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# OccuTriage: An AI Agent Orchestration Framework for Occupational Health Triage Prediction

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# Problem Statement

## Critical Challenges in Occupational Health Triage

- **Manual Process Limitations**

- High variability in clinical decision-making (practitioners prefer judgment over algorithms)
- Inconsistent triage outcomes, especially in borderline cases
- Resource allocation inefficiencies

- **Existing AI System Gaps**

- Single-agent LLMs show variable accuracy (67.6% in complex cases)
- Most systems target emergency medicine, not occupational health
- Limited integration of domain-specific knowledge

- **Safety-Critical Requirements**

- Under-triage leads to inadequate care (safety risk)
- Over-triage causes resource waste (efficiency loss)

# Research Contributions

## Novel AI Agent Orchestration Framework – Occupational Health

### Key Innovations:

- **Multi-Agent System** with specialised clinical expertise simulation
- Retrieval Augmentation with **occupational health knowledge bases**
- **Bidirectional Decision Architecture** for comprehensive triage coverage
- Safety-Prioritised Protocols with conservative default mechanisms

### Impact:

- 53% reduction in discordance rate vs. baseline (20.16% vs 43.05%)
- 20% improvement over human expert performance (25.11%)
- 66% reduction in critical under-triage rates for assessor decisions

# Dataset & Problem Formulation

## Real-World Clinical Data

### Dataset Characteristics:

- 2,589 occupational health cases from Heales Medical
- 12 medical categories (Mental Health 34.1%, Musculoskeletal 29.6%)
- Referral forms + attachments (medical records, job descriptions)

# System Architecture Overview

## Multi-Stage Processing Pipeline

### Stage 1: Document Processing

- LLM-based anonymization (M'i)
- Medical entity extraction
- PDF content processing (Llama 3.2 13B Vision)

### Stage 2: Knowledge Augmentation

- External knowledge integration (NCI Thesaurus + O\*NET)

- Dragon dual-encoder semantic retrieval

- Comprehensive summarization

### Stage 3: Multi-Agent Orchestration

- Dual-crew specialized agent system
- Iterative consensus building (5 rounds)
- Safety-prioritized decision protocols

# AI Agent Orchestration Framework

## Dual-Crew Architecture

### Crew 1: Appointment Type Decisions ( $C^1_m$ )

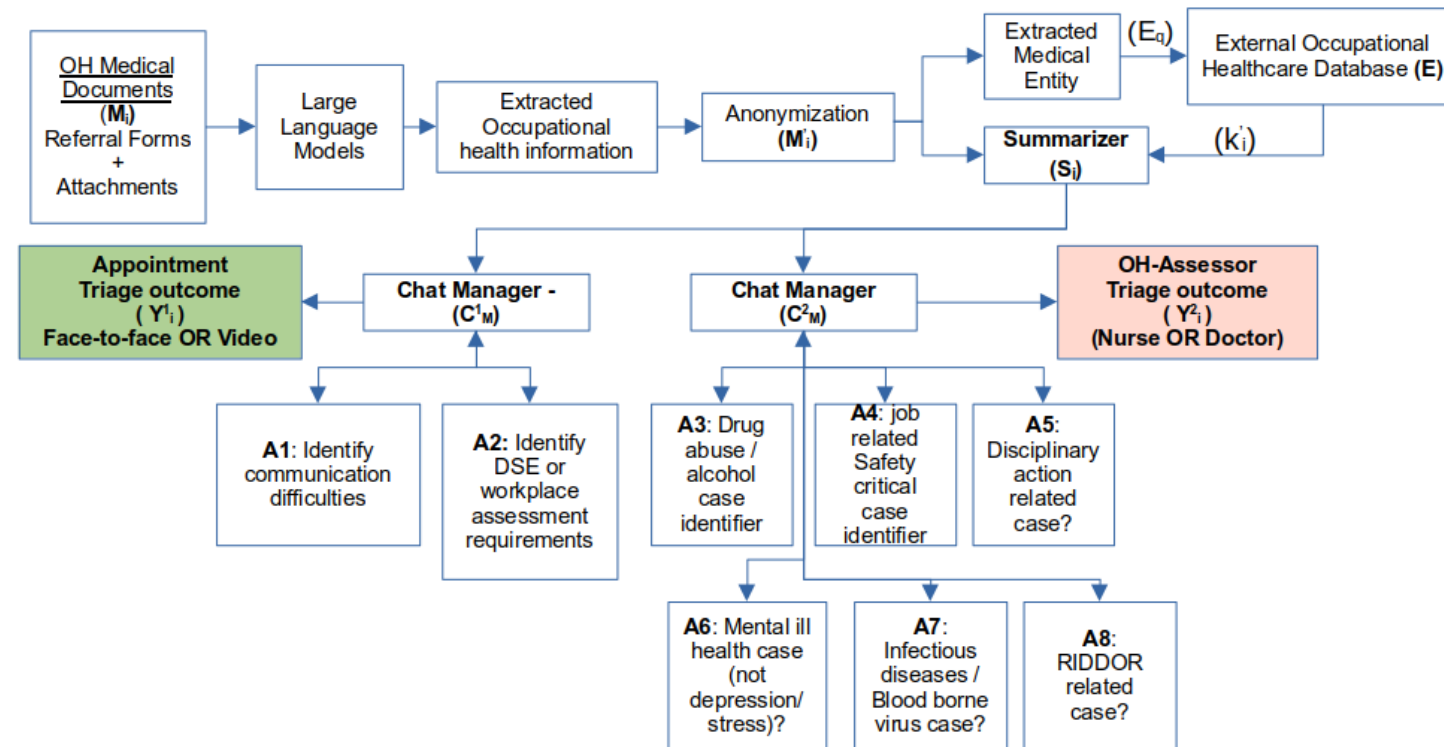
- A1: Communication difficulties assessment
- A2: Workplace assessment requirements

### Crew 2: Assessor Type Decisions ( $C^2_m$ )

- A3: Substance abuse identifier
- A4: Job-related safety concerns
- A5: Disciplinary action issues
- A6: Mental health conditions
- A7: Infectious diseases
- A8: RIDDOR-related cases

## Decision Protocol:

- Parallel processing → Iterative discussion → Majority voting → Safety override



# Technical Implementation

## Technology Stack & Configuration

### Core Models:

- Llama 3.1 8B, Llama 3.2 13B Vision
- Asclepius-Llama3-8B (domain-specific)
- Dragon dual-encoder (retrieval)

### Infrastructure:

- 4x Nvidia H100 GPUs, Text Generation Inference
- Microsoft AutoGen framework
- Temperature: 0.7, Top\_p: 0.95

### Safety-Prioritized Rules:

- Face-to-face default: Any Crew 1 agent recommends in-person
- Physician default: Any Crew 2 agent suggests doctor consultation
- Early stopping: After 3 consistent decisions



# Experimental Results

Configuration	Appointment Type	Assessor Type	Average
Single-agent Baseline	47.00%	39.1%	43.05%
+ RAG	37.50%	32.5%	35.00%
+ Chain of Thought	35.00%	30.5%	32.75%
OccuTriage	22.32%	18.0%	20.16%
Human Expert	26.22%	24.0%	25.11%

## Key Findings:

- 53% reduction vs. baseline discordance
- Outperforms human experts by 20%
- Consistent improvement across both triage dimensions

# Safety Analysis - Under-triage Reduction

## Critical Safety Metric Improvements Under-triage Rates (Safety-Critical):

Method	Appointment Type	Assessor Type
Baseline	19.82%	6.8%
Human Expert	11.84%	9.0%
<b>OccuTriage</b>	<b>9.84%</b>	<b>3.1%</b>

### Safety Impact:

- 17% reduction in appointment under-triage vs. humans
- 66% reduction in assessor under-triage vs. humans
- Conservative bias ensures high-risk cases receive appropriate care

### Processing Efficiency:

- ~12 seconds per case (suitable for non-emergency triage)
- Early stopping optimizes computational resources

# Error Analysis & System Insights

## Understanding Remaining Discordance

### Residual 20.16% Error Analysis:

- Complex multi-comorbidity scenarios (traditional clinical judgment varies)
- Rare medical conditions with non-standard terminology
- Edge cases requiring knowledge base expansion

### Model-Specific Findings:

- Asclepius: Superior clinical accuracy, requires sentiment analysis overhead

- Llama: Direct structured output, slightly lower domain performance
- RAG Impact: 4.93% improvement with domain-specific models

### Multi-Agent Effectiveness:

- Crew 2 (6 agents) achieves 18.0% vs. 24.0% human performance
- Iterative consensus resolves borderline cases effectively
- Simple cases match human performance, complex cases show improvement

# Clinical Impact & Integration

## Real-World Deployment Readiness

### Clinical Workflow Integration:

- JSON-formatted outputs compatible with EHR systems
- Complete audit trails for clinical governance
- Professional override capabilities preserved

### Quality Assurance:

- Comprehensive reasoning chains for practitioner review

- Structured decision protocols for regulatory compliance
- Safety-prioritized design aligns with clinical practices

### Scalability Considerations:

- Handles typical occupational health referral volumes
- Parallel processing architecture supports concurrent evaluation
- Knowledge base expandable for emerging medical knowledge

# Conclusions & Future Work

## Advancing AI-Assisted Healthcare Triage

### Key Achievements:

- First specialized AI framework for occupational health triage
- Demonstrated superiority over single-agent approaches and human experts
- Safety-critical under-triage reduction (66% for assessor decisions)
- Real-world validation on 2,589 clinical cases

### Clinical Significance:

- Bridges clinical judgment and algorithmic consistency
- Optimizes resource allocation while

maintaining safety

- Provides structured decision support for healthcare professionals

### Future Directions:

- Knowledge base expansion for rare conditions
- Integration with additional healthcare specialties
- Longitudinal outcome studies for long-term validation
- Advanced consensus mechanisms for complex edge cases



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# Thank you for your attention