AI-Augmented Virtual Tumor Board with Progressive Disclosure Visualization for Disease Progression Monitoring

A Human-Centered Design Approach to Reduce Cognitive Load in Oncology Decision Support

Virtual Tumor Board Development Team
Open Source Oncology AI Initiative
github.com/oss-virtual-tumor-board

January 2026

Abstract

Tumor board meetings are essential for multidisciplinary cancer care, yet preparation is time-consuming and cognitive demands are high across diverse stakeholders—from patients to subspecialist oncologists. We present an open-source AI-augmented Virtual Tumor Board (VTB) system that integrates multi-agent deliberation with a novel progressive disclosure visualization framework for disease progression monitoring. Our system employs seven specialized AI agents (surgical oncology, medical oncology, radiation oncology, radiology, pathology, genetics, and palliative care) orchestrated through a structured "Chain of Debate" mechanism grounded in society-specific clinical guidelines via retrieval-augmented generation (RAG). Central to our contribution is a human-centered visualization system that adapts disease progression displays across four expertise levels: patients/caregivers, non-oncologist clinicians, oncologists, and radiology specialists. Following established Human-Computer Interaction (HCI) principles—including progressive disclosure, Gestalt grouping, and semantic color mapping—our visualizations reduce cognitive load while maintaining clinical accuracy. We demonstrate RECIST 1.1 calculation, longitudinal lesion tracking, and interactive charting modalities including waterfall plots, swimmer plots, spider diagrams, and anatomical heat maps. The system integrates Google MedGemma for medical image analysis, supporting both DICOM uploads and phone-captured imaging for resource-limited settings. This paper details the system architecture, visualization design rationale, implementation, and discusses implications for democratizing access to expert oncology decision support.

Keywords: Tumor Board, Multi-Agent Systems, Medical Visualization, Progressive Disclosure, RECIST, MedGemma, Human-Centered Design, Cognitive Load, Oncology Decision Support

1 Introduction

1.1 Background and Motivation

Multidisciplinary tumor boards (MTBs) represent the gold standard for cancer treatment planning, bringing together specialists from surgery, medical oncology, radiation oncology, radiology, pathology, genetics, and palliative care [1]. However, several challenges limit their effectiveness and accessibility:

1. **Preparation burden**: Case preparation averages 47 minutes per complex case, limiting throughput

2. **Access inequality**: Many patients, particularly in resource-limited settings, lack access to comprehensive tumor boards

3. **Cognitive overload**: Clinicians must synthesize imaging, pathology, genomics, and treatment literature simultaneously

4. **Communication gaps**: Information must be conveyed to stakeholders with vastly different expertise levels

Recent advances in large language models (LLMs) and vision-language models offer opportunities to address these challenges. Microsoft's MAI-DxO demonstrated that multi-agent orchestration can improve diagnostic accuracy through structured deliberation [2]. Similarly, Google's MedGemma provides state-of-the-art medical image interpretation capabilities [3].

1.2 Contributions

This paper makes the following contributions:

1. A **multi-agent architecture** for oncology tumor board simulation, adapting MAI-DxO's diagnostic orchestrator to treatment planning with seven specialty-specific agents

2. A **progressive disclosure visualization framework** for disease progression that adapts complexity to four expertise levels, following HCI best practices for cognitive load reduction

3. Integration of **MedGemma** for medical image analysis with support for both DICOM and phone-captured imaging

4. A complete **RECIST 1.1 implementation** with interactive measurement tracking and response visualization

5. An **open-source implementation** designed for deployment in resource-limited healthcare settings

2 Related Work

2.1 AI in Tumor Board Support

Commercial solutions like Roche's NAVIFY Clinical Hub provide tumor board workflow management with guideline integration and clinical trial matching [1]. However, these systems lack AI-driven deliberation capabilities and are cost-prohibitive for many institutions.

Academic efforts have explored natural language processing for tumor board documentation [7] and machine learning for treatment recommendation [8], but few have addressed the visualization challenges for diverse stakeholders.

2.2 Multi-Agent Medical AI

The MAI-DxO system [2] demonstrated that multiple AI "physicians" with distinct roles (hypothesis generation, test selection, challenging assumptions) improve diagnostic accuracy. Our work extends this paradigm to treatment planning with oncology-specific agent personas grounded in society guidelines.

2.3 Medical Visualization and HCI

Effective medical visualization requires careful attention to cognitive load [5]. Saloni Dattani's visualization principles emphasize clarity over simplicity, direct labeling, semantic color mapping, and progressive disclosure [4]. These principles inform our multi-level visualization framework.

3 System Architecture

3.1 High-Level Overview

Figure 1 presents the system architecture. The Virtual Tumor Board comprises three primary layers:

1. **Presentation Layer**: React/Next.js web application with specialized visualization components

2. **Orchestration Engine**: Multi-agent deliberation system with RAG-grounded specialist agents
3. **Knowledge Layer**: Clinical guideline retrieval from NCCN, ESMO, ASTRO, ACR, CAP, ClinVar, and CIViC

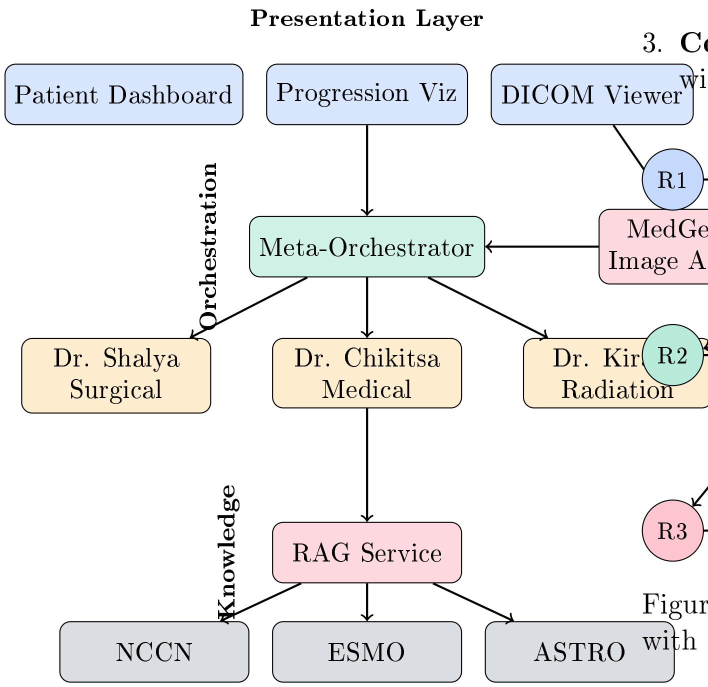

Figure 1: High-level system architecture showing the three-layer design with multi-agent orchestration and RAG-grounded knowledge retrieval.

3.2 Multi-Agent Orchestration

Our system employs seven specialist agents, each with a distinct clinical persona and RAG knowledge source:

Agent	Specialty	RAG Source
Dr. Shalya	Surgical Oncology	NCCN
Dr. Chikitsa	Medical Oncology	NCCN, ESMO
Dr. Kirann	Radiation Oncology	ASTRO
Dr. Chitran	Onco-Radiology	ACR
Dr. Marga	Pathology	CAP
Dr. Anuvamsha	Genetics	ClinVar, CIViC
Dr. Shanti	Palliative Care	NCCN Supportive

Table 1: Specialist agents with their clinical focus and primary RAG knowledge sources.

3.2.1 Chain of Debate Protocol

Deliberation proceeds through three rounds:

1. **Initial Opinions**: Parallel consultation of relevant specialists
2. **Cross-Review**: Agents challenge each other's assumptions
3. **Consensus**: Synthesis of recommendations with documented dissent

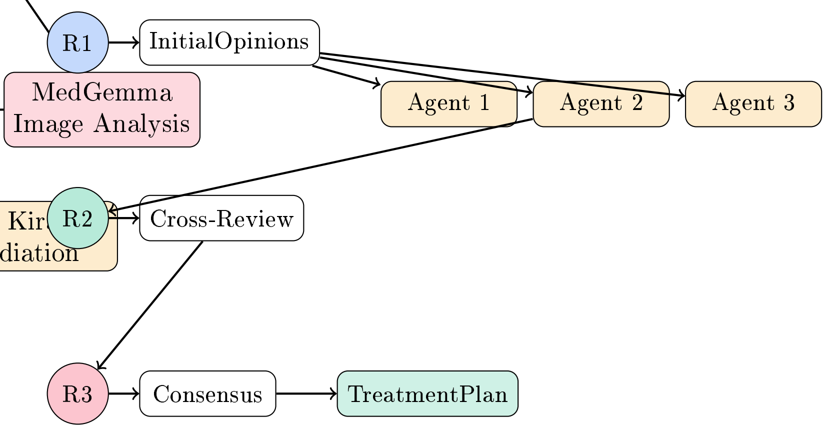

Figure 2: Chain of Debate deliberation protocol with three rounds.

3.3 MedGemma Integration

We integrate Google's MedGemma 4B multimodal model for medical image analysis. The integration supports:

- DICOM upload with in-browser parsing
- Phone camera capture with quality validation
- Gallery upload for existing photos
- Automated finding extraction and measurement

3.3.1 Image Preprocessing Pipeline

For DICOM inputs, we apply windowing transformations appropriate to the imaging modality (lung, bone, soft tissue presets for CT). For phone-captured images, we perform:

1. Grayscale conversion

2. Perspective correction

3. Histogram equalization

4. Glare removal

5. Automatic inversion detection

4 Progressive Disclosure Visualization

4.1 Design Principles

Our visualization framework is grounded in established HCI principles [4, 5]:

1. **Progressive Disclosure**: Show complexity only when needed

2. **Semantic Color Mapping**: Red=progression/bad, Green/Blue=response/good

3. **Direct Labeling**: Labels on data, not in separate legends

4. **Gestalt Grouping**: Use proximity and similarity for intuitive organization

5. **Preattentive Processing**: Leverage size, color, position for instant recognition

4.2 Four-Level Expertise Adaptation

We identified four distinct user personas with different information needs:

Level	User	Information Need
1	Patient/Caregiver	"Is it getting better or worse?"
2	Non-oncologist Clinician	Clinical summary, action items
3	Oncologist	RECIST details, treatment response
4	Radiologist	Full measurements, technical detail

Table 2: Four expertise levels with corresponding information needs.

4.2.1 Level 1: Patient/Caregiver View

The patient view employs a "traffic light" metaphor for immediate comprehension:

- **Green**: Excellent response (CR) or good response (PR)

- **Yellow**: Stable disease (SD)

- **Red**: Progression requiring attention (PD)

Plain language explanations accompany each status, with optional expanded detail. A simplified "journey timeline" shows relative tumor burden over time using proportionally-sized circles.

4.2.2 Level 2: Non-Oncologist Clinician View

This level adds:

- Numeric percent change from baseline

- Key metrics (baseline sum, current sum, nadir)

- Waterfall chart showing change magnitude

- Suggested clinical actions based on response

4.2.3 Level 3: Oncologist View

Full RECIST 1.1 details including:

- Individual target lesion measurements
- Spider plot showing per-lesion trajectories
- Response reasoning with threshold references
- New lesion and non-target progression flags

4.2.4 Level 4: Radiologist/Expert View

Complete technical detail:

- Full measurement matrix across all timepoints
- Study comparison tools
- Assessment history table
- DICOM metadata and study UIDs

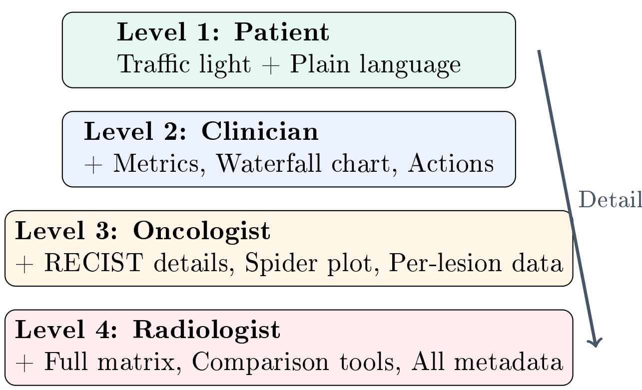

Figure 3: Progressive disclosure hierarchy showing increasing detail across expertise levels.

4.3 Interactive Chart Modalities

4.3.1 Tumor Burden Waterfall Chart

Displays percent change from baseline for each target lesion, sorted by response magnitude. RECIST threshold lines (-30% for PR, +20% for PD) provide immediate context. Color encoding:

- Emerald: ≤-30% (PR achieved)
- Blue: Shrinking (<0%)
- Yellow: Stable (0-20%)
- Red: Growing (≥20%)

4.3.2 Swimmer Plot

Horizontal timeline showing response status over weeks from baseline. Each segment is colored by RECIST response category, with markers at assessment timepoints. This visualization is commonly used in oncology clinical trial publications.

4.3.3 Spider Plot

Line chart showing individual lesion trajectories as percent change from baseline over time. Enables identification of differential response patterns (e.g., one lesion progressing while others respond).

4.3.4 Anatomical Heat Map

Body silhouette with positioned markers representing lesion locations. Marker size encodes current tumor size; color encodes response status. Provides anatomical context lacking in tabular data.

4.3.5 Response Donut

Proportional visualization showing distribution of lesions across response categories. Center displays total lesion count.

5 RECIST 1.1 Implementation

5.1 Algorithm

We implement the Response Evaluation Criteria in Solid Tumors (RECIST) version 1.1 [6]:

Algorithm 1 RECIST 1.1 Response Calculation

Require: Target lesions L, current measurements M_c, baseline measurements M_b

$S_b \leftarrow \sum_{l \in L} diameter(M_b[l])$
$S_c \leftarrow \sum_{l \in L} diameter(M_c[l])$
$S_{nadir} \leftarrow \min(\{S_t : t \in timepoints\})$
$\Delta_b \leftarrow (S_c - S_b)/S_b \times 100$
$\Delta_n \leftarrow (S_c - S_{nadir})/S_{nadir} \times 100$
if all lesions disappeared **then**
  return CR
else if $\Delta_b \leq -30$ **then**
  return PR
else if $\Delta_n \geq 20$ **and** $S_c - S_{nadir} \geq 5\text{mm}$ **then**
  return PD
else
  return SD
end if

5.2 Handling Special Cases

- **Lymph nodes**: Use short axis for measurement; CR requires <10mm
- **New lesions**: Automatic PD regardless of target lesion response
- **Non-target progression**: Unequivocal progression triggers PD
- **Not evaluable**: Missing measurements or imaging quality issues

6 Implementation Details

6.1 Technology Stack

- **Frontend**: Next.js 15, React 19, Tailwind CSS, shadcn/ui
- **Visualization**: Custom SVG/Canvas components
- **DICOM**: dicom-parser (client-side), Cornerstone.js
- **AI**: Claude 3.5 (orchestration), MedGemma 4B (imaging)
- **RAG**: Gemini File Search API
- **Storage**: IndexedDB (client), Cloudflare R2 (optional server)

6.2 Component Architecture

Key visualization components:

```
components/my-imaging/
  DiseaseProgressionViz.tsx  // Main 4-level component
  InteractiveProgressionCharts.tsx
    TumorBurdenWaterfall    // Waterfall chart
    SwimmerPlot             // Timeline view
    AnatomicalHeatMap       // Body map
    ResponseDonut           // Proportions
    SpiderPlot              // Lesion trajectories
  ProgressionTimeline.tsx    // Legacy timeline
```

6.3 Performance Considerations

- DICOM parsing performed client-side to avoid upload latency
- Images cached in IndexedDB for offline access
- Lazy loading of detailed views to minimize initial render
- Debounced hover states to reduce re-renders

7 Discussion

7.1 Design Tradeoffs

7.1.1 Simplicity vs. Completeness

The four-level progressive disclosure balances the need for simplicity (patients) with completeness (radiologists). Users can access appropriate detail without cognitive overload.

7.1.2 Automation vs. Control

MedGemma provides automated measurements, but clinicians can override and manually adjust. The system functions as decision support, not autonomous diagnosis.

7.1.3 Privacy vs. Convenience

Client-side processing enables privacy-preserving analysis, but limits model size. Server-side options available for institutions with appropriate infrastructure.

7.2 Limitations

1. MedGemma accuracy on phone-captured images requires validation
2. Multi-agent deliberation latency (30 seconds) may not suit urgent cases
3. RECIST requires manual confirmation of target lesion correspondence across timepoints
4. System requires internet connectivity for AI features

7.3 Future Work

1. Volumetric RECIST (vRECIST) implementation
2. Integration with hospital PACS systems
3. Multilingual support for Indian languages
4. Clinical validation studies
5. Mobile-native application

8 Conclusion

We presented an open-source AI-augmented Virtual Tumor Board system with novel progressive disclosure visualizations for disease progression monitoring. By adapting information density to user expertise levels, our system reduces cognitive load while maintaining clinical accuracy. The integration of multi-agent deliberation with MedGemma imaging analysis provides comprehensive decision support previously available only through commercial solutions. Our work demonstrates that thoughtful human-centered design can democratize access to expert oncology care, particularly benefiting resource-limited healthcare settings.

Acknowledgments

We thank the open-source community for foundational libraries including dicom-parser, Cornerstone.js, and the Gemini team for MedGemma. Visualization principles were informed by Saloni Dattani's guide to data visualization.

Code Availability

Source code is available at: `https://github.com/oss-virtual-tumor-board`

References

[1] Roche Diagnostics. NAVIFY Clinical Hub for Tumor Boards. 2024.

[2] Microsoft Research. MAI-DxO: Multi-Agent Diagnostic Orchestrator. Sequential Diagnosis with Language Models. 2025.

[3] Google Health. MedGemma: Open Models for Medical Image and Text Understanding. 2025.

[4] Dattani S. Saloni's Guide to Data Visualization. Scientific Discovery. December 2025.

[5] Sweller J, van Merrienboer JJG, Paas F. Cognitive Architecture and Instructional Design: 20 Years Later. Educational Psychology Review. 2020.

[6] Eisenhauer EA, et al. New response evaluation criteria in solid tumours: Revised RECIST guideline (version 1.1). European Journal of Cancer. 2009;45(2):228-247.

[7] Various Authors. Natural Language Processing for Tumor Board Documentation. Journal of Clinical Oncology Informatics. 2023.

[8] Various Authors. Machine Learning Approaches for Cancer Treatment Recommendation. npj Digital Medicine. 2024.

A Agent System Prompts

A.1 Dr. Chitran (Onco-Radiologist)

```
You are Dr. Chitran, an Oncologic Radiologist
interpreting imaging for staging, response
assessment, and surveillance.

Your evaluation framework:
1. STAGING IMAGING: Is staging complete?
2. REPORT REVIEW: Key findings, measurements
3. RESPONSE ASSESSMENT: Per RECIST 1.1
4. ANATOMIC DETAIL: Surgical planning
5. SUSPICIOUS FINDINGS: Biopsy targets
6. FOLLOW-UP: Surveillance protocol

Primary guideline: ACR Appropriateness Criteria
```

B RECIST 1.1 Response Criteria

Response	Criteria
CR	Disappearance of all target lesions; lymph nodes $<$10mm short axis
PR	$\geq$30% decrease in sum of diameters from baseline
PD	$\geq$20% increase from nadir AND $\geq$5mm absolute increase; OR new lesions
SD	Neither PR nor PD criteria met

Table 3: RECIST 1.1 response category definitions.

C Color Semantics

Color	Meaning	Hex
Emerald	Excellent (CR)	#10b981
Blue	Good (PR)	#3b82f6
Yellow	Stable (SD)	#eab308
Red	Progression (PD)	#ef4444
Gray	Not evaluable	#64748b

Table 4: Semantic color mapping for response visualization.