

## **CLINICAL RESEARCH STUDY RESULTS**

# Enhancing equitable study distribution using an automated worklist algorithm

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# Clinical research study: enhancing equitable study distribution using an automated worklist algorithm

Integrated into Merge® Workflow Orchestrator™

# Introduction

Imaging organizations are experiencing increasing workloads and staffing shortages, leading to challenges in balancing workloads across teams and contributing to radiologist burnout and daily work dissatisfaction. Imbalanced workloads occur when radiologists selectively choose (or avoid) cases from a shared worklist based on factors such as the exam's complexity, familiarity with the patient, or personal preferences. Commonly called "cherry-picking", this behavior can lead to problems that can have significant implications for healthcare quality and resource allocation [1, 2].

Merge Workflow Orchestrator (MWO) is a component of the Merge Imaging Suite, a cloud-based diagnostic imaging solution. The purpose of MWO is to simplify activities for reading clinicians as a medical imaging workflow management tool. It provides a caseload distribution capability for medical imaging studies and orders which are stored in another component of Merge Imaging Suite, the enterprise archive. MWO provides a web browserbased user interface for the reading clinicians to view and manage medical imaging exams through the whole workflow. The automated caseload distribution algorithm is designed to enhance study distribution across teams of radiologists, to alleviate – or even avoid - the problems that can arise with individuals manually selecting cases off the worklist.

The following study was designed and conducted to evaluate study distribution equitability with and without the automated worklist functionality. The hypothesis is that the automated worklist will provide a more equitable distribution of studies when compared to manual study selection.

# Overview of Merge Workflow Orchestrator automated worklist

The automated distribution algorithm learns how to make decisions based on radiologists interaction with the worklist system. The algorithm receives ranking requests from the PACS system containing an exam to be assigned and a list of candidates who are available to read the exam. This information is encoded in the state, which is a 2D array containing information about the exam, such as RVU (Relative Value Unit) value and due time, and the study assignment status of radiologists.

This state is given as input for the algorithm that returns a probability vector ranking the candidates in order of suitability to read the given exam.

The algorithm chooses the highest-ranked candidate to assign the exam. When a second request is received, the new state is observed, and a reward is calculated based on the prior action history, considering factors such as fairness and preferences (using the number of rejections per modality).

Figure 1 shows the architecture of the automated worklist.

# **Priority adjusted reward Update the study assignment status for each radiologist** Learning agent Policy **State** Action decoding **Worklist environment** Radiologist (assigned studies) new study with different priority Assign study

#### **Figure 1. Study distribution algorithm.**

# Study design and dataset

## **1. Study design and methods**

Table 1 summarizes the study design.

## **Table 1. Study design**



#### **2. Study procedures**

The study involved a manual phase and an automated distribution phase.

a. Manual phase:

- There was an 8-hour concurrent reading period in which all study selection was performed manually by the radiologists.
- Radiologists read studies for 8 hours with the algorithm operating in training mode.

b. Automated distribution phase:

- There was an 8-hour concurrent reading period in which all study selection was provided by the algorithm and assigned to the radiologists.
- Information about which studies were read by which radiologists was logged for all phases.

Radiologists were not informed about the study objective to avoid altering their behavior. Radiologists were instructed to read as many RVUs as possible.

The overall study procedure is summarized in Figure 2.

#### **Figure 2. Study design (manual phase, auto phase)**



#### **3. Dataset**

The following criteria were applied for data selection:

- Study distribution: 30% CT, 30% MR, 40% CR
- STAT distribution: 10%
- At the start of each study phase, 100 studies were randomly selected, with a distribution of 30 CT, 30 MR, 40 CR, and made available for reading. Of these, 10% were STAT studies with the same distribution. After one hour, additional studies were added to maintain a total of 100 studies, preserving the distribution of study types and including STAT studies.
- No duplicate studies were distributed during the manual and automated phases. Studies that had been assigned and left unread were excluded to prevent the possibility of radiologist cherry-picking.

#### **4. Evaluation method**

The study distribution differences between the manual and automated phases were analyzed. The equitability of study distribution was determined by comparing the variance in the overall distribution of RVU readings among all radiologists.

#### **5. Study results**

A total of 481 studies were reviewed by five radiologists, and 1404 log messages were recorded to track assignment and reading statuses.

Table 2 shows the study numbers by modality in each phase. Table 2(a) summarizes the total RVU read by each radiologist. During the manual phase, there was a preference for reading more CR studies, and CT studies were also favored over MR studies. Most radiologists continued this preference to some extent during the automated phases.

The average RVU for CR, CT, and MR, estimated from the radiologists' reading time, was 1.34, 3.4, and 5.3, respectively. The standard deviation of the RVU sum for each modality was calculated as shown.

Table 2(b). We observed a 35% decrease in standard deviation from the manual phase to the automated phases. This reduction in standard deviation contributes to the study distribution equitability.

Figure 3 shows bar charts illustrating the study numbers and RVU readings by all radiologists by modality for both the manual and automated phases.

#### **Table 2. (a) Number of the study read, (b) Sum of RVU of each study modality and std**



#### **Figure 3. Study numbers (left graphic) and RVU (right graphic) read by all radiologists per modality (manual phase, auto phase)**





Figure 3 shows bar charts illustrating the study numbers and RVU readings by all radiologists by modality for both the manual and automated phases.

Table 3 shows the total RVU read by each radiologist. Radiologist 4 read the highest amount of RVU. The variance among radiologists' RVU sum between the phases (210.23, 219.06, 206.19) was not significantly different, with a similar pattern of variation maintained across phases.

#### **Table 3. Total RVU read by each radiologist (manual phase, auto phase)**



Figure 4 provides a summary of the study ratios read by each radiologist. During the manual phase, radiologist 2 showed the highest CT+MR ratio compared to CR studies. Radiologist 5 did not read any MR studies in manual phase, but read MR studies in auto phase.















#### **6. Discussion and conclusion**

This study aimed to assess the impact of the automated worklist functionality on improving study distribution equitability. We observed a significant 35% reduction in the standard deviation of RVU readings when transitioning from the manual phase to the automated phase for total study readings.

All radiologists demonstrated an improved ratio of MR study readings compared to other modalities when transitioning from the manual to the automated phase.

However, there is a limitation in this study in that it did not assess the effectiveness of how the automated worklist algorithm distributed studies based on user preferences (which would be measured by rejection by radiologists of assigned cases) compared to the manual phase. Due to the length of the study, there were not enough rejections to allow for statistically significant analysis of the effect of user preferences on study distribution. This aspect is expected to be explored in future studies.

# Acknowledgments

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