The Impact of Information-Granularity and Prioritization on Patients' Care Modality Choice

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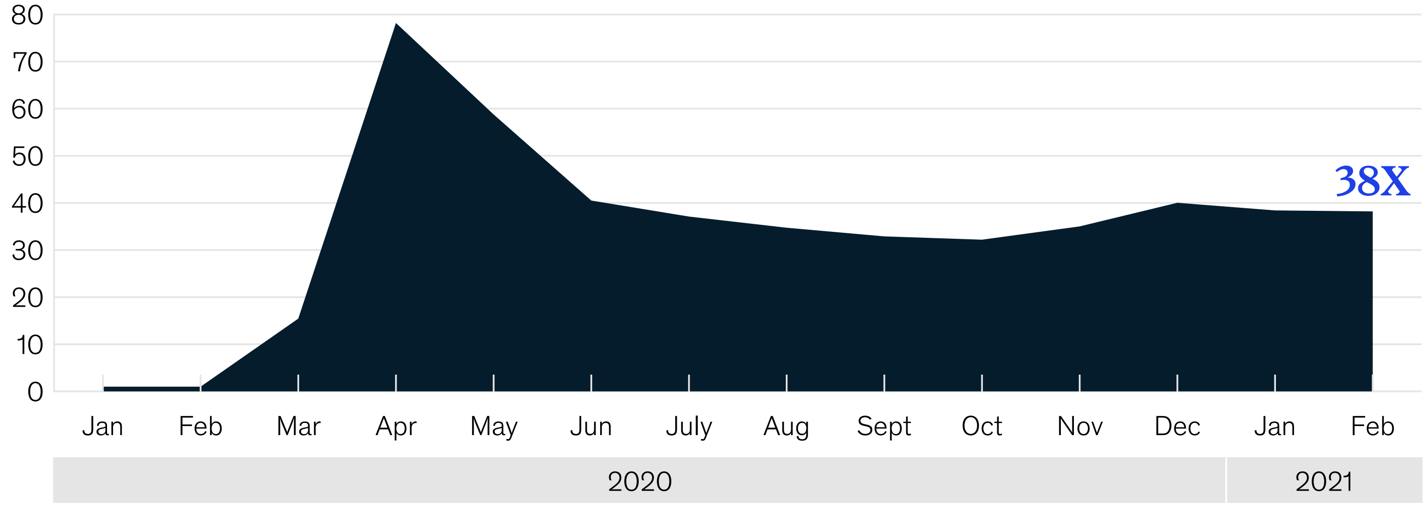
Telemedicine Adoption

- Growth in telemedicine usage peaked during April 2020 but has since stabilized

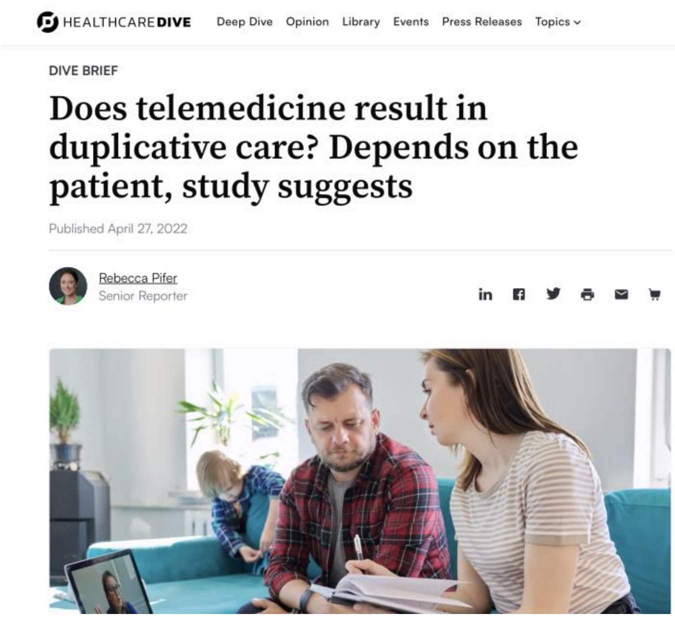
Telehealth claims volumes, compared to pre-Covid-19 levels (February 2020 = 1)[1]



https://www.mckinsey.com/industries/healthcare/our-insights/telehealth-a-quarter-trillion-dollar-post-covid-19-reality

Pros and Cons of Telemedicine

- Pro:
  - Could get appointment sooner
  - Save time and money
  - In the safety of patient’s own home or workplace
- Con:
  - Telemedicine is not right for every situation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DIVE BRIEF

Does telemedicine result in duplicative care? Depends on the patient, study suggests

Published April 27, 2022

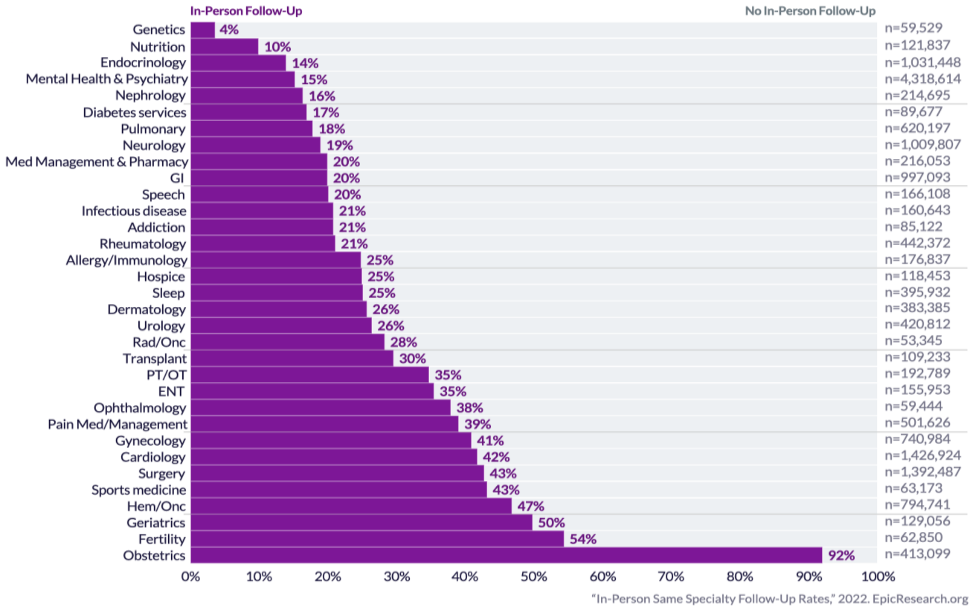
Rebecca Pifer
Senior Reporter

Duplicative care: Unsuitable telemedicine visits lead to **redundant** in-person evaluation, which in turn generates more workload for the system

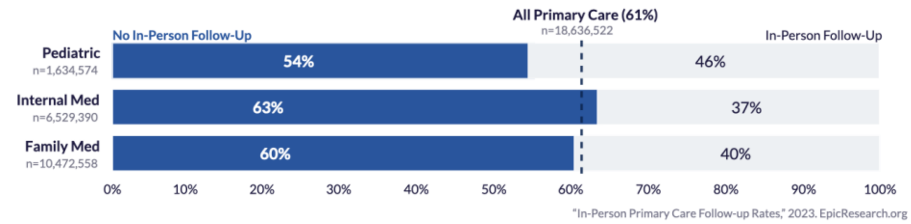
Pros and Cons of Telemedicine

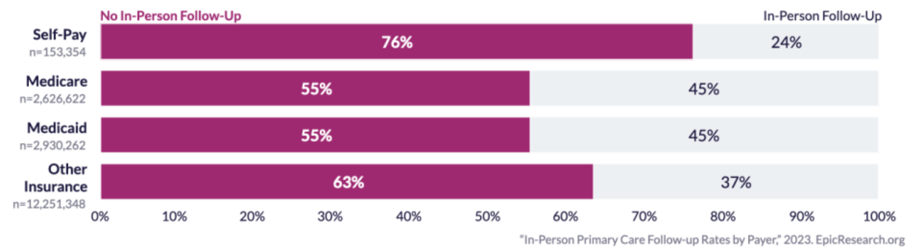
- The level of duplicative care after telemedicine is heterogeneous, and depends highly on the specialty and the patient

Specialty care



Primary care





https://www.epicresearch.org/articles/telehealth-visits-unlikely-to-require-in-person-follow-up-within-90-days

The Choice Is in Patients' Hands

*"**Growing Pains:** […] As the system grew quickly, providers were also frustrated with having **inappropriate patients scheduled for video visits** versus in-person visits and wanted **changes to the triaging and scheduling system**"*
- Srinivasan et al. *Annals of internal medicine* (2020)

Problem:
Patients lack information to make self-interested decisions

Possible remedy:
Design an online-triage tool to provide information and recommendation

Questions:
Does providing more information to patients reduce duplicate care?
Are there other operational tools that can improve system performance?

Related Literature

- Telemedicine adoption and patients' behavior:
    - Bavafa et al. (2018), Lekwijit et al. (2023) , Qin et al. (2023) , Staats et al. (2017), Li et al. (2021), Sun and Wang (2021), Delana et al. (2023), Saghafian et al. (2018) , Bavafa et al. (2021), Cakıcı and Mills (2022), Rajan et al. (2019) , Ding et al. (2022) , Liu et al. (2023)
- Information Design for Service Systems:
    - Aksin et al. (2017), Yu et al. (2017, 2022), Ibrahim (2018) , Argon and Ziya (2009), Sun et al. (2022), Singh et al. (2024) , Hu et al. (2022)
- Strategic Behavior in Queueing Systems:
    - Naor (1969), Edelson and Hilderbrand (1975), Hassin (1986), Hassin and Haviv (2003) , Hassin (2016), Hassin and Roet-Green (2017, 2021), Mendelson and Whang (1990), Afeche and Mendelson (2004), Afeche et al. (2019), Hu et al. (2022) , Cui et al. (2023), Shumsky and Pinker (2003), Freeman et al. (2017), Hathaway et al. (2023) , Roet-Green and Shetty (2022)

Our Contribution

Addressing the question of care redundancy: **How and when** to implement **online triaging** and **prioritization** in a dual care modalities system

Model

- **A queueing-game model** that incorporates:
  - Patients' choices between care modalities
  - Two operational levers: Information, Prioritization

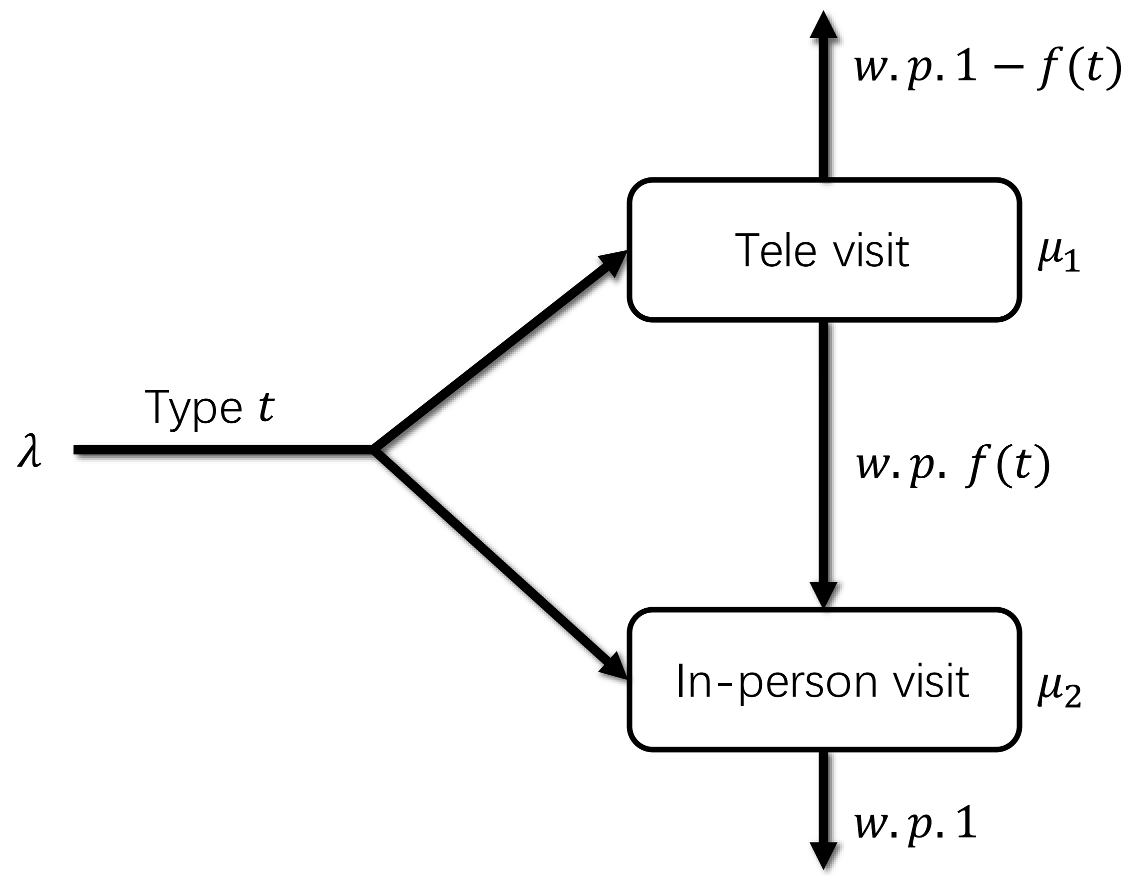
Case study

- **A prediction model** that forecasts the need for a follow-up visit after a telemedicine visit
- **Model calibration:** how priorities and triage impact waiting times?

QUEUEING-GAME MODEL

Motivation | Queueing Game | Case Study | Summary

The Model



$w.p. 1 - f(t)$
Tele visit
μ_1
Type t
λ
$w.p.\ f(t)$
In-person visit
μ_2
$w.p. 1$

Two Information Granularity Regimes

Information	Average chance for a follow-up	Patient’s own chance for a follow-up
Crude Information	Know	Unknow
Refined Information	Know	Know

Patients' Strategies

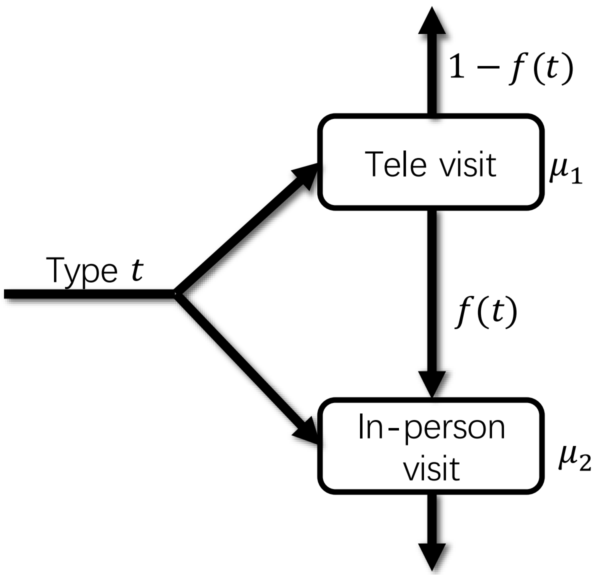
- Patients' decision is based on wait-time comparison
- If the patient chooses in-person visit:

$$W_{in\_person} = W_2$$

- If the patient chooses telemedicine:

$$W_{tele} = W_1 + W_2 * 1_{\{follow-up\}}$$

Patients' objective: minimize the expected total waiting time
Patients' strategy: a probability of joining tele-visits



Patients’ Equilibrium Strategy

Crude information regime:

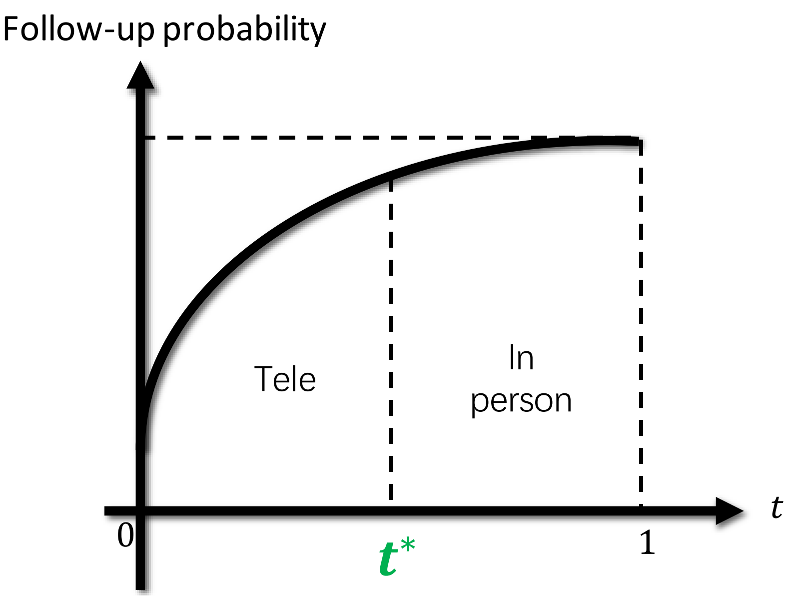
- There exists a unique crude equilibrium strategy:

P% of the patients choose telemedicine

(1-P)% of the patients choose in-person

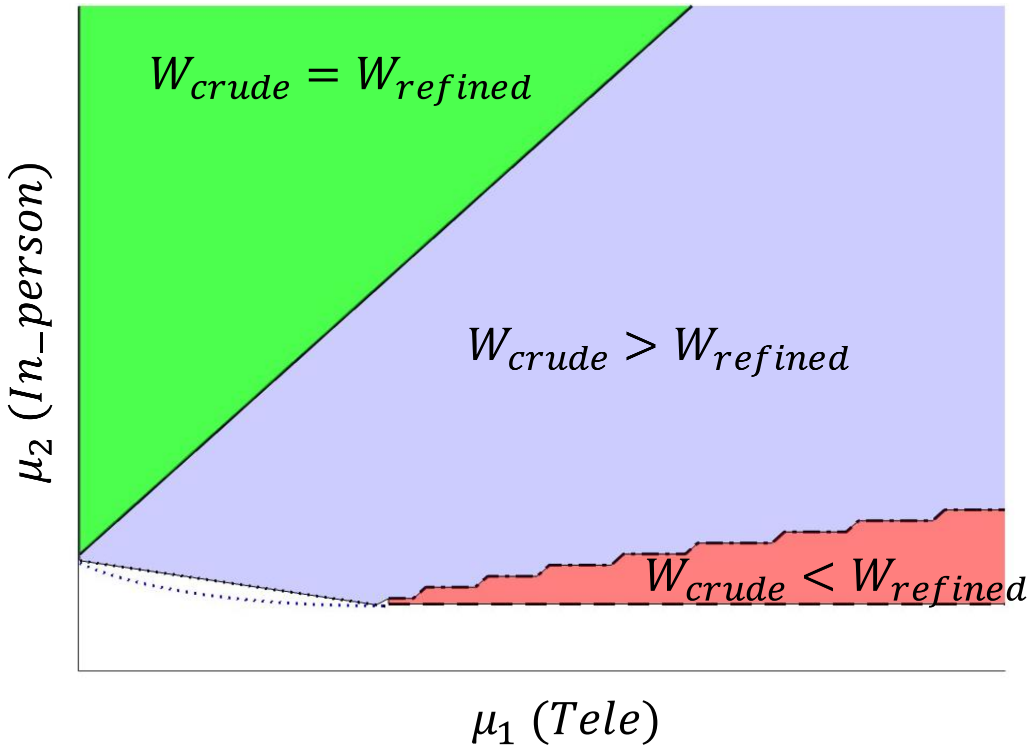
Refined information regime:

- There exists a unique refined equilibrium that depends on patient’s health severity level



Does Providing More Information Help?

- Assessing the online triage tool in terms of average waiting time

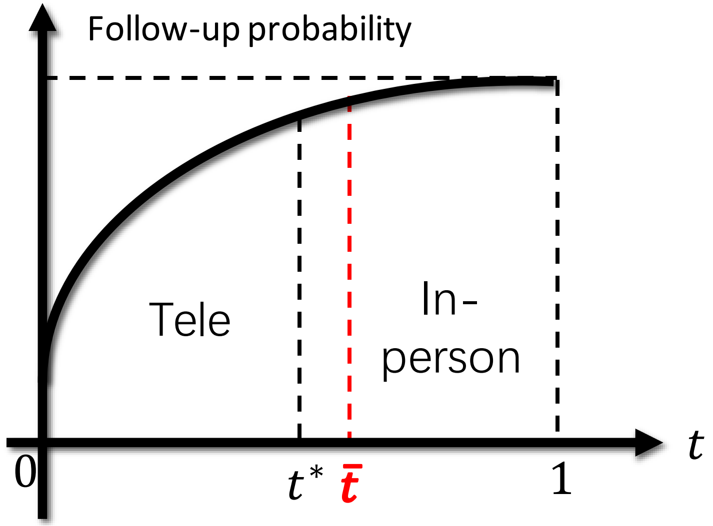


Conclusion: Providing more information may increase the average waiting time!

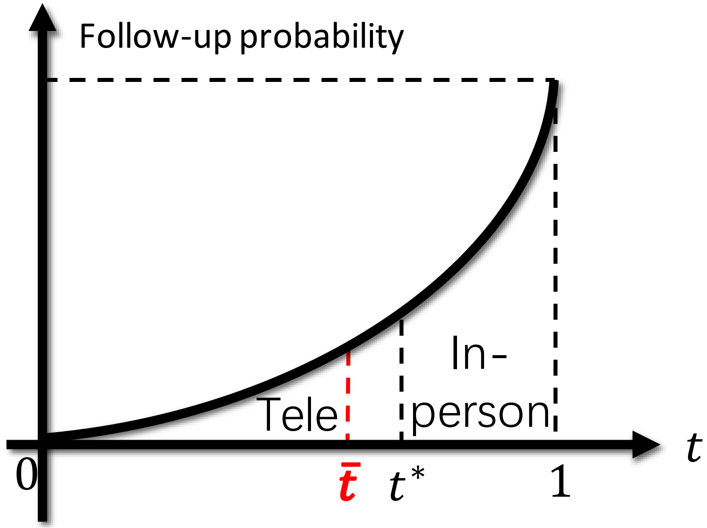
System's First Best

- System's first best strategy $\bar{t}$: Centralized routing decisions with refined information to achieve the minimum average waiting time

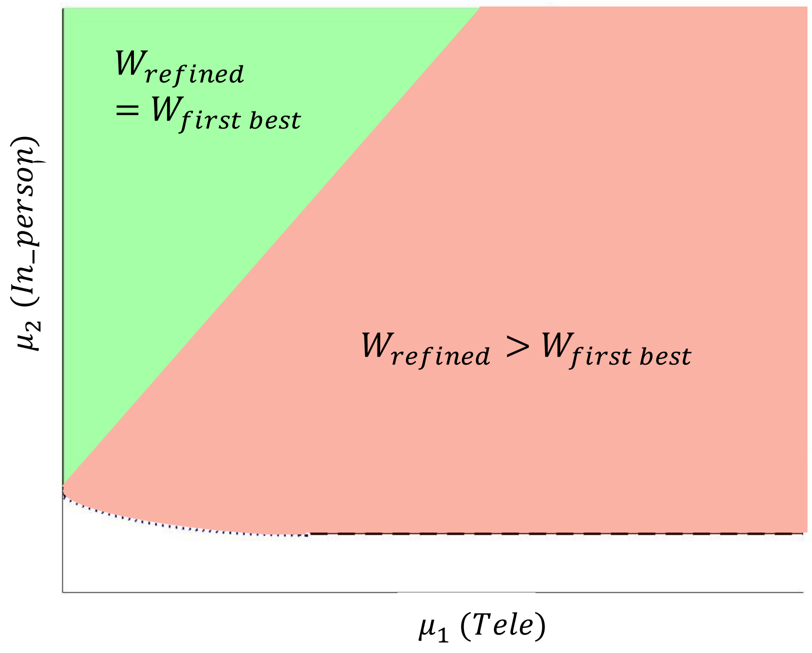
Avg follow-up prob high: Conservative



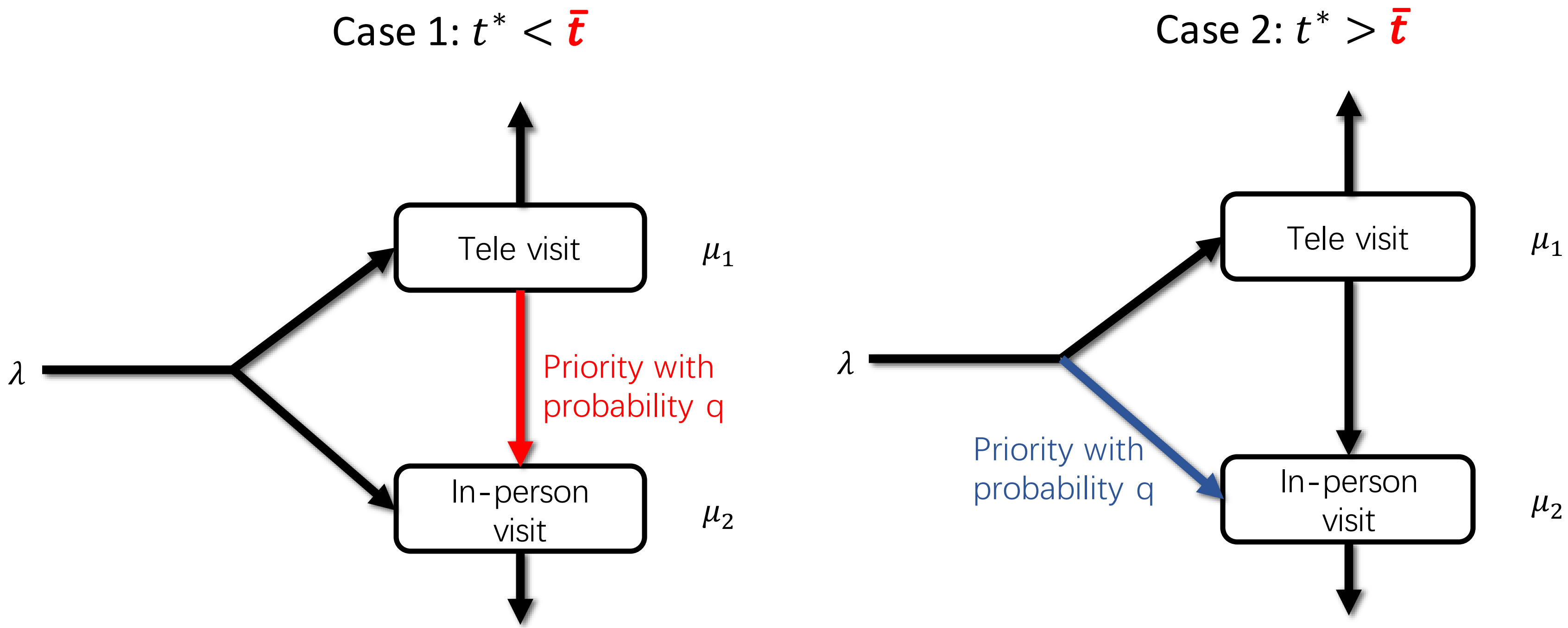
Avg follow-up prob low: Proactive



System's First Best vs. Refined Equilibrium



Coordination Mechanism: Priority Rule



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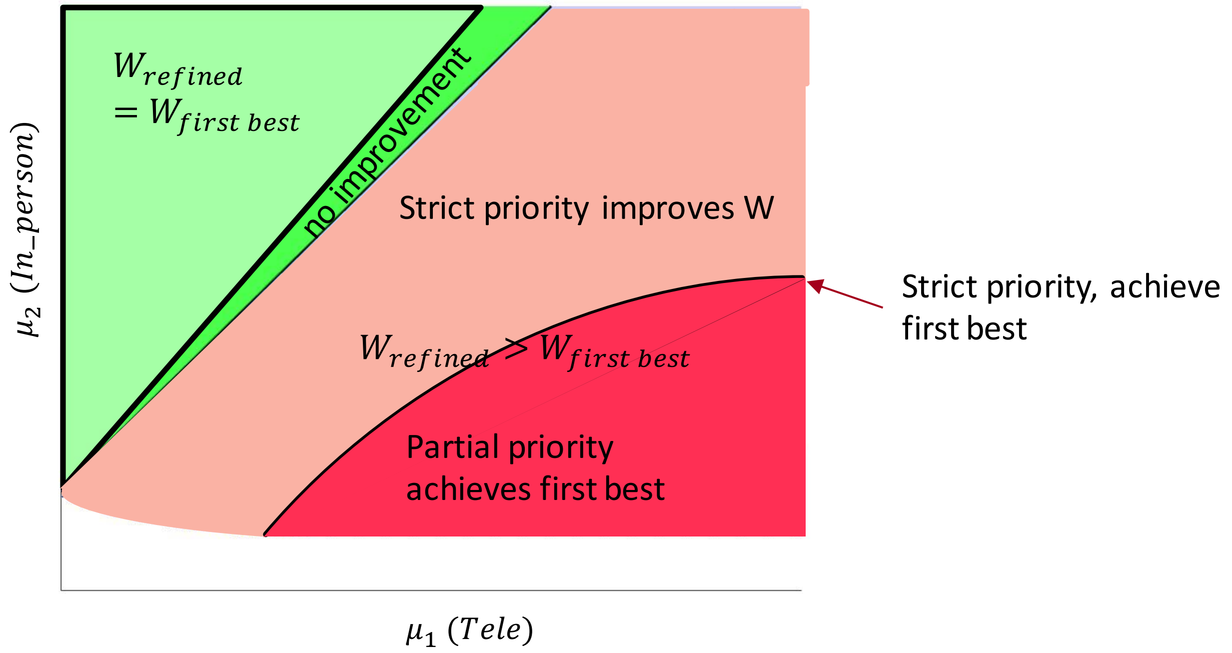
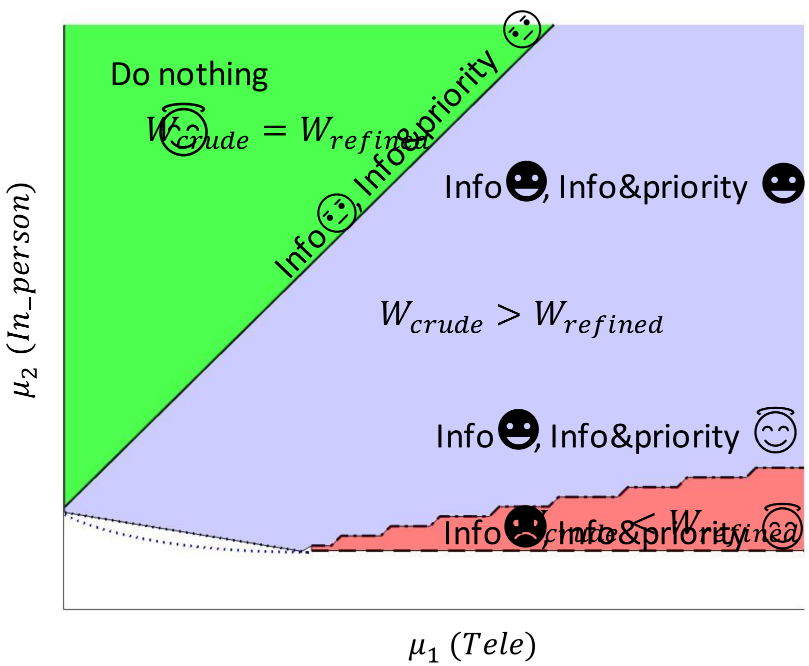
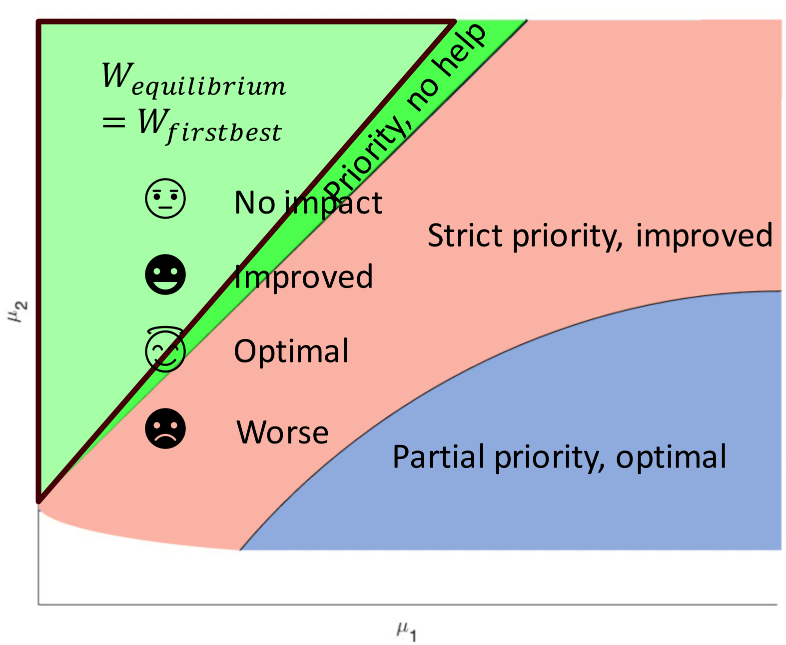


Effect of The Two Operational Levers

- Performance measure: Average waiting time





CASE STUDY

Prediction Model

- We collect data regarding outpatient visits at a large academic hospital in Maryland from 01/2020 to 09/2023
- Starting from 2021, the hospital provided telemedicine options for a variety of preprocedural examinations
- Visit code = Z01818
- 3,275 total visits, 210 telemedicine visits (6.412% usage rate)

Prediction Model

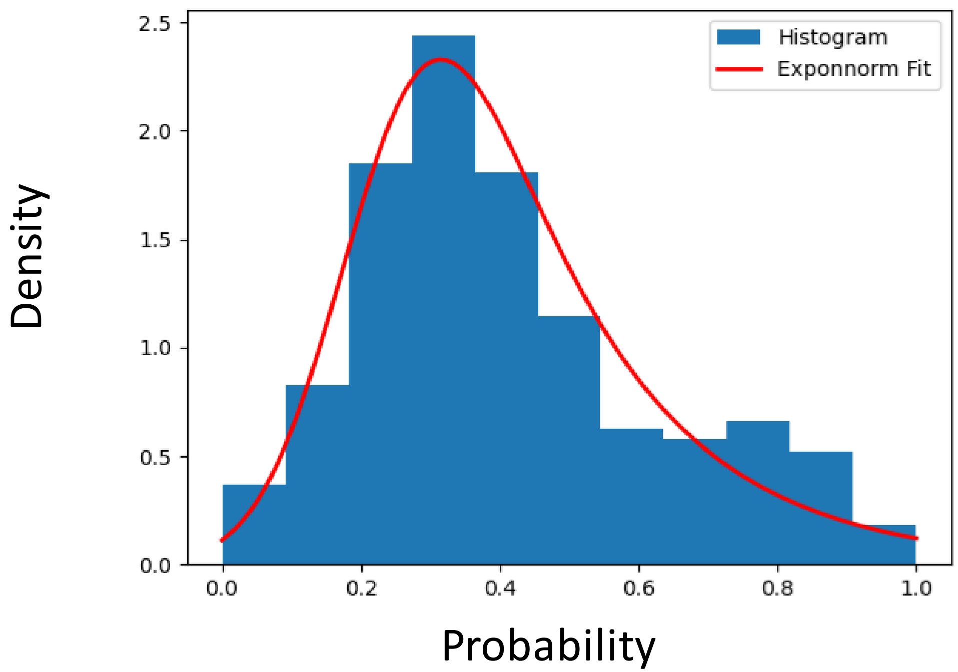
- Prediction target: whether a patient requires an in-person follow-up visit within 7, 14, 21, and 30 days of a prior visit

- Logistic regression with the following covariates:
  - Time fixed effect: year, quarter
  - Patient demographic information: age, sex, ethnicity, county
  - Ailment types: diagnosis codes
  - Payment type: commercial insurance, self-pay, Medicare, Medicaid, charity
  - Source of arrival: home, other hospital sites
  - Comorbidities: Charlson comorbidity index
  - Personal preference for in-person visits: # in-person visits in 2020
  - Care modality: telemedicine, in-person visit

Prediction Model

- The logistic regression outputs the probability of requiring an in-person follow-up visit after telemedicine

Distribution of 7-day in-person follow-up probabilities



- Heterogeneity in the efficacy of telemedicine treatment across patients

Model Calibration

- Hourly arrival rate of the sample patients

$$\lambda = \frac{\text{\# sample patients}}{\text{\# working hours}} = 0.572 \text{ patients/hour}$$

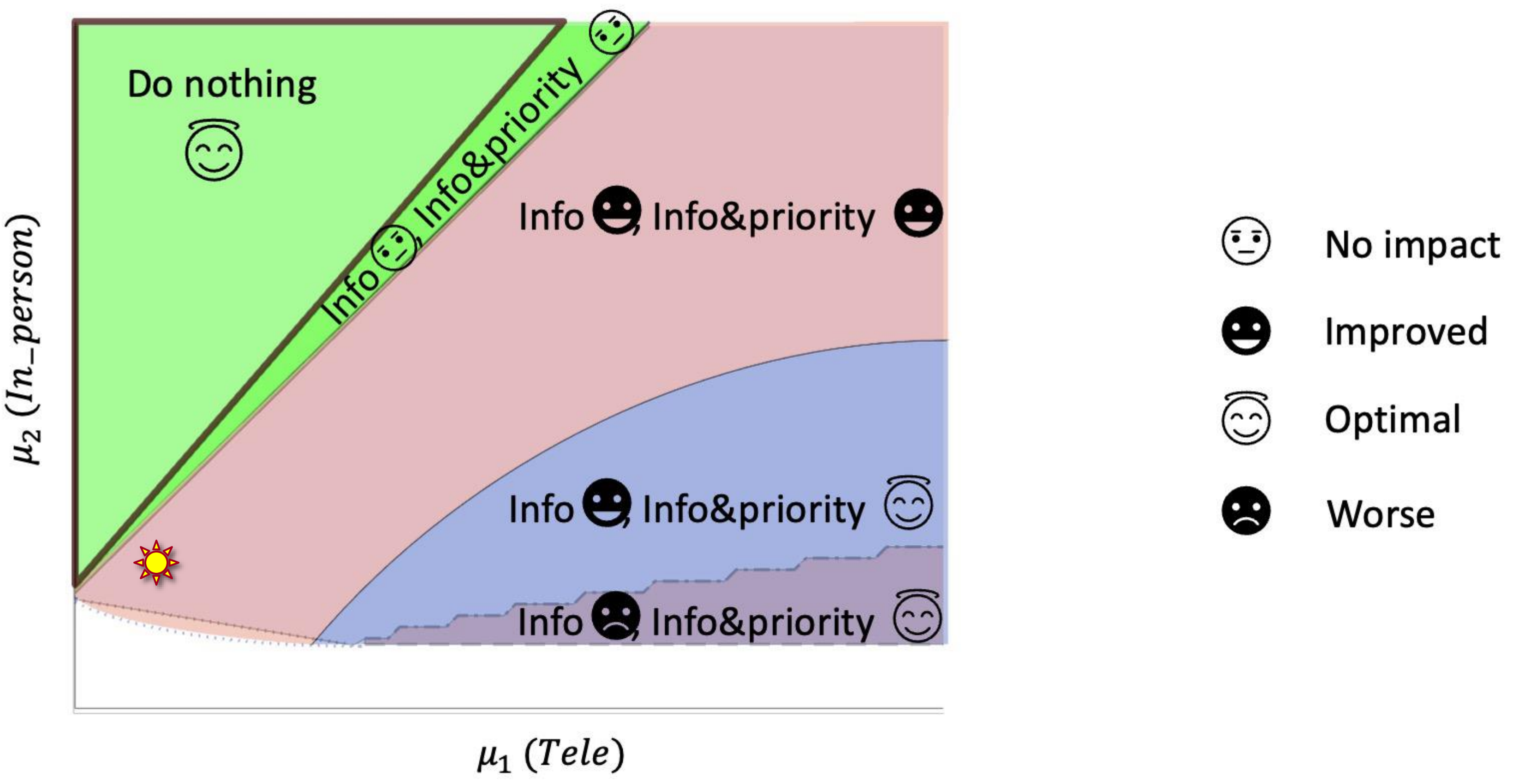
- Hourly service speed of the sample patients via telemedicine

$$\mu_1 = \frac{\text{60 min per hour}}{\text{23 min per telemedicine visit}} \times \text{ proportion of sample patients}$$
$$= 0.039 \text{ patients/hour}$$

- Hourly service speed of the sample patients via in-person visits

$$\mu_2 = \text{telemedicine service rate} \times \frac{\text{in–person throughout}}{\text{telemedicine throughput}}$$
$$= 0.566 \text{ patients/hour}$$

Counterfactual Analysis



Counterfactual Analysis

- Parameter regime: Information☻, information & priority ☻
- Crude equilibrium, refined equilibrium, system's first best

	Crude	Refined	First Best
	p^*	t^*	$\bar{t}$
Strategy	4.3%	3.9%	5.6%

- Average waiting time (days)

Average waiting time	Crude	Refined	First Best
Across all patients	14.48	8.56 **41%↓**	6.18
At the telemedicine queue	8.76	7.62	19.14
Average waiting time	14.48	8.58	5.38

Counterfactual Analysis

- Parameter regime: Information☻, information & priority ☻
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Strategy	4.3%	3.9%	5.6%

- Average waiting time (days)

Average waiting time	Crude	Refined	Priority	First Best
Across all patients	14.48	8.56	8.13 +5%↓	6.18
At the telemedicine queue	8.76	7.62	8.08	19.14
At the in-person queue	14.48	8.58	8.11	5.38

Summary

- Our Contribution
  - A queueing-game model
  - Two operational levers
  - Case study using real-world data

- Takeaway
  - With the online triage tool, equilibrium under refined information may not outperform the equilibrium under crude information
  - Proper priority rule can turn the information disadvantage into advantage

Thank you!