Evaluation of Computed-Aided Triage (CADt) Devices Using Queueing Theory

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Abstract

Background: Radiological Computer-Aided Triage and Notification (CADt) device is an image processing prescription software intended to aid in prioritization and triage of radiological medical images. Commonly, an effective triage software device uses artificial intelligence (AI) to process patient images and prioritize them based on disease conditions such that a radiologist gets to the more life-threatening patients quicker. These devices assist in prioritization and triage so that clinicians can make earlier diagnosis and treatment of time-sensitive diseases such as large vessel occlusion (LVO) stroke. For example, in cases involving suspected LVO, a notification from an effective CADt device allows a neuro-interventionalist to emergently remove the clot, reducing the associated morbidity and mortality. However, as CADt devices become more common in daily clinical workflow, questions and concerns remain when it comes to a rigorous, quantitative assessment of their effectiveness.

Purpose: This work investigates an approach based on queueing theory to characterize the time performance of CADt devices under various clinical environments. Simulation and theoretical computation tools developed in this project will be made publicly available to evaluate the effectiveness of CADt devices.

Methodology: Both the queueing theory and a simulation model are applied to quantitatively assess the effectiveness of a simulated CADt device in a simulated yet realistic clinical environment. The amount of time savings for diseased patients who are correctly identified by the AI algorithm is studied, as well as the amount of time delay for diseased patients who are missed by the AI. The relationship between time performance and a wide range of clinical parameters, such as disease prevalence, AI accuracy, patient arrival rate, and the number of radiologists, are also investigated.

Findings: The simulation model suggests that CADt devices are most effective in a busy, short-staffed clinical environment. These preliminary results are consistent with both clinical intuition and the theoretical computation using queueing theory under different simulation conditions.

Objective

Develop a quantitative method to evaluate the time performance of a CADt device

Introduction

WHAT — CADt devices prioritize AI positive cases, so likely diseased cases are read first.

WHY — To evaluate the effectiveness: quantify time savings for diseased patients

HOW — Use queueing theory: a mathematical model that studies waiting in line

1. Assume a Simple Model

- Poisson patient arrival process
- Exponential radiologist reading process
- 1 disease condition & 1 modality
- Each radiologist treats every patient the same

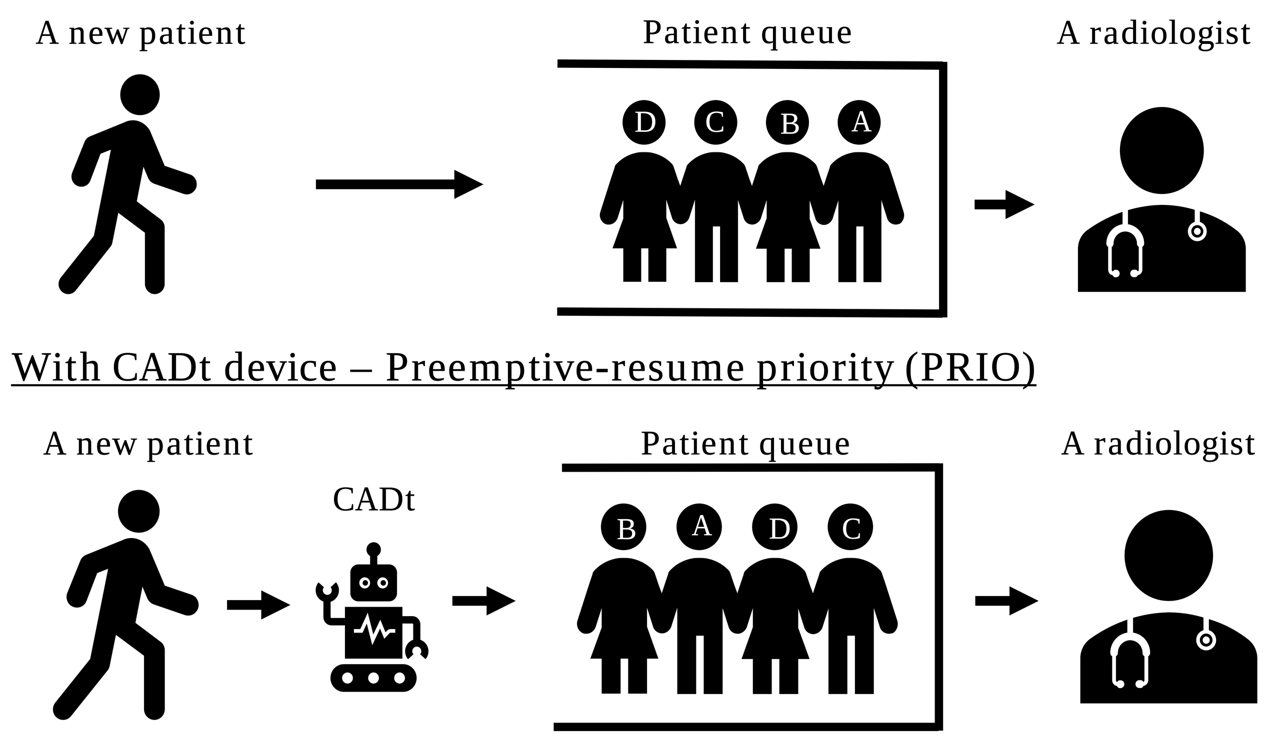
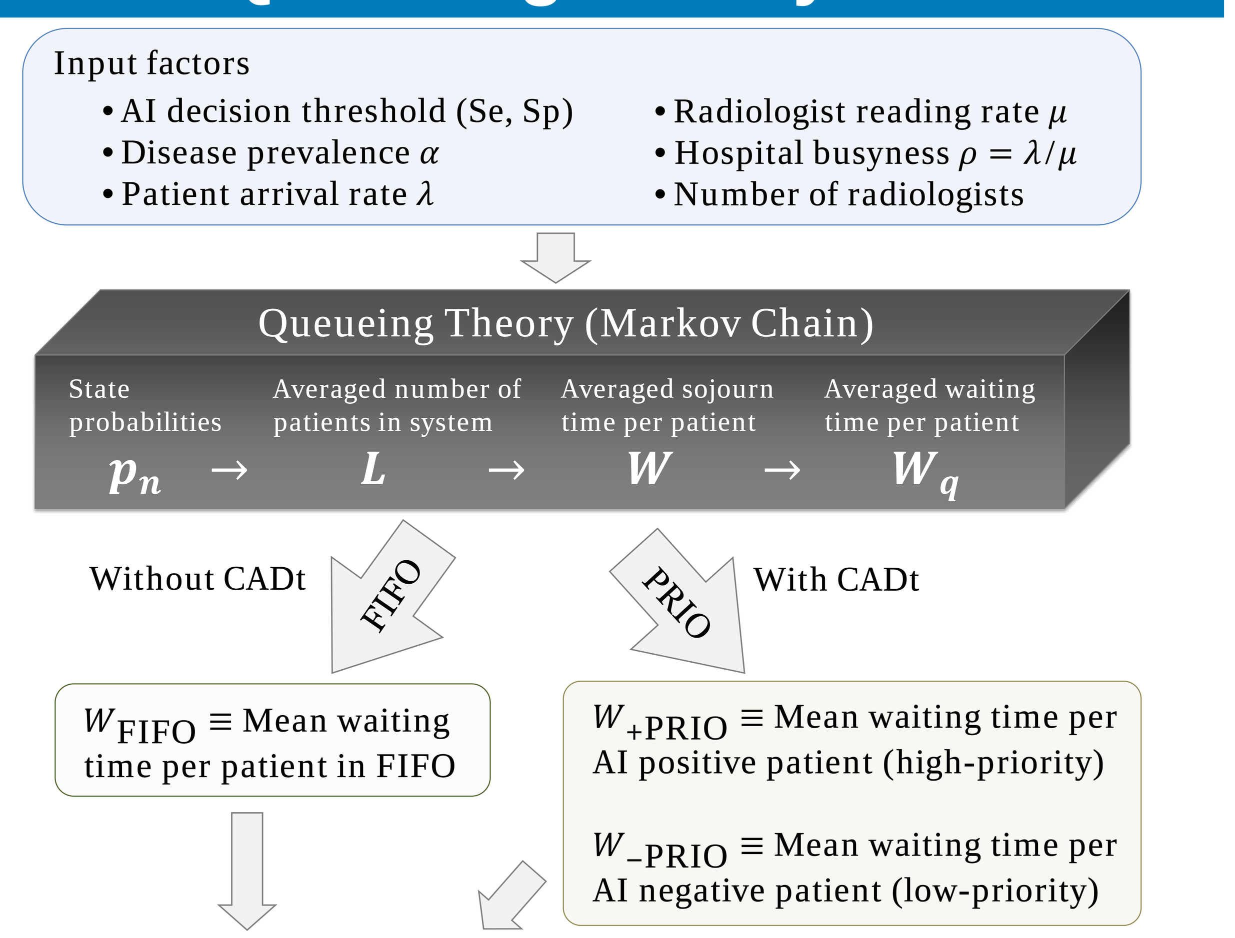


Figure 1. A simple radiologist's workflow with and without a CADt device.

2. Use Queueing Theory



Mean time savings per AI positive patient: $\delta W_{+} \equiv W_{+\text{PRIO}} - W_{\text{FIFO}}$

Mean time delay per AI negative patient: $\delta W_{-} \equiv W_{-\text{PRIO}} - W_{\text{FIFO}}$

Time performance of a CADt device is based on diseased (truth) patients: $\delta W_{D} \equiv W_{D\text{PRIO}} - W_{\text{FIFO}}$

$$\delta W_D = \frac{W_{+\text{PRIO}} \times N_{TP} + W_{-\text{PRIO}} \times N_{FN}}{N_D} - W_{\text{FIFO}}$$

If $\delta W_D < 0$, a diseased patient spends less time, on average, waiting in the priority queue than in the standard FIFO queue.

That is, an overall time savings for truly diseased patients due to the CADt device

Figure 2. Mean waiting times calculated from queueing theory are used to define a time performance metric δW_D. It takes into account the proportion of true-positive (TP) and false-negative (FN) patients with respect to the total number of diseased (truth) patients. The more negative δW_D is, the more effective the CADt device is.

3. Quantify Device Effectiveness

- Disease prevalence $\alpha = 10\%$
- Hospital busyness $\rho = 0.8$ (relatively busy hospital)
- Averaged radiologist reading time $1/\mu = 10$ minutes
- Number of radiologist = 1

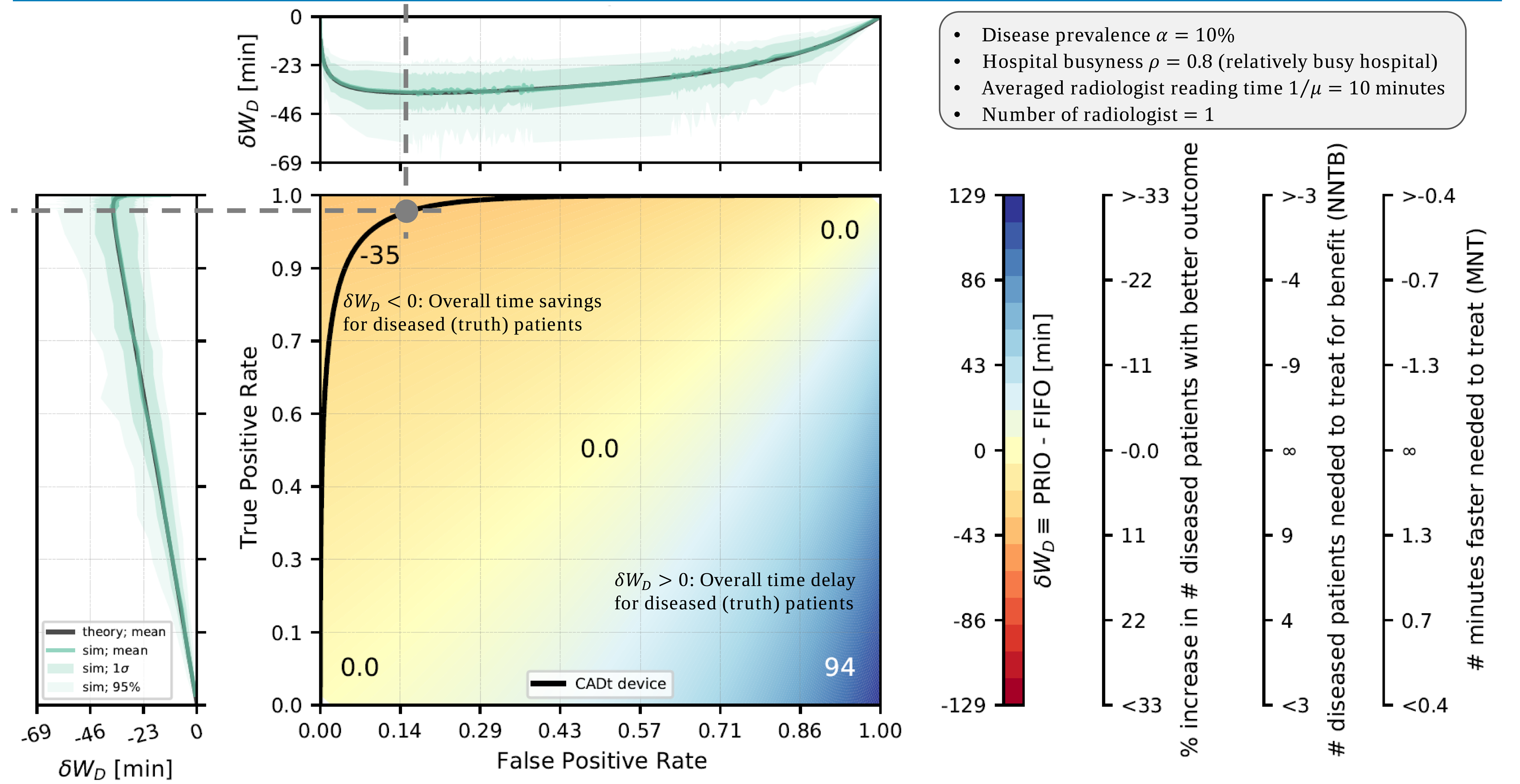


Figure 3. A summary plot showing both time performance and diagnostic ability of a CADt device under the assumptions stated in the gray box (top right). In case of LVO stroke, 3.9% of stroke patients have less disability for every 15 minutes faster (eTable 12 in [1] provided by Saver *et. al.* [2]). Hence, δW_D color axis can be translated to LVO stroke patient outcome metrics (right axes). The gray dot shows that, under the assumed conditions, the expected mean time savings $|\delta W_D|$ is ~40 minutes at a decision threshold of (0.15, 0.97). This corresponds to less than 11% increase in the number of stroke patients with better outcome.

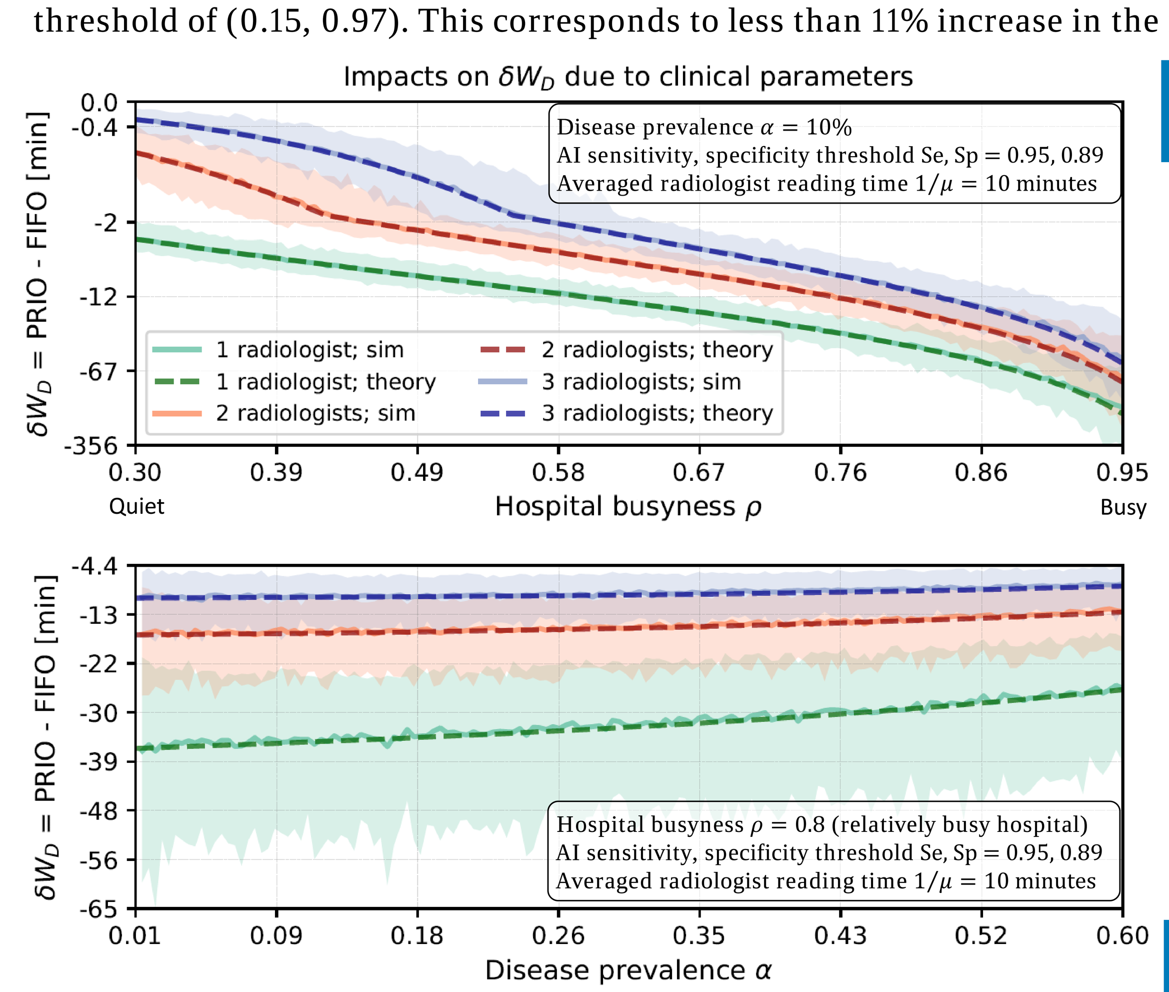


Figure 4. Impacts on δW_D per diseased (truth) patient due to hospital busyness (top) and disease prevalence (bottom) with 1, 2, and 3 radiologists. Shaded areas represent 95% confidence intervals. Under the assumed conditions, the amount of time savings $|\delta W_D|$ increases in a busy, short-staffed hospital. Disease prevalence may become more important in a realistic radiologist's workflow.

Conclusion

- ✓ Developed a theoretical approach to quantify time performance of a CADt device
- ✓ With a simple model, a CADt device is most effective in a busy, short-staffed clinical environment
- ✓ Analytical results are consistent with clinical intuition and verified by simulation
- ✓ Proposed a summary plot with both diagnostic and time-saving ability of the device for CADt evaluation

Future work:

- Expand our model to a realistic, complex radiologist's workflow
- Include emergency cases as the highest priority
- Apply our model to real-world data
- Study the impact of using multiple AI devices targeting multiple diseases
- Release our tools (both computational and simulation software) to the public

Acknowledgement

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References

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[2] Saver JL, Goyal M, van der Lugt A, et al. Time to Treatment With Endovascular Thrombectomy and Outcomes From Ischemic Stroke: A Meta-analysis. *JAMA.* 2016;316(12):1279–1289.