet hospital operations. It is also integrated with institutional systems, including the hospital information system (HIS), laboratory information system (LIS), picture archiving and communication system (PACS), electronic medical records, and online payment systems, thereby enabling seamless data flow across the care continuum.

The platform operates around core processes of patient screening and assessment, case enrollment, care plan allocation, plan implementation, and management evaluation. Through coordinated patient and provider portals, it enables stage-specific, precision-oriented case management throughout the disease trajectory.

3.1. Patient portal

The patient portal supports self-directed health management across six functional categories: *i*) individualized records with automated synchronization and dynamic updating of diagnostic, treatment, and care bundle information spanning the perioperative, discharge, and follow-up phases; *ii*) real-time synchronization of laboratory and examination results, with capacity for manual entry of home-based health data shared with the provider portal; *iii*) multimodal patient–provider communication *via* text, voice, and images across all treatment phases, with records retained; *iv*) stage-appropriate health education in text, graphic, and video formats; *v*) intelligent follow-up scheduling with automated reminders, secondary alerts for overdue tasks, and data feedback to providers; and *vi*) recovery stories, experience sharing, and peer support groups to facilitate psychological well-being.

3.2. Healthcare personnel portals

The healthcare personnel portals—serving oncologists, nurses, nutritionists, and other team members—support efficient management and precision intervention. Providers access patient records, risk assessments, and care plans in real time, with group-based management by treatment stage, age, family history, medication regimen, and risk labels to facilitate differentiated care. Communication features include text, image, and voice messaging with quick-reply templates, ensuring both efficiency and traceability.

For follow-up management, the portals enable individualized plan customization, automatic progress tracking, and alerts for incomplete tasks, abnormal

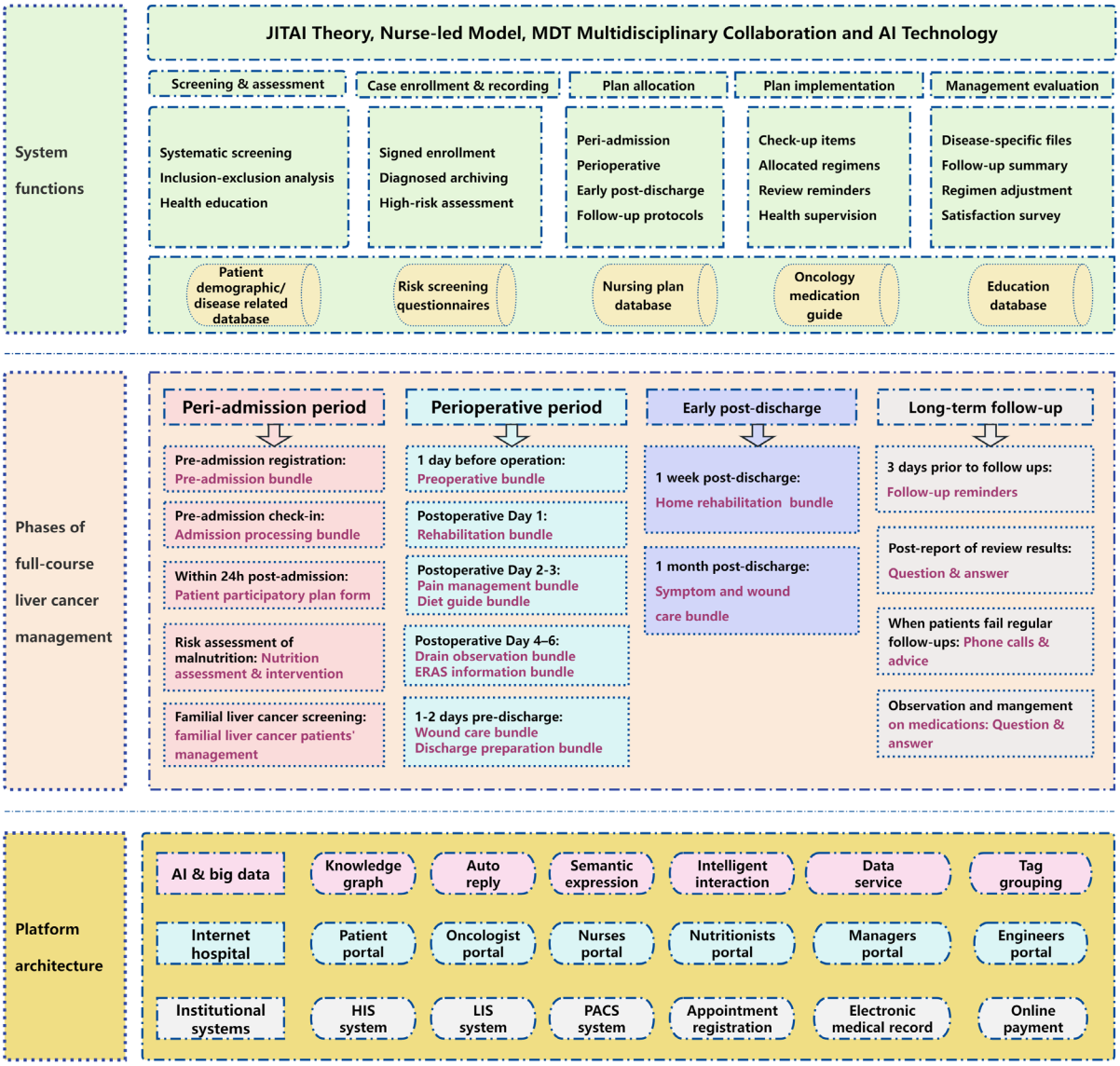

Figure 1. AI-assisted full-course case management model for primary liver cancer patients based on just-in-time adaptive intervention theory. *Abbreviations*: HIS, hospital information system; LIS, laboratory information system; PACS, picture archiving and communication system.

symptom feedback, and high-risk situations. For health education, evidence-based content is delivered on demand with reading status tracking and secondary reminders for non-engaged patients. For risk management, the platform integrates data on pain, nutrition, liver function, medication adherence, appointment completion, and symptom changes, pushing alerts to providers when anomalies are detected to facilitate earlier risk identification.

3.3. AI-assisted decision triggering and risk alerts

AI represents a key differentiating feature of this model. Drawing on Internet hospital data and institutional information system connections and integrating natural language processing, risk prediction algorithms, and label-based grouping, the platform continuously analyzes patient-reported content and clinical data. AI-assisted functions identify risk signals within patient-reported symptoms, match corresponding educational content, trigger medication or appointment reminders, and flag patients requiring priority attention.

Importantly, AI serves as an assistive role rather than replacing clinical judgment. High-risk alerts, intervention adjustments, and treatment-related recommendations require review and confirmation by case managers, specialist nurses, or physicians. This design improves efficiency while preserving humanistic care, professional judgment, and meaningful patient–provider communication.

4. Preliminary practice outcomes

From March to May 2026, we conducted a pilot study with 25 patients undergoing surgery for primary

liver cancer who received individualized full-course management *via* the intelligent platform. Our preliminary observations suggested this model's feasibility: antiviral medication adherence increased from 80 to 96%, oral targeted therapy adherence increased from 96 to 100%, and patient satisfaction reached 99.8%. Missed appointments and delays in symptom reporting—common in conventional management—also decreased.

From the patient's perspective, the platform provided timely reminders for preoperative preparations and examinations, promptly addressed preoperative questions, and helped patients gain a comprehensive understanding of the perioperative process and prevention of complications. It also simplified follow-up workflows, making appointment reminders, medication guidance, rehabilitation education, and symptom reporting easier. For postoperative patients requiring long-term surveillance and home monitoring, the platform offered continuous care support that may enhance the capacity for self-management.

From the perspective of healthcare personnel, this AI-assisted management system reduced certain manual workload components—such as patient registration, data compilation, routine notifications, and repetitive follow-up tasks—thereby allowing providers to focus more effectively on identifying high-risk patients, delivering individualized education, and engaging in meaningful clinical communication. In addition, the standardized workflow, grounded in the JITAI framework, helped reduce inter-provider variability and enhanced the traceability of patient management.

A point worth noting is that these results only represent our preliminary practice findings from 25 cases rather than confirmatory evidence of clinical effectiveness. Our study's limitations include the small sample size, short observation period, and absence of a control group. The impact of this model on liver cancer recurrence, survival, complication rates, provider workload, and cost-effectiveness remains to be determined through rigorous evaluation.

5. Practical considerations and future directions

Although this model remains in a preliminary stage, we believe that AI-assisted full-course case management for primary liver cancer offers practical value in several key respects.

First, at the technological level, AI facilitates the operationalization of JITAI theory. While JITAI emphasizes dynamic adaptation and precision intervention, conventional models are limited by subjective judgment, inefficient manual screening, and insufficient standardization. By drawing on Internet hospital platforms, natural language processing, risk prediction, and automated decision triggering, management can shift from a reactive response to proactive anticipation (*13*).

Second, at the management level, this model has the advantages of multidisciplinary physician–nurse coordination combined with multidisciplinary collaboration. Cancer chronic disease management frequently suffers from a disconnection between oncologists and nurses, disciplinary fragmentation, and gaps between inpatient and outpatient care (*14*). Our model positions case managers and specialist nurses as primary implementers who coordinate with physicians, dietitians, psychologists, and other team members (*15*). Monitoring, follow-up, rehabilitation, and education are integrated through the AI platform, bridging the gap between in-hospital treatment and home-based care.

Third, at the clinical practice level, AI assistance must adhere to a humanistic-first principle. Postoperative patients require not only surveillance reminders and risk alerts but also ongoing support with regard to their disease uncertainty, fear of recurrence, and treatment burden. Intelligent management should augment rather than replace professional judgment and communication, helping providers identify needs earlier, respond to risks more rapidly, and deliver more continuous care.

Fourth, several challenges warrant acknowledgment. Disparities in digital literacy may affect equitable platform access; elderly patients or those with severe symptoms may require caregiver assistance. Provider trust in AI-assisted decision-making needs to be gradually cultivated through sustained use. For symptom recognition, risk prediction, and individualized recommendations specifically, clear mechanisms for manual review, adverse event protocols, and delineation of responsibilities must be established.

Fifth, future optimization should address AI algorithms, stratification rules, health education knowledge bases, and provider workflows, with further integration across HIS, LIS, PACS, electronic medical records, and Internet hospital systems. With regard to research design, multicenter controlled studies with long-term follow-up need to be conducted to evaluate impacts on follow-up adherence, medication adherence, symptom reporting timeliness, recurrence detection, complication identification, patient experience, provider workload, cost-effectiveness, and survival outcomes.

Lastly, this framework may also have broader applicability. Its adaptation to other perioperative cancers—including lung, gastric, and colorectal—could be explored and potentially expanded to high-risk population screening and life-course health management, providing a reference for smart hospital development and refined cancer care delivery.

6. Conclusions

The AI-assisted full-course case management model for patients with primary liver cancer, guided by JITAI theory, offers a potential pathway for improving continuous care across in-hospital and out-of-hospital settings. Through

multidisciplinary physician–nurse coordination and collaboration, platform-based management, and AI-assisted alerts, the model integrates symptom monitoring, medication reminders, appointment management, health education, and risk identification within a unified framework. Our preliminary single-center pilot study involving 25 patients suggests that this model has preliminary feasibility and patient acceptability and may help improve medication reminders, follow-up management, and symptom feedback. However, its clinical effectiveness, safety, cost-effectiveness, and long-term sustainability need to be validated in larger, multicenter, controlled studies. Future efforts should further integrate AI technology with full-course case management while maintaining humanistic care and professional judgment.

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