

An Approach of Sandbox Technology for Improving the Security in Online Healthcare Systems

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ABSTRACT

Medical Surgical procedures, especially those in neurology, are high risk stakes, intricate situations that require a significant mental investment from surgical teams. Despite being intent the security is the serious problem in the online Healthcare systems. Although practice and education can improve cognitive abilities, there are still few opportunities for surgical training because of patient safety concerns. We propose medical SurgBox, an agent-driven sandbox framework designed to methodically improve surgeons' cognitive abilities in realistic surgical simulations in order to address these cognitive difficulties in surgical training and practice. Our SurgBox specifically uses Multi Large Language Models (MLMs) with customised Retrieval-Augmented Generation (RAG) to simulate a variety of surgical jobs in an authentic manner, providing realistic training settings for purposeful practice. To reduce the cognitive strain on surgical teams during surgery, we specifically developed Surgery Copilot, an AI-driven assistant that actively coordinates the surgical information stream and aids in clinical decision making. Through the use of a unique Long-Short Memory mechanism, our Surgery Copilot is able to successfully strike a balance between providing prompt procedural help and having extensive surgical expertise. Our Med SurgBox framework's ability to improve surgical cognitive capacities and assist clinical decision-making has been validated through extensive tests utilising actual neurosurgical procedure records. Our SurgBox architecture improves surgical education and practice by offering an integrated training and operational support solution to solve cognitive obstacles, which has the potential to revolutionise surgical results and healthcare quality.

Keywords: Healthcare Systems, Neurosurgery, Surgery Copilot, Surgery Simulation, and Multi Large Language Models

1. INTRODUCTION :

Medical Surgical operations are complex and high-risk scenarios in medicine, with results affecting therapeutic efficacy and life quality [1]. Neurosurgical procedures need complex processes and decision-making during multiple stages [2], [3]. Surgical teams face significant cognitive challenges when processing various information streams and maintaining precision in their activities due to procedural complexity. Research indicates that high cognitive demands during surgery can increase the chance of surgical errors, potentially leading to negative patient outcomes [4-5].

While purposeful instruction has been shown to improve cognitive ability [6], it is important to prioritise safety and ethical practices. Medical Surgeons have significant limitations in practicing actual surgical procedures, particularly for high-risk or unusual illnesses [7]. Advanced AI algorithms can help coordinate surgical information and improve clinical decision-making, addressing cognitive problems in both training and operations.

AI breakthroughs have led to an increasing interest in creating safe and controllable virtual environments using generative agents to model real-world circumstances. Small ville [8] uses

architectural and interaction patterns to simulate human behaviour, whereas MetaGPT [9] offers collaborative software engineering solutions based on efficient human workflows. Pioneer experiments in healthcare, such as AI Hospital [10] and MedAgents [11], have used Multi large language models (MLMs) to simulate clinical responsibilities, interactions, and decision-making. Agent Hospital [12] intends to develop AI systems with interactive pipelines for diverse medical settings. Based on MLM-based simulation methodologies, we developed medical SurgBox, an agent-driven framework that improves surgeon cognitive abilities through immersive surgical simulations. Our framework utilises MLM agents with specialised Retrieval-Augmented Generation (RAG) banks to accurately simulate surgical positions such as chief surgeon, assistant surgeon, nurses, and anaesthetists. Practicing high-fidelity simulations can improve surgeons' ability to comprehend complex information and make vital judgements under pressure. Experimenting with various surgical scenarios in a safe environment strengthens cognitive schemas, allowing for more effective information processing and decision-making during surgeries.

To enhance the training benefits of Medical SurgBox and minimise cognitive load during live surgeries, we created the Surgery Copilot, an AI-powered assistant that supports surgical decision-making and workflow management in real-time. This specialised agent assists surgeons in maintaining situational awareness by organising and filtering information streams, providing contextual assistance, and proactively recognising possible dangers before they become difficulties. We added a Long-Short Memory feature to the Surgery Copilot.

Short Memory allows for leveraging knowledge from multiple surgical instances while focussing on the most important information. Surgery Copilot's balanced approach provides focused help during the process, decreasing cognitive stress on surgical teams and perhaps enhancing patient outcomes.

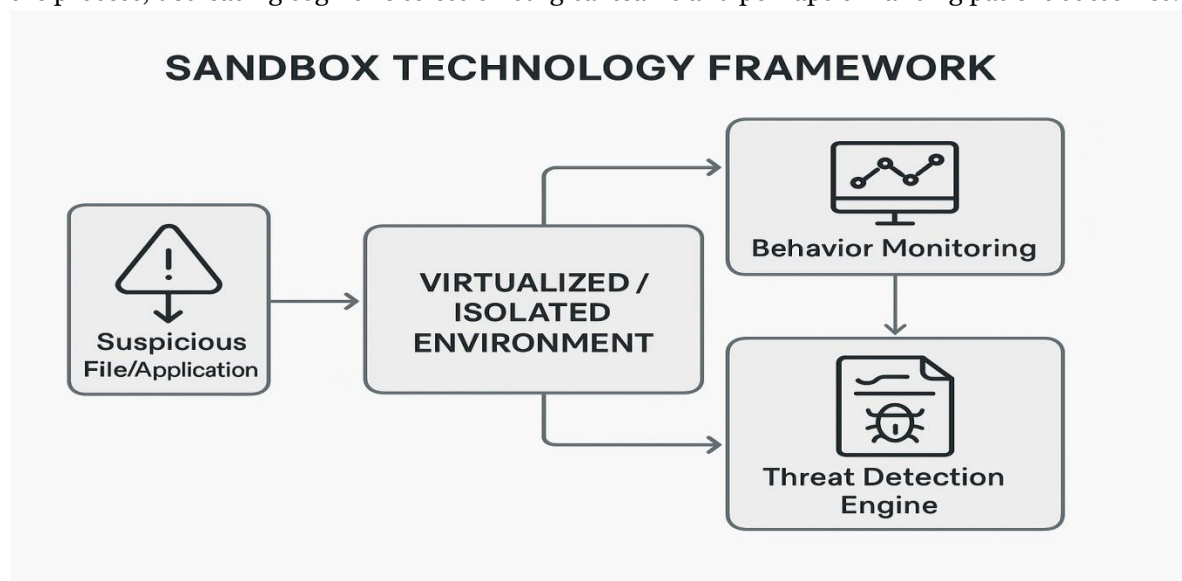


Fig 1: Sand Box Framework

The sandbox Framework mentioned in the (Fig 1) has the it owns integrated approach, we conducted extensive tests using real neurosurgical procedure records from 400 patients with varying diseases, including pituitary adenomas. The Medical SurgBox outperforms current MLMs with accuracy rates of 900% and 93.02% in surgical path selection and planning tasks, respectively. Our technology excels at identifying specific problems, maintaining good performance across surgical phases, and managing complex scenarios with smaller sample sizes. Our technique can improve surgical cognitive performance through both preparation and real-time help, as demonstrated by these data. Our

solution improves surgical results and healthcare quality by developing cognitive skills through high-fidelity simulations and intelligent operation support.

The contributions to this study are summarised as follows:

- Medical SurgBox is an agent-driven sandbox framework that improves surgeons' cognitive powers through immersive simulations and purposeful practice.
- Our innovative role-playing technique uses MLM agents with specific RAG knowledge to accurately replicate the behaviours and interactions of all surgical team members.
- Our AI helper, Surgery Copilot, uses Long-Short Memory to coordinate surgical teams, provide assistance, and optimise learning throughout simulated procedures.

SurgBox has been shown to improve surgical teams' cognitive and clinical decision-making abilities in real-world neurosurgical procedures (Surgery Copilot).

The sand box Technology Framework consists of the following layers with the components listed below.

- Input Layer (suspicious file/app)
- Virtualized/Isolated Environment
- Behaviour Monitoring
- Threat Detection Engine
- Reporting & Analysis Output

II. RELATED WORK

A. MLM-Based Multi-Agent Framework

Recent studies [11] shows that MLMs may model real-world dynamics and interact in competitive simulations, particularly in domains like epidemiology, sociology, and economics. MLM-based agents improve predictive and analytical models by replicating human decision-making processes [14]. Current agent-related studies often replicate human behaviour to create instructions [15] and allow complicated interactions and decision-making in various contexts [16], [17]. For example, game simulation [18] demonstrates the capability of massive Models can participate in complicated communication games. Software businesses [19] use Standard Operating Procedures (SOPs) to coordinate multi-agent systems via LLMs, thereby implementing meta-programming technologies. Social simulation [20] uses LLM-based agents to simulate social networks, making it a ground breaking approach.

Although MLMs have demonstrated potential for mimicking real-world dynamics, further research is needed in certain areas. Current medical and health simulation research typically focusses on replicating therapeutic tasks rather than the entire patient treatment process [21]. This study intends to close a research gap by using LLMs to improve medical decision-making, diagnosis, and treatment regimens.

B. Healthcare and Data Agents:

Healthcare data is very sensitive and precious, making it one of the most Industries require safe data storage and tailored access to meet their objectives. Secure data storage and effective access control are crucial for ensuring the privacy and security of electronic health information, particularly in Healthcare 4.0.

Healthcare data can be maintained in two formats: electronic health records (EHRs) and personal health records (PHRs). EHRs are commonly used by hospital staff to collect and maintain clinical information about patients [22, 23]. Personal health records (PHRs)

empower individuals to access and manage their health information.

This raises privacy and security concerns as these systems are typically not enclosed and can be accessed from any location. Both methods of data storage might be coupled or distinct.

Open-source fundamental models have tremendous potential, and research is now focussing on role-playing models. These models can adapt to complicated contexts [22], retrieve crucial information from long-term memory, and exhibit ongoing learning skills. [23] describes a linguistic agent role-playing system that uses a modular method for memory processing, decision-making, and interactive learning in the environment. [24] improves the agent's capabilities by fine-tuning to a role-specific corpus. [25] provides a comprehensive evaluation approach for role-playing agents, ranging from individual to group assessments. [26] Improves the agent's role-playing ability by incorporating retrieval procedures. AI Hospital [10] studies the use of LLMs as clinical diagnosticians in real-time interactive consultations. However, maintaining strong diagnostic capability is a huge task. The MedAgent-Zero [12] technique simulates disease onset and progression using a knowledge base and LLM. This allows doctors to learn from both successful and unsuccessful situations. However, its usefulness in complex medical circumstances is limited.

Our research aims to bridge the gap in the use of intelligent agents in clinical surgery.

Our comprehensive clinical simulation system can manage complex surgical situations and simulate risk outcomes based on many clinical parameters. This approach helps intelligent agents learn from both successful and suboptimal surgical situations, synthesise lessons from failures, and constantly improve their skills, leading to better surgical decision-making and execution. This clinical surgery simulation system [27] attempts to improve the use of LLM technology in medicine and help practitioners make better decisions.

III METHODOLOGIES :

This section introduces Medical SurgBox, a framework that simulates the complete surgical process, as illustrated in Figure 1. Medical SurgBox's role-playing system properly represents the varied medical experts in an operating room. This technique accurately represents the complex relationships and collaborative dynamics required for successful surgical procedures. Section III-B introduces the Surgery Copilot, a key SurgBox feature designed to improve surgical safety and inter-professional collaboration efficiency. The Surgery Medical Copilot now includes a sophisticated long-short memory system that enhances surgical planning and interactions

A. Role Playing for SurgBox:

The Medical SurgBox creates surgical roles and uses MLM-based agents to correctly replicate operating dynamics establish key clinical duties for patients, chief surgeons, surgeon assistants, scrub nurses, ward nurses, room nurses, and anaesthetists. A personalised LLM generates the information and actions for each role, ensuring realistic and context-aware interactions. The characters engage in communication with their counterparts while doing actions based on the stage task theme and progression. The medical SurgBox uses a complex role-playing mechanism to simulate a surgical environment. This is accomplished by specified role-specific knowledge bases, contextual awareness, and dynamic interaction logic. Each function, such as Chief Surgeon or Anaesthesiologist, has a database with domain-specific terminology, processes, and responsibilities. This enables the MLM to engage in role-appropriate conversations and behaviours. The system's contextual awareness watches surgery progression and ensures that each role's reactions are appropriate for the present stage. Predefined interaction rules control communication patterns and hierarchical structures found in real-world settings. An operation room. The MLM generates dynamic responses based on previous discussions and present situations, allowing for a natural flow of discourse. Integration. By using specialised medical and surgical jargon improves the authenticity and professionalism of discussions.



Fig 4: Role-play for SurgBox

Each job is assigned distinct tasks Figure(2) and obligations, such as the anaesthetist checking vital signs and the nurse preparing instruments. The system uses event-triggered processes, where certain discussions or actions might trigger certain events, such as changes in patient status, influencing replies from other roles. The LLM ensures conversational coherence by preserving and applying earlier information in subsequent talks.

Role-specific knowledge enhancement. To improve the simulation's authenticity, effectiveness, and adaptability, we use augmented domain knowledge retrieval and generation (RAG). Create a specialised medical knowledge base for each essential job in the operating room. The specialised knowledge bases cover both broad medical information and the specific expertise needed for each function in the procedure.

The Doctor in the MLM agent and the chief surgeon is knowledgeable about surgical techniques, anatomical information, and complication treatment methods, while the anaesthetist focuses on anaesthetic drug properties and patient monitoring protocols. The nurse provides information on instrument preparation, aseptic techniques, and patient care. This knowledge base design allows virtual roles to access relevant and specialised knowledge during simulations, resulting in more accurate decision-making and actions.

C. The Medical Surgbox Techniques:

The Medical SurgBox divides operations into stages and subtasks for collaborative discussion, several rounds of interaction, and solution proposition and verification. The simulation covers the complete surgical process, including three stages: preoperative, intraoperative, and postoperative. The stages depict the patient's progression through essential phases such as transport, anaesthesia, surgical preparation, surgery, and postoperative care. Each phase requires the presence of matching medical specialists. This holistic technique simulates surgical procedures, including preoperative preparation and postoperative care. It allows medical teams to practise and optimise the entire process in a Virtual environment.

Consider a hypothetical neurosurgical procedure using MedSurgBox: During the preoperative phase, the Chief Surgeon evaluates the patient's MRI scans and medical history and

works with the Anaesthetist to create a personalised anaesthesia strategy. The Scrub Nurse prepares surgical tools according to the procedure needs. During the intraoperative phase, the Chief Surgeon follows the surgical plan and communicates with the Surgical Assistant for any necessary auxiliary operations. The anaesthetist watches the patient's vital signs and adjusts anaesthesia as needed, while the scrub nurse prepares and distributes necessary instruments. After surgery, nurses monitor vital signs and manage pain as directed by the anaesthetist to ensure the patient's recovery. Each position uses their specialised knowledge to make informed decisions and actions, creating a realistic and instructional simulation of the surgical experience.

The SurgBox system has the revolutionary Surgery Medical Copilot, an advanced MLM-based assistance that optimises the surgical process. This Copilot coordinates, plans, and provides support for virtual operating rooms. Role playing. The Surgery Copilot is a sophisticated virtual assistant that integrates easily into the SurgBox ecosystem, improving surgical performance and outcomes. Figure 4 illustrates the major tasks of this system, which include real-time guidance, decision assistance, and adaptive learning. The Copilot continuously monitors surgical procedures and analyses several roles to provide contextual insights and recommendations. It provides step-by-step advice and notifications.

Alerts the team to potential dangers and recommends appropriate approaches based on the surgical environment and patient-specific characteristics. The Copilot uses a large database of surgical experiences.

D. Advanced Medical Research in online Health care:

Our team stays up-to-date on medical research and best practices, providing evidence-based suggestions for each surgical circumstance. The Copilot integrates with other SurgBox components to improve team coordination, optimise resource utilisation, and give real-time risk assessments. The natural language interface facilitates communication with the surgical team and provides fast access to pertinent information, including patient history and surgical plan. This comprehensive support system helps surgeons make educated decisions quickly, potentially lowering procedural time and increasing patient outcomes. It also serves as a helpful training tool for surgical trainees.

E. Interaction of Copilot and Roles.

The Surgery Copilot ensures efficient workflow management and team coordination during three crucial phases of the surgical process.

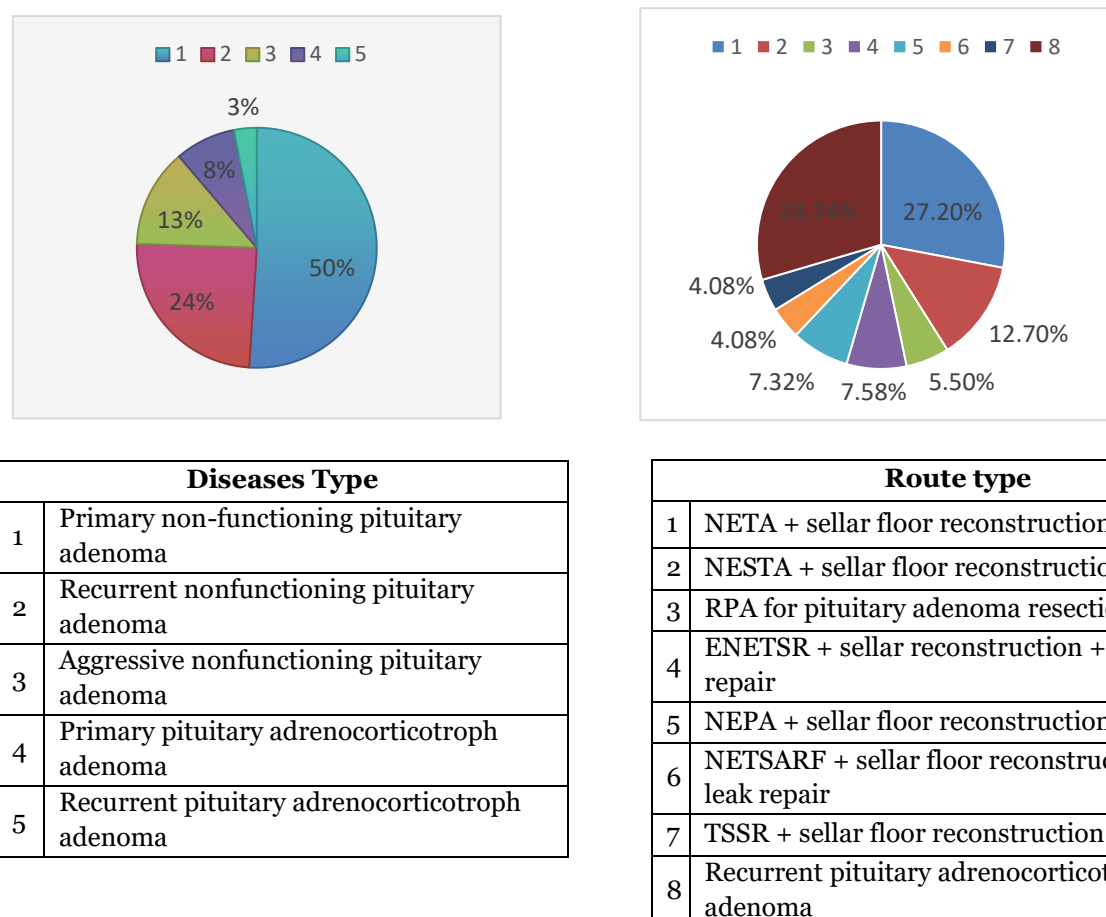
During the preoperative phase, the team works with surgeons to improve surgical plans, anaesthetists to discuss anaesthesia strategies, and nurses to prepare the operating room.

During the intraoperative phase, the Copilot provides real-time guidance to surgeons, assists scrub nurses with instrument preparation and aseptic techniques, monitors patient vitals, and coordinates with circulating nurses on equipment and supply management. During the postoperative period, the Copilot helps design care plans, monitor complications, implement pain management measures, and arrange debriefing sessions. The Copilot's tailored interactions with each role throughout the surgical process improve communication, coordination, and patient care, leading to increased efficiency and teamwork.

For a simulated neurosurgical procedure in Med SurgBox, perform these steps:

- Preoperative: The Copilot analyses the patient's MRI scans and medical history to create a complete surgical plan. They also inform the team about anticipated obstacles and guide instrument preparation.

- During essential tumour resection, the Copilot offers real-time guidance to the surgeon. moni-Route type



Fig(4) – Disease Type and Route Types

- Postoperative: The Copilot helps create a thorough recovery plan, give critical care instructions to the ICU crew, and lead a debriefing session to highlight learning points. The Surgery Copilot improves team coordination, decision-making, and surgical results in the Surg-Box environment, making it an effective tool for medical training and simulation.

F. Long-short memory for surgical copilot

a)Short memory : The Surgery Copilot now includes a short-term memory mechanism to capture real-time information during surgery, such as environmental data, inter role discussions, and ongoing operations. This capability allows the Copilot to quickly collect important information for each stage and role during a single operation, resulting in timely and effective guidance without interference from historical data. Short-term memory enhances the Copilot's ability to respond quickly to changes in surgical situations and handle emergencies.

b)Long memory : The Surgery Copilot's long-term memory component builds on short-term

memory by accumulating experience from repeated procedures. This knowledge repository includes detailed records of operations, as well as summaries of experience to guide future practices. Long-term memory is updated by an iterative learning process that evaluates simulations, extracts significant lessons, and integrates new ideas. This method helps the Copilot accumulate surgical knowledge and best practices over time. Our approach combines short-term and long-term memory to increase Surgery Copilot's surgical planning and execution capabilities. While short-term memory. Authorised, licensed

This strategy improves pre-operative planning by using previous processes while ensuring real-time support. The Copilot analyses performance metrics, manages unforeseen events, and identifies best practices for several scenarios. Surgery Copilot improves its ability to optimise workflows, anticipate issues, and provide personalised assistance for each case.

G. Real Surgery Report Dataset

We have collected a dataset of 428 true clinical surgical reports, as shown in . To improve physician agent performance, we included contextual information to operation reports, such as patient history and MRI findings . This dataset, distributed in Fig. , allows medical agents to practise and improve their decision-making skills. The dataset helps increase bots' capabilities in complex contexts that mimic real-world surgical circumstances. Our ultimate goal is to provide physician agents with credible and useful knowledge for clinical settings.

E. Simulated Surgery Reports Dataset

This dataset contains 1,000 simulated surgical reports created by several Med SurgBox simulation procedures. The system is based on surgical procedures and patient examinations, and includes preoperative, surgical, and postoperative information.

We divided the healthcare area into four categories: electronic health records (EHRs), personal health records (PHRs), data storage, and access control. We analysed the article to see whether it addressed privacy, security, or both.

V. EXPERIMENT RESULTS & EVALUATION :

We have used real neurosurgery records as an experimental dataset. These records include extensive MRI analysis results, surgical procedures, and clinical decision information. To ensure patient privacy, all data were anonymized before analysis. The dataset includes neurosurgeries using different surgical procedures. We separate the dataset into training and testing sets. The training set initialises and optimises the SurgBox system, while the test set evaluates its performance.

We analyse SurgBox's performance using two metrics built exclusively for it.

1) **Surgical path Accuracy:** Assess LLM-based agents' ability to choose the optimal surgical path for a certain patient situation. We compare the system's decisions to those of expert neurosurgeons.

Model	Surgery Route	Surge ry Plan
Baseline	73	82.69
w/ Domain-RAG	85	86.02
w/ React [31]	70	81.56

w/ Copilot [32]	79	78.32
Surgery Copilot	88	88.52

2) Surgical Plan Accuracy: Assess LLM-based agents' ability to accurately plan and complete surgeries.

Model	Surgery Route	Surgery Plan
InternLM2 [28]	55	77.42
LLaMA3 [29]	62	81.33
GPT-3.5	77	83.26
GPT-4 [30]	81	87.68
Surgery Copilot	91	89.02

Table I: Comparison of Surgery Copilot Table II: Ablation study of Surgery Copilot with diverse LLMs

Model	Stage-1 (25%)		Stage-2 (50%)		Stage-3 (75%)		Stage-4 (100%)	
	Comp	Acc	Comp	Acc	Comp	Acc	Comp	Acc
InternLM2	96	73.32	83	65.26	61	57.28	52	55.33
LLaMA-3	100	86.33	93	79.41	67	69.62	60	65.41
GPT-3.5	100	85.26	95	82.06	77	72.42	67	39.73
GPT-4	100	91.68	100	84.12	81	78.89	77	71.77
Surgery Copilot	100	88.00	100	83.96	93	81.06	85	78.21

TABLE III: Evaluation of completeness (Comp) and accuracy (Acc) on each model across different stages.

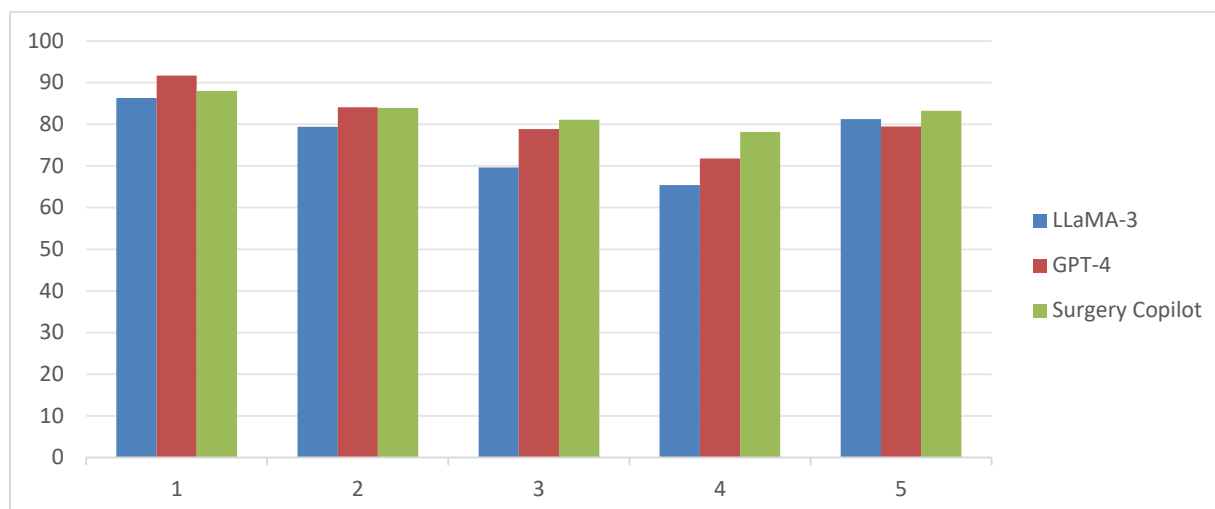


Fig. 5: Comparison in specific diseases. 1: Primary nonfunctioning pituitary adenoma, 2: Recurrent nonfunctioning pituitary adenoma, 3: Aggressive nonfunctioning pituitary adenoma, 4: Primary pituitary adrenocorticotroph adenoma, 5: Recurrent pituitary adrenocorticotroph adenoma

Implementation Details. The SurgBox system utilises advanced MLMs and simulation experiments using the GPT-3.5-turbo-16k API. Prompt engineering approaches are used to enhance the model's understanding of medical language and surgical procedures. To replicate several surgical responsibilities, knowledge bases and behaviour models are developed for each role. Surgery Copilot, a crucial component, has increased decision weights and knowledge access. Training is done using an iterative optimisation strategy. The system was trained on a small number of surgical records before gradually expanding the training set. Model parameters and decision logic were constantly adjusted based on expert comments. To ensure consistency and fairness, we conducted all experiments in a fixed hardware environment and initialised it.

B. Experimental Results and Analysis

The Figure – 5 shows our Surgery Copilot outperforms in both the Surgery Route and Surgery Plan. The Categories and ratings of 98.00% and 93.02%, respectively.

Surgery Copilot significantly improves surgical route planning and plan formation.

Implementing domain-specific RAG technology improved the baseline model's performance, especially in the Surgery Route category. Using external knowledge retrieval can improve model performance in specialised domains. SurgBox outperformed previous models by integrating surgical field-specific knowledge into the React approach, reducing hallucinations and improving accuracy. The Med SurgBox performs exceptionally well in all stages, including in the TABLE II. The method regularly achieved high completion rates, especially in Stages 2 and 3. The accuracy remained excellent across all stages, with particularly strong and consistent performance in the later stages, indicating robustness and reliability in difficult surgical circumstances. The completion rate and accuracy of all models decreased as the phases advanced, indicating growing complexity.

Complexity and obstacles arise in the later stages of the surgical procedure.

SurgBox's completion rate decreased slightly, but its accuracy did not considerably decline.

Table III shows the Evaluation of completeness (Comp) and accuracy (Acc) on each model across

different stages ferent technologies affect the baseline model's surgical planning and routing performance. Our RAG technique improved significantly, especially in the Surgery Route area, resulting in an increased score. The Surgbox, which combines surgery-specific knowledge with the React technique, outperformed in both categories, with an accuracy of 98.00% for surgical routes and 83.02% for surgery plans. Using domain-specific information and advanced reasoning techniques reduces hallucinations and improves accuracy in surgical planning and routing tasks.

VI. CONCLUSION.

The research work presents an integrated method to addressing cognitive problems during surgical operations. We introduce medical SurgBox, an agent-driven sandbox framework that helps surgeons improve their cognitive skills through risk-free virtual practice. SurgBox simulates operating room dynamics using LLM-based agents and personalised RAG knowledge libraries, helping doctors establish cognitive schemas for difficult surgical scenarios. We developed Surgery Copilot, which uses Long-Short Memory to lessen cognitive burden during live surgeries through intelligent information coordination and decision support. Extensive experiments confirm the superiority of our technique for surgical training and operational aid. Our study advances surgical education and practice by improving cognitive capacities and reducing cognitive stress, potentially leading to better surgical results and quality healthcare.

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