

Assortment Optimization for Patient-Provider Matching

Naveen Raman & Holly Wiberg

Carnegie Mellon University

Harvard | October 10th

Doctors are Important

Doctors are Important



Regular Checkups

Doctors are Important



Regular Checkups



Injury Treatment

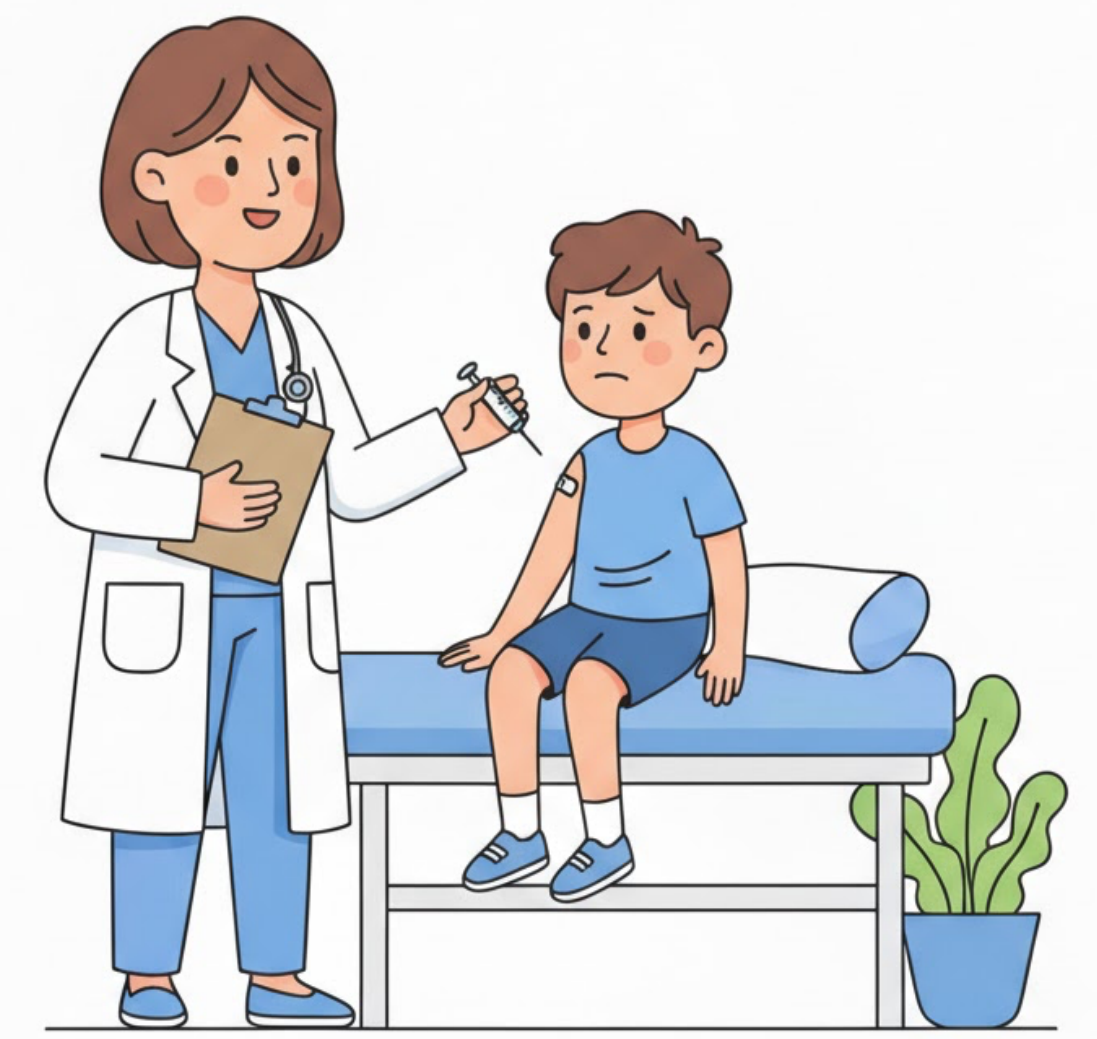
Doctors are Important



Regular Checkups



Injury Treatment

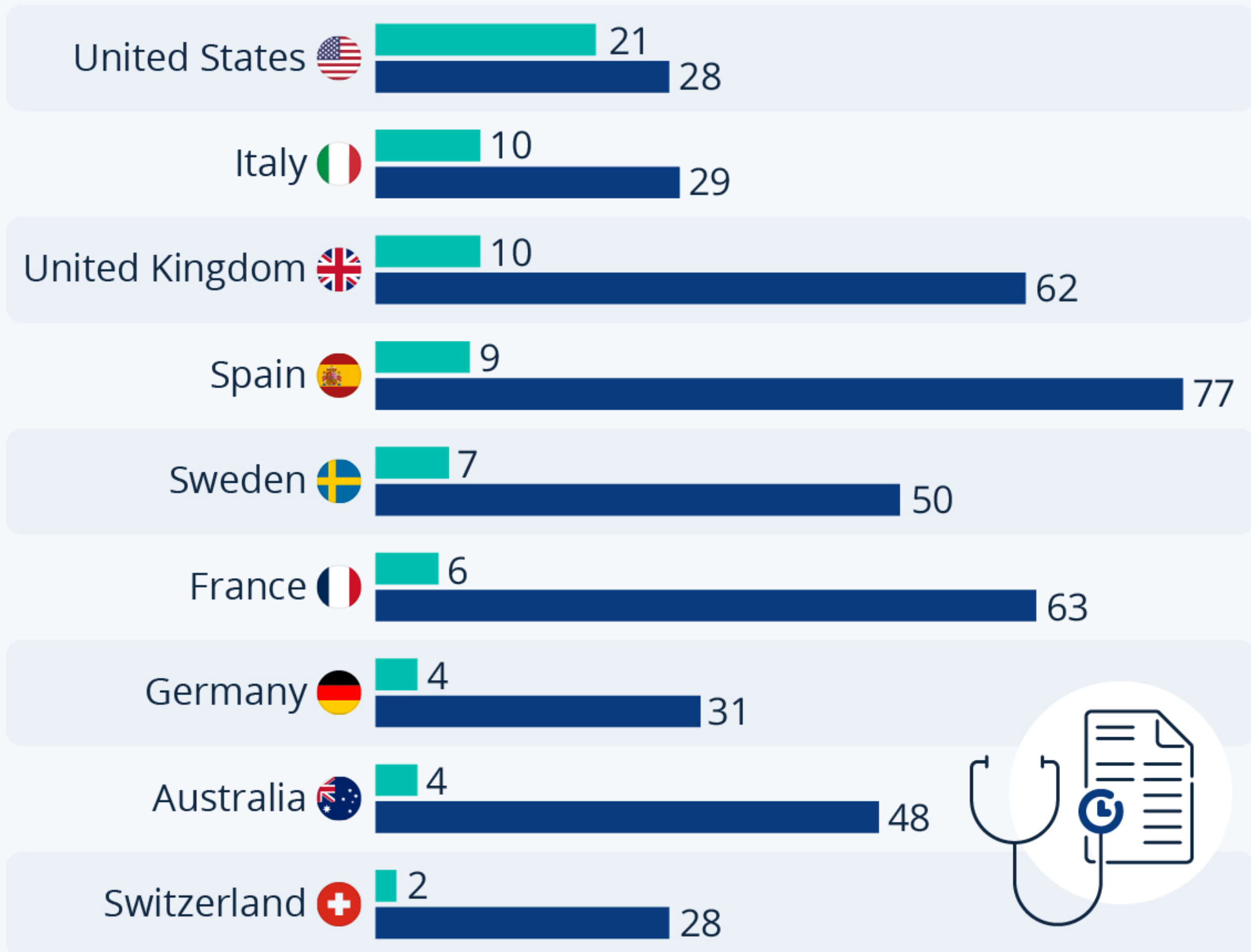


Disease Prevention

Healthcare: How Long Do Patients Have To Wait?

Average waiting time for a doctor's appointment and for non-emergency surgery in 2023 (in days)

■ General practitioner ■ Non-emergency surgery



Facts & Figures 2024

Numbers alone can't express the work of our colleagues, and our impact on our communities.

But data explains the breadth and depth of our commitment in service of our mission: "To improve the health and healing of all."



\$6.5

BILLION

Operating
Revenue

500

Locations



185

Towns in
Service
Area



44,000

Colleagues



6,389

Physicians
on Staff



6,803

Nurses
(all types)



25,227

Inpatient
Surgeries



948,473

Primary Care
Visits



480,686

ED Visits



109,479

Transitions from
Inpatient Care



104,229

Ambulatory
Surgeries

Includes Hospital
OP surgeries and
ASC surgeries,
excludes GI cases



2,488

Licensed Beds
(including
bassinets)

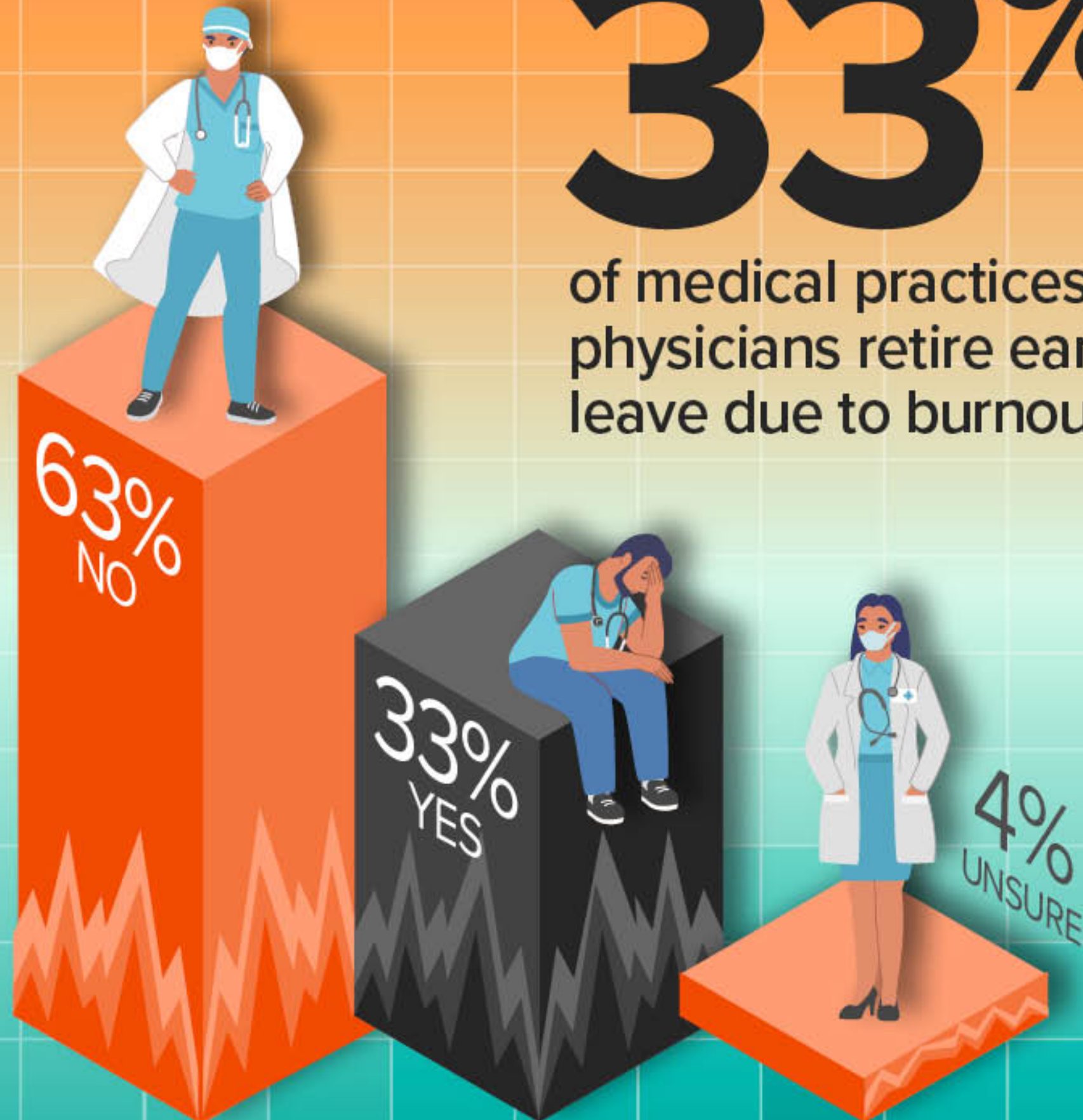


8,822

Newborn
Admissions

33%

of medical practices had
physicians retire early or
leave due to burnout in 2021.



MGMA Stat poll. October 26, 2021 | Have physicians retired early or left your practice in 2021 due to burnout?
930 responses. [MGMA.COM/STAT](https://mgma.com/stat), [#MGMASAT](https://twitter.com/MGMASAT)



MGMA Stat poll. October 26, 2021 | Have physicians retired early or left your practice due to burnout?
930 responses

MGMAStat

MGMA®

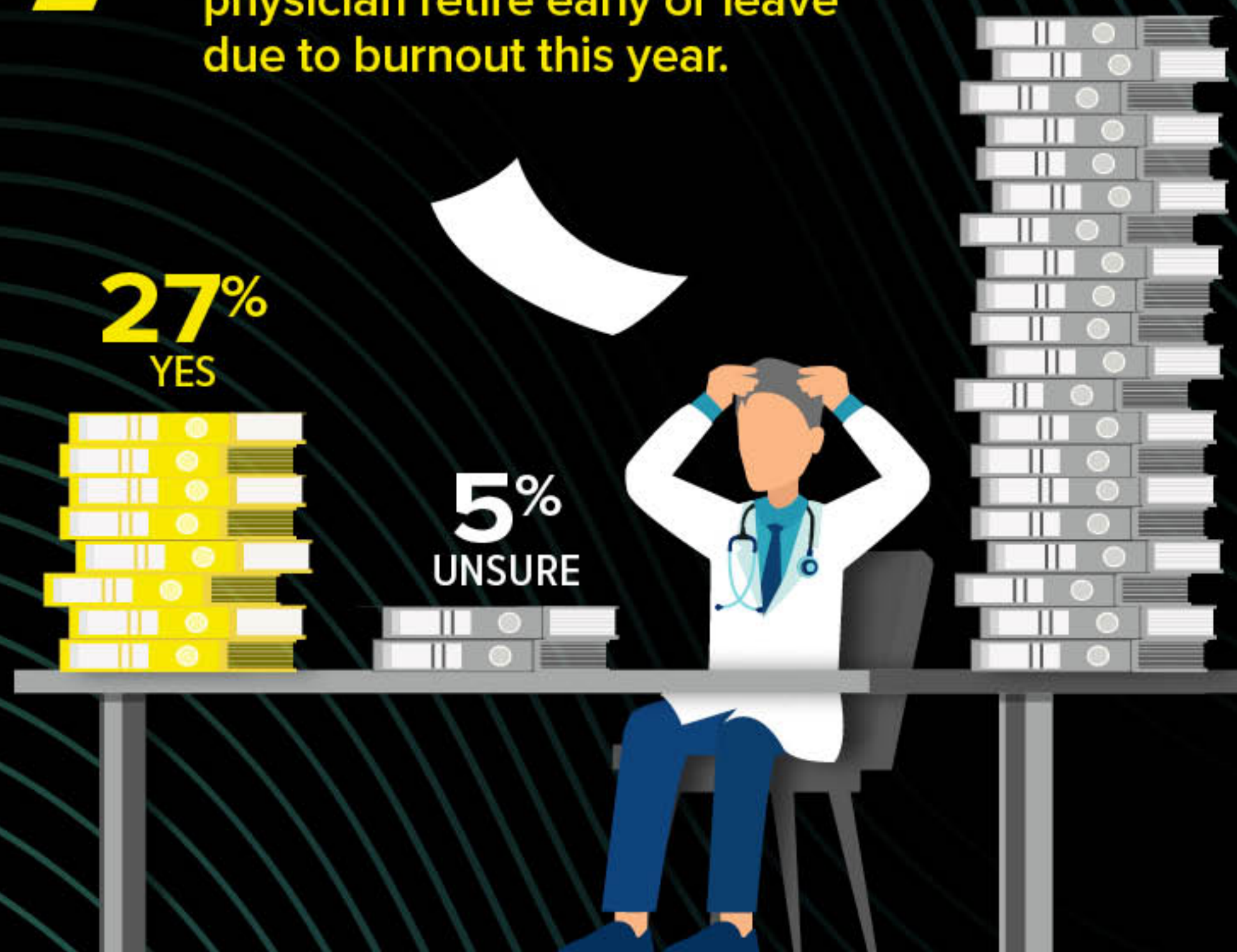
27%

of medical groups have had a physician retire early or leave due to burnout this year.

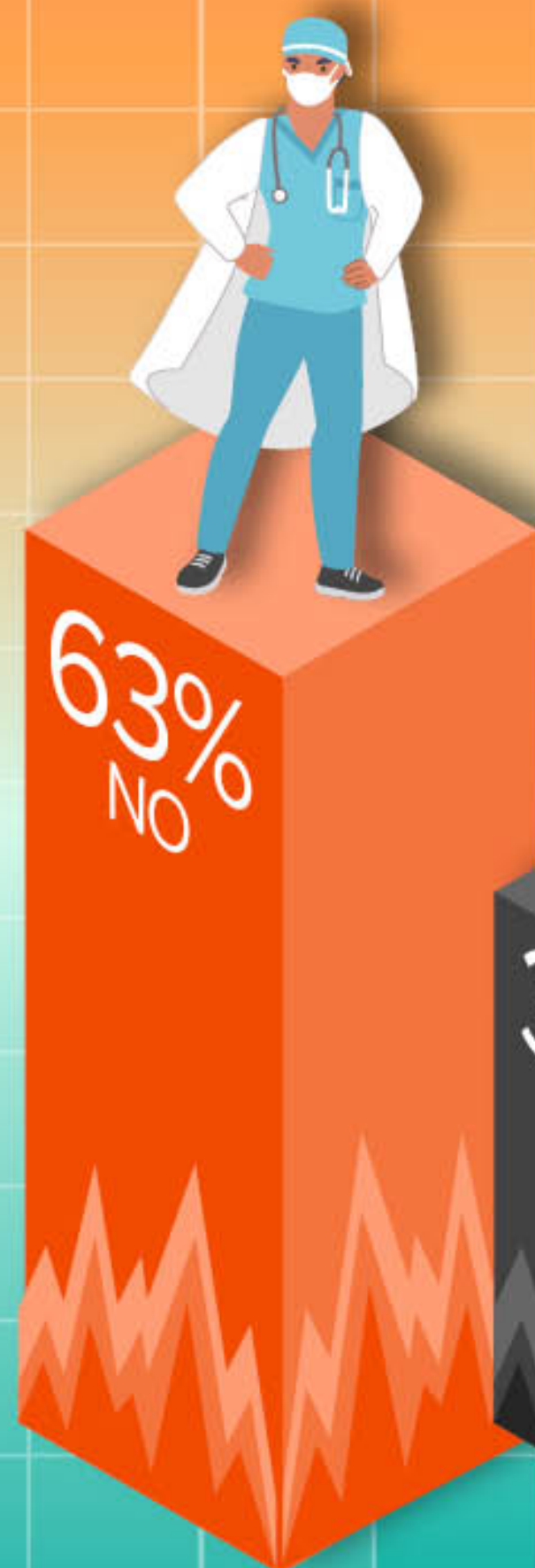
68%
NO

27%
YES

5%
UNSURE



MGMA Stat poll. September 3, 2024 | Has a physician retired early or left your practice in 2024 due to burnout?



MGMA Stat poll. October 26, 2021 | Have physicians experienced burnout?
930 responses

\$4.6 BILLION

Estimated annual costs of physician burnout, attributed to turnover and reduced clinical hours



Push Towards Centralization

Push Towards Centralization

Book a Doctor, In All Areas

Doctors In

All Areas



Book

Dr Johanna Hartmann
Orthopaedic Surgeon



Book

Dr Paul Holland
Orthopaedic Surgeon



Book

Dr Stephanie Zhang
Orthopaedic Surgeon



Book

Dr Susan Grey
Orthopaedic Surgeon



Book

Dr Thomas Richards
Orthopaedic Surgeon

Upcoming Appointments

8

Appointment

Attend

You Pay

What to Do

Follow Up

With Dr Susan Grey

@ Sydney

When Wednesday, 27 January 2021 at 10:00am - 10:15am

Where Sydney, Level 9 70 Pitt St SYDNEY NSW 2000

\$150.00

estimated rebate \$75.05

Confirm

Call (02) 3438 - 4938 to
Cancel

How does patient choice
impact overall utility and
fairness?



Three Components



Patient Utility



Patient Choice



Response Order

Three Components



Patient Utility



Patient Choice



Response Order

Three Components



Patient Utility



Patient Choice



Response Order

Three Components



Patient Utility



Patient Choice



Response Order

Three Components



Patient Utility



Patient Choice



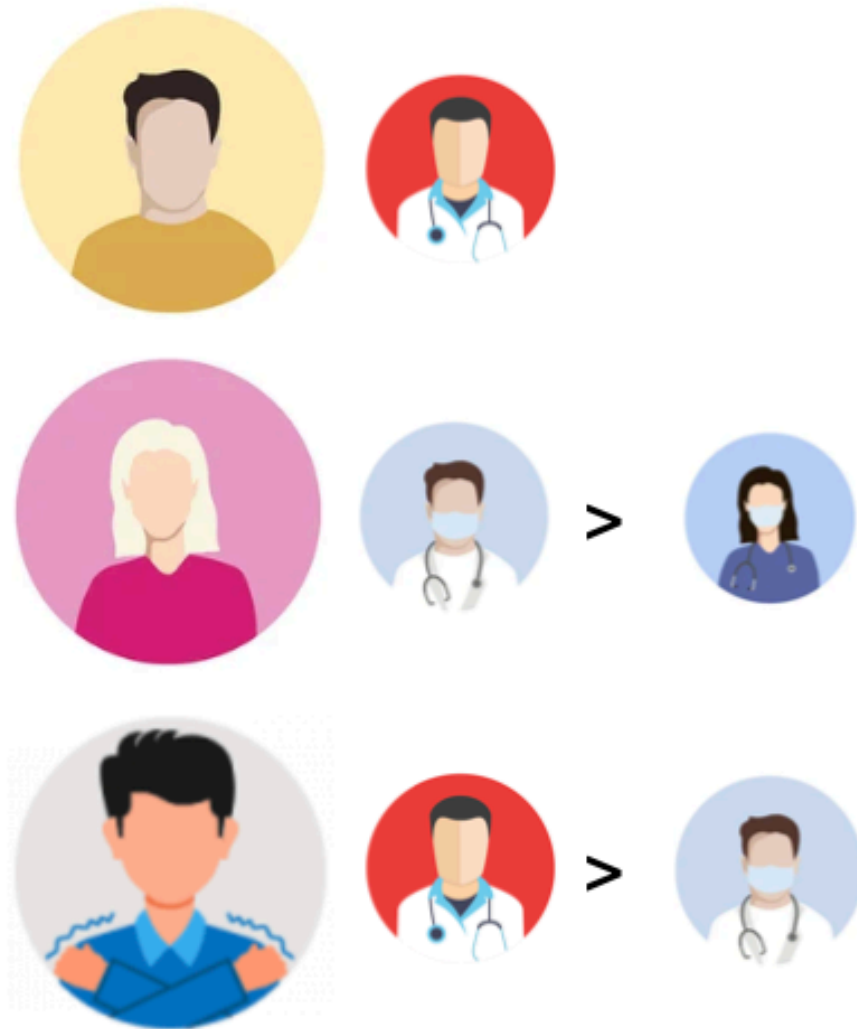
Response Order

Which providers should we offer to each patient?

Offline Offering and Online Matching

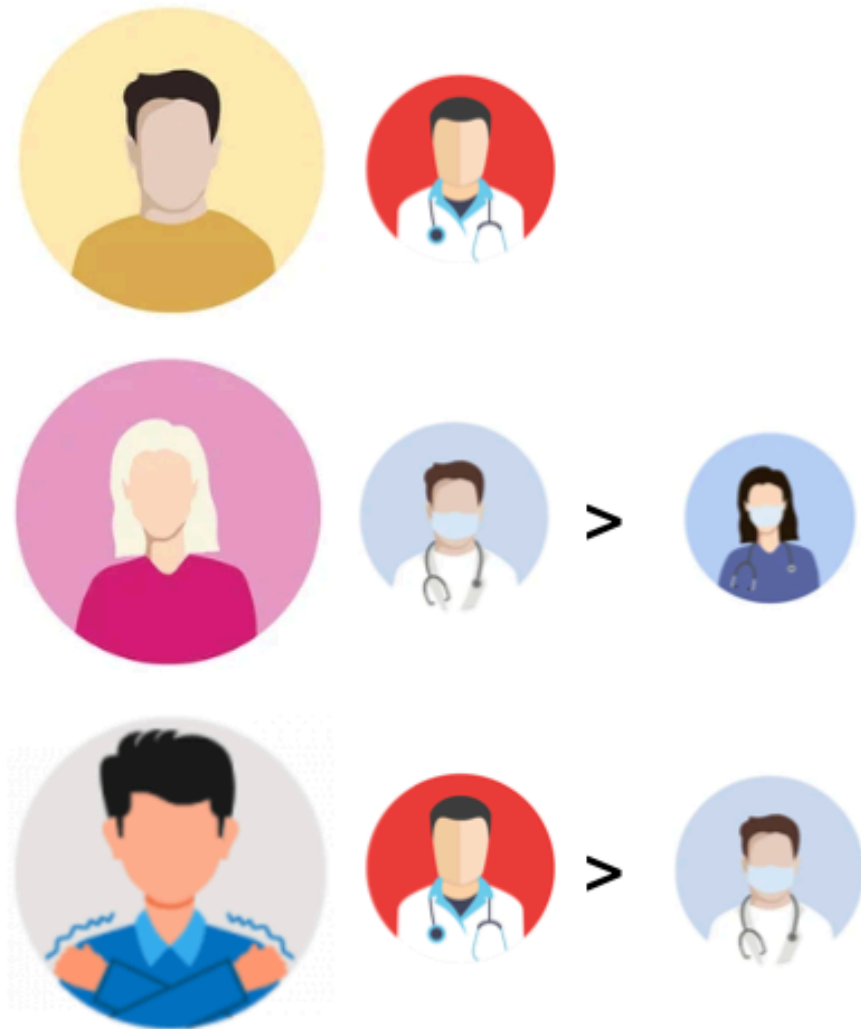
Offline Offering and Online Matching

Upfront Menu Offering



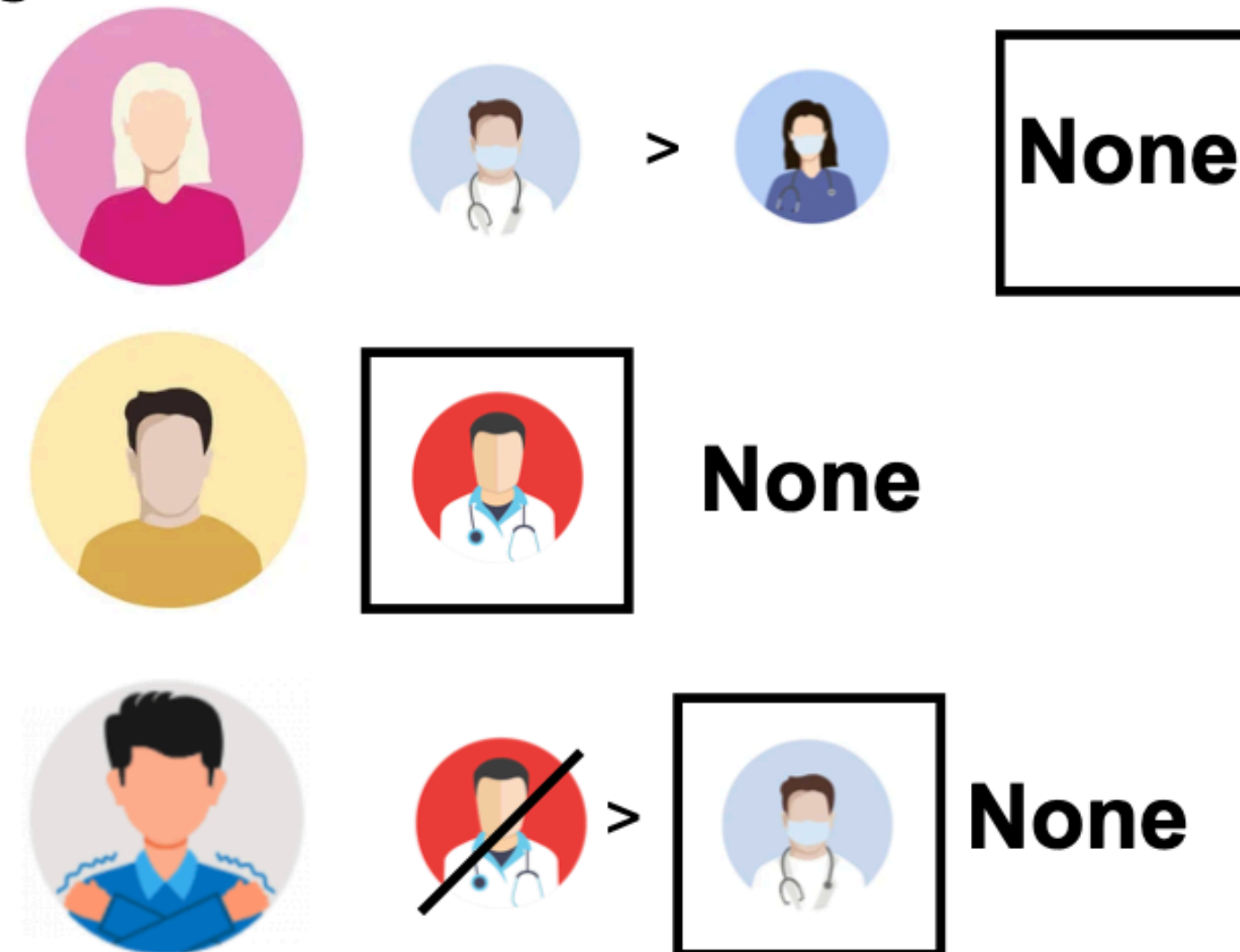
Offline Offering and Online Matching

Upfront Menu Offering



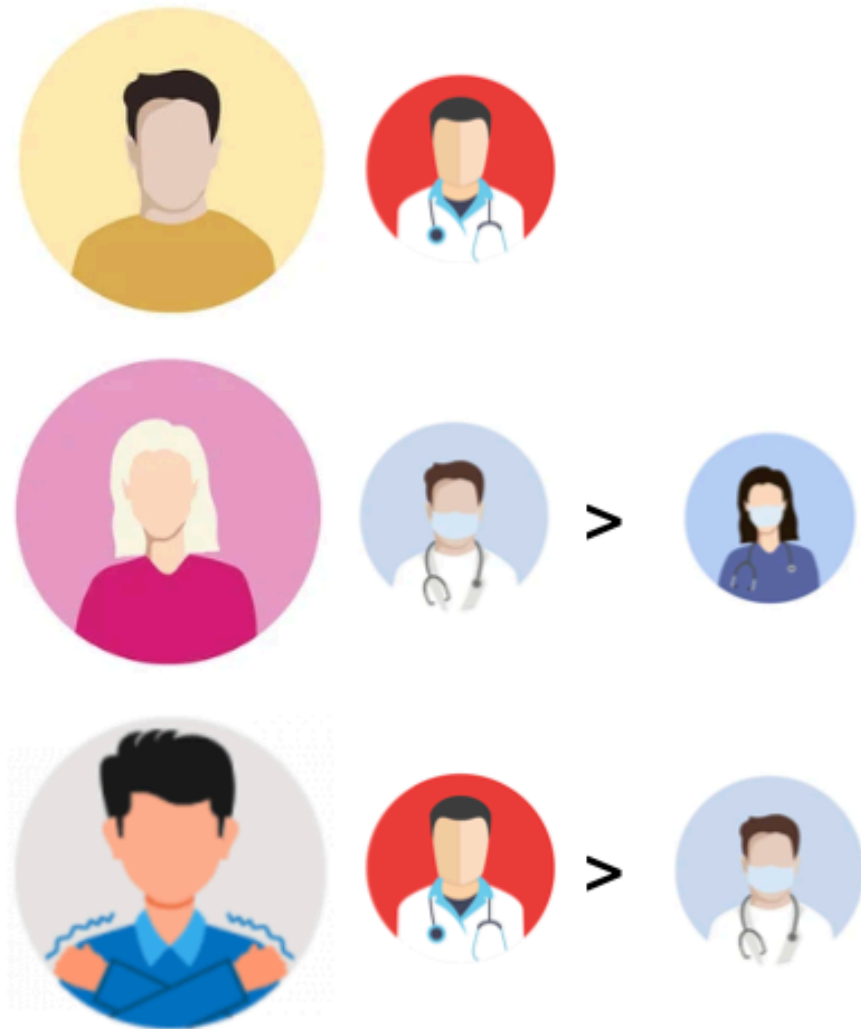
Patient Response

Response
Order

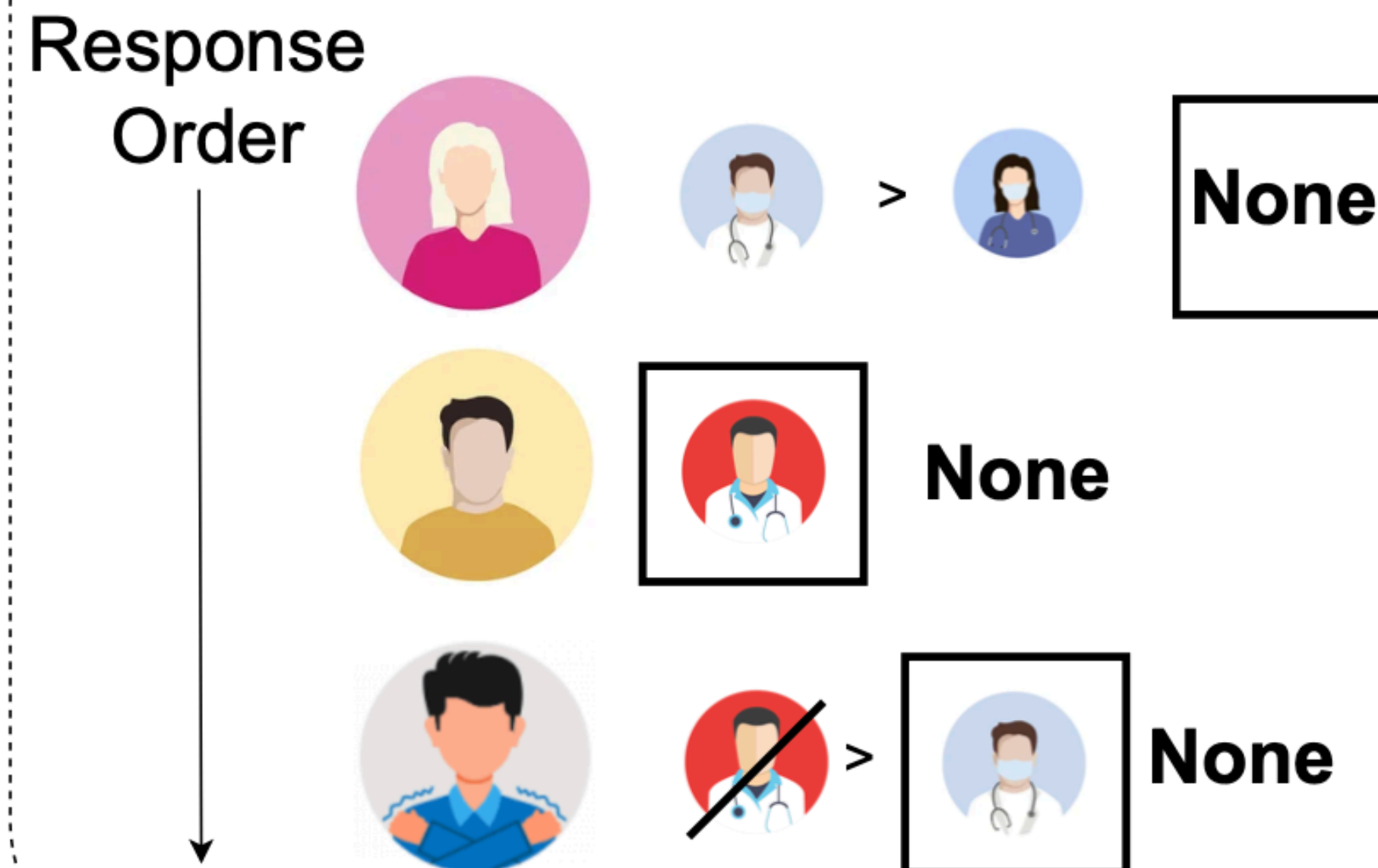


Offline Offering and Online Matching

Upfront Menu Offering



Patient Response



Final Matches



Why Offline-Online Hybrid?

Why Offline-Online Hybrid?

Offline Matching



Disadvantage: No Autonomy

Why Offline-Online Hybrid?

Offline Matching



Disadvantage: No Autonomy

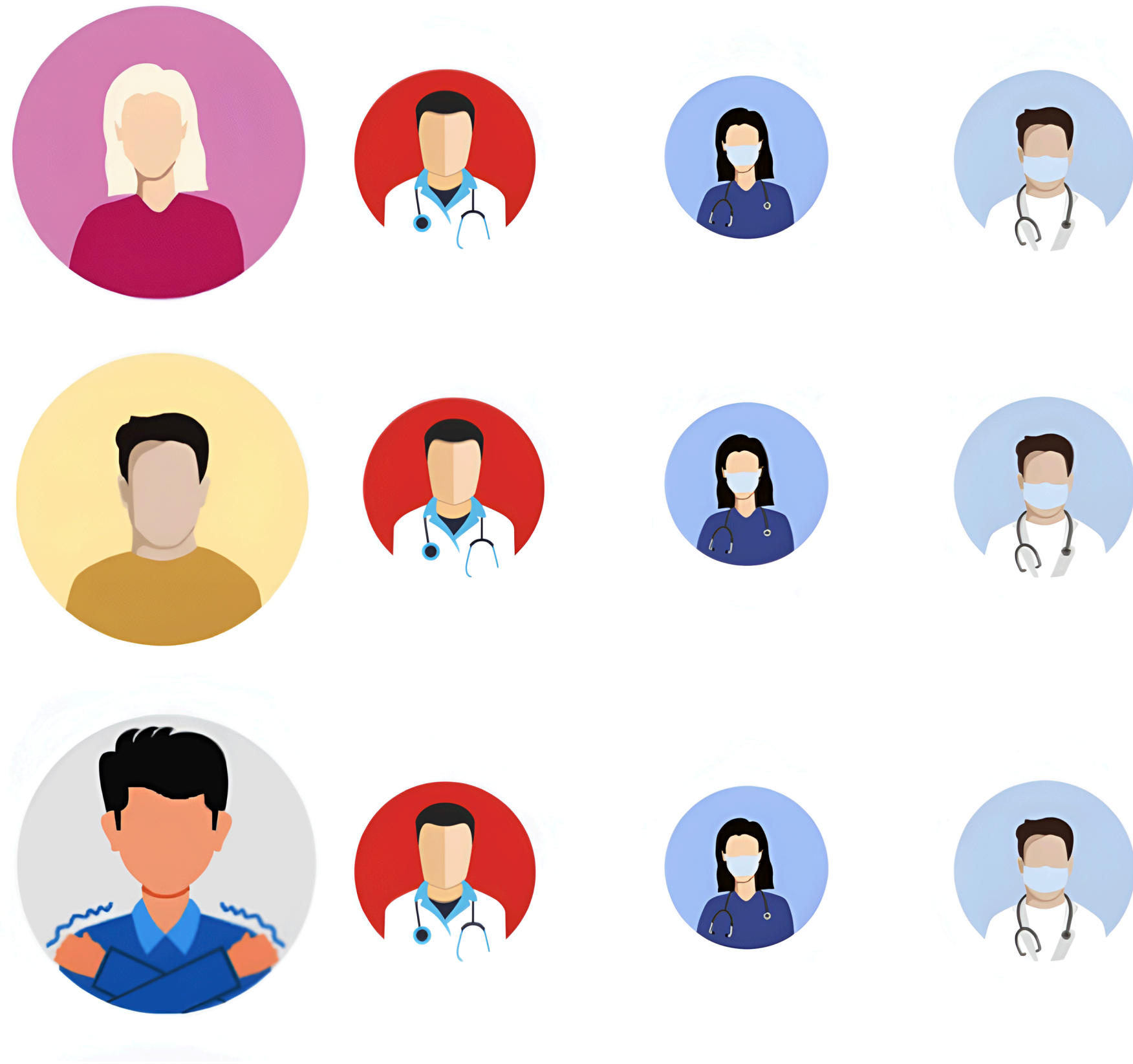
Online Matching

Response
Order

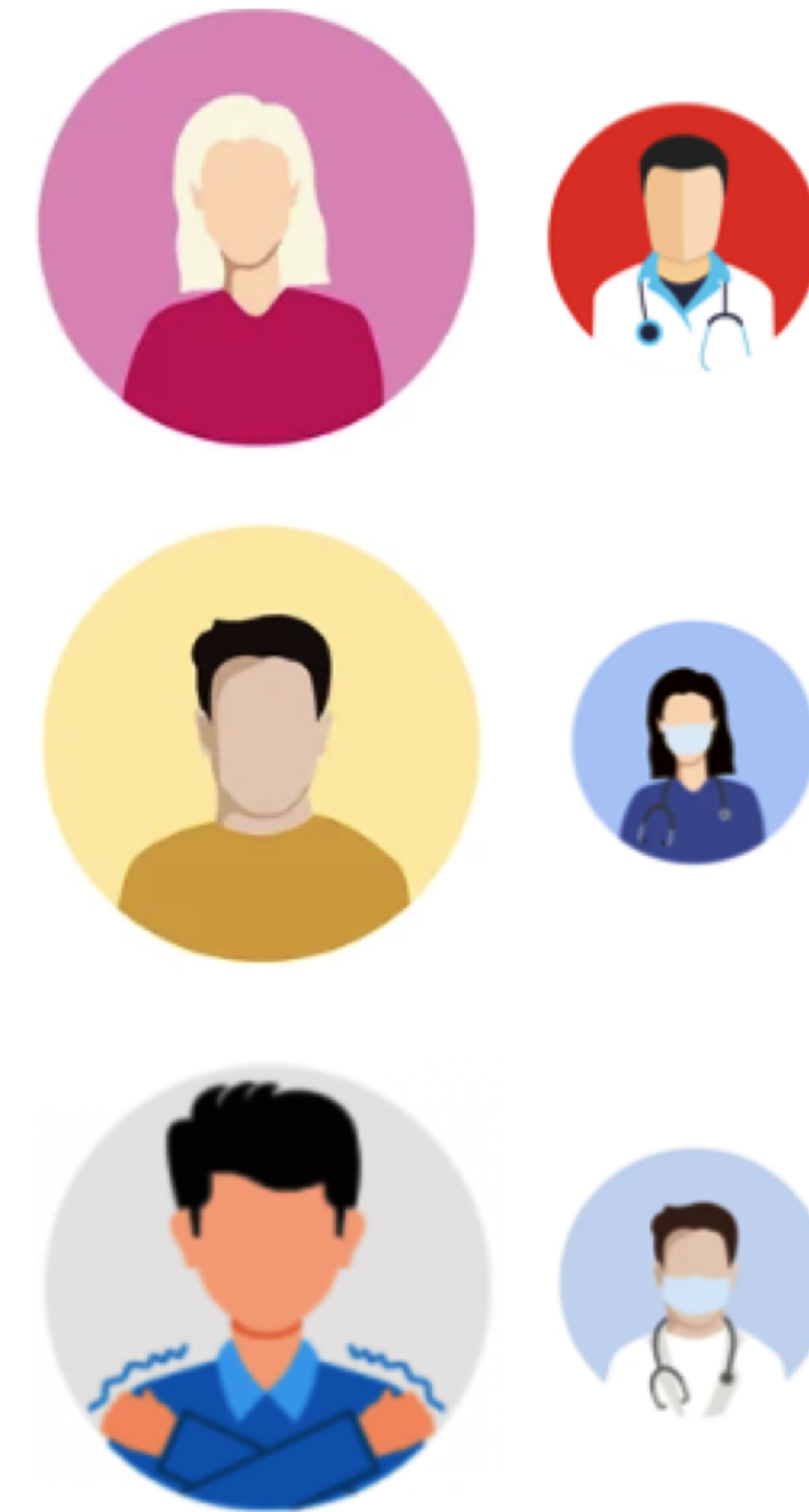


Disadvantage: Patients might wait to match; incentive compatibility

Two Extreme Policies



Greedy

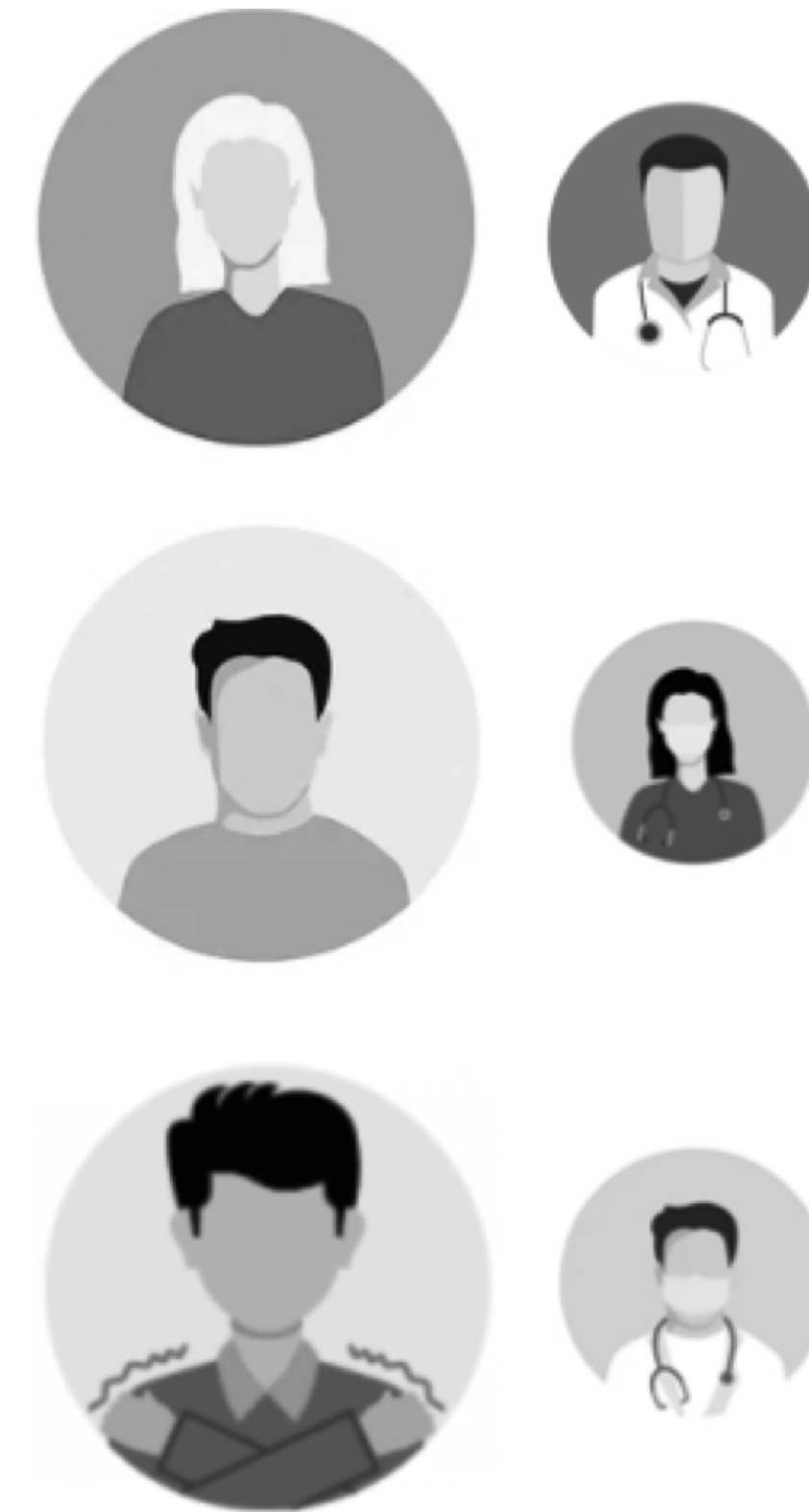


Pairwise

Two Extreme Policies



Greedy



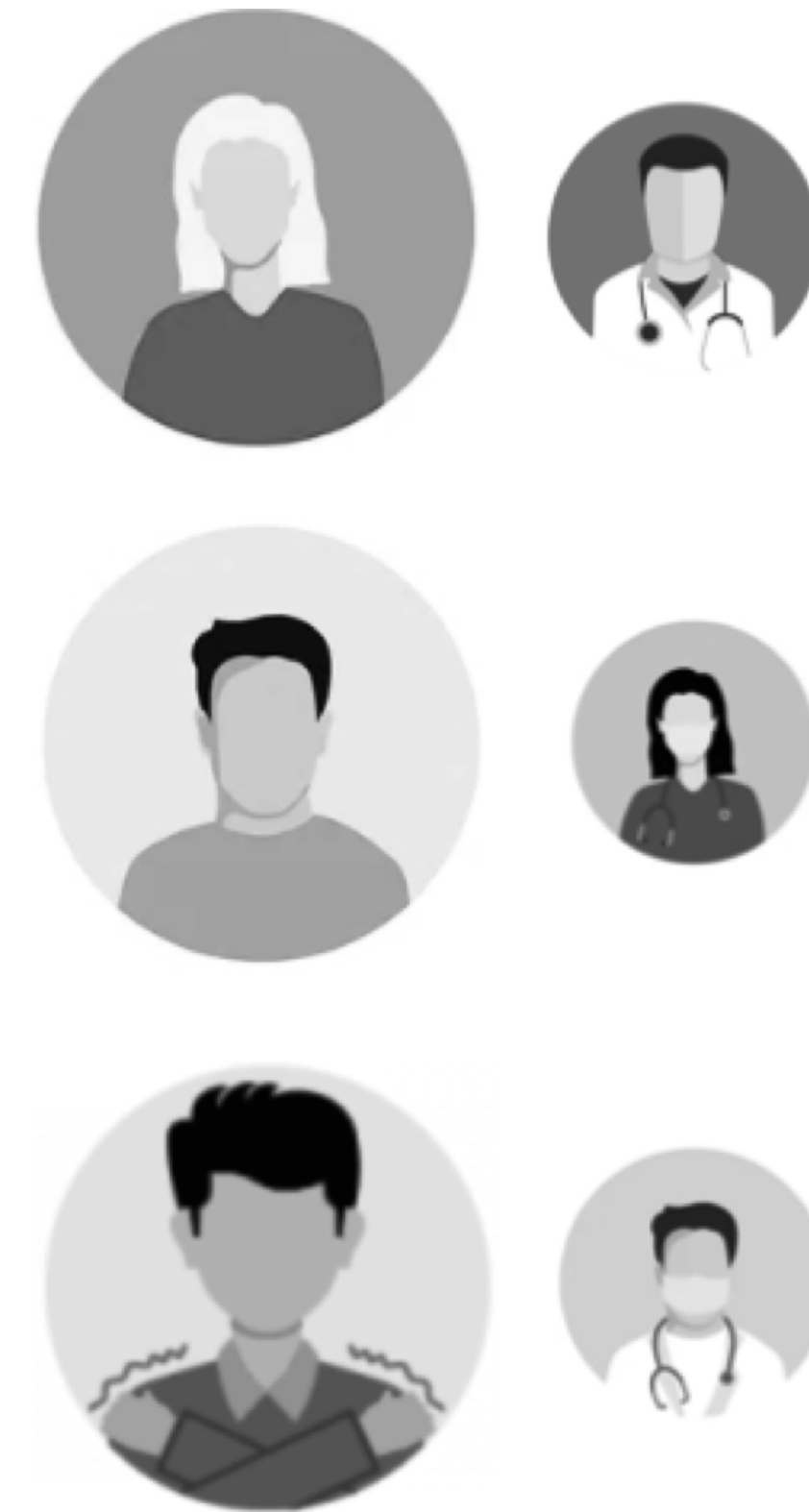
Pairwise

Two Extreme Policies



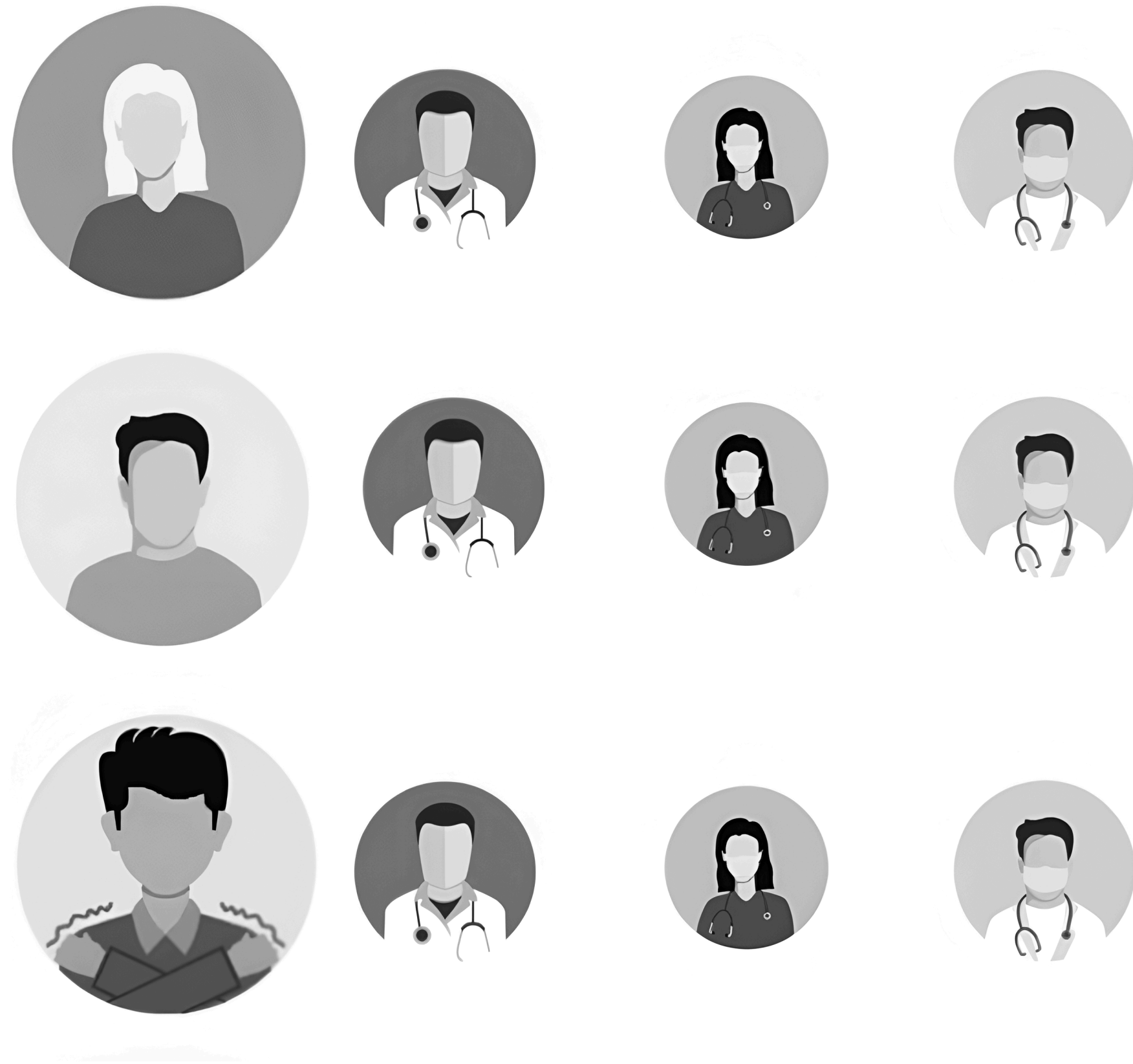
Greedy

Beneficial when there's
uncertainty in patient selections

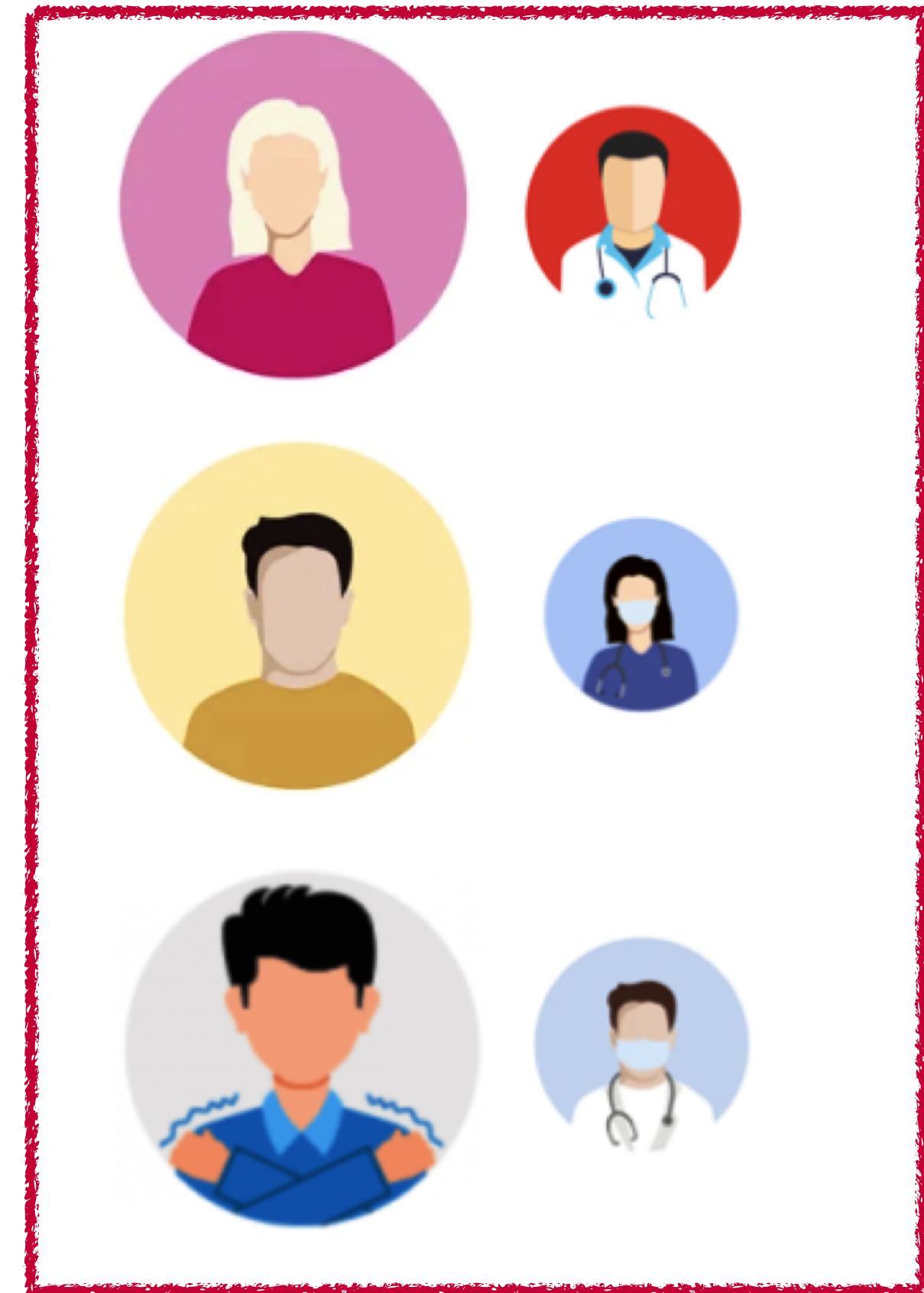


Pairwise

Two Extreme Policies

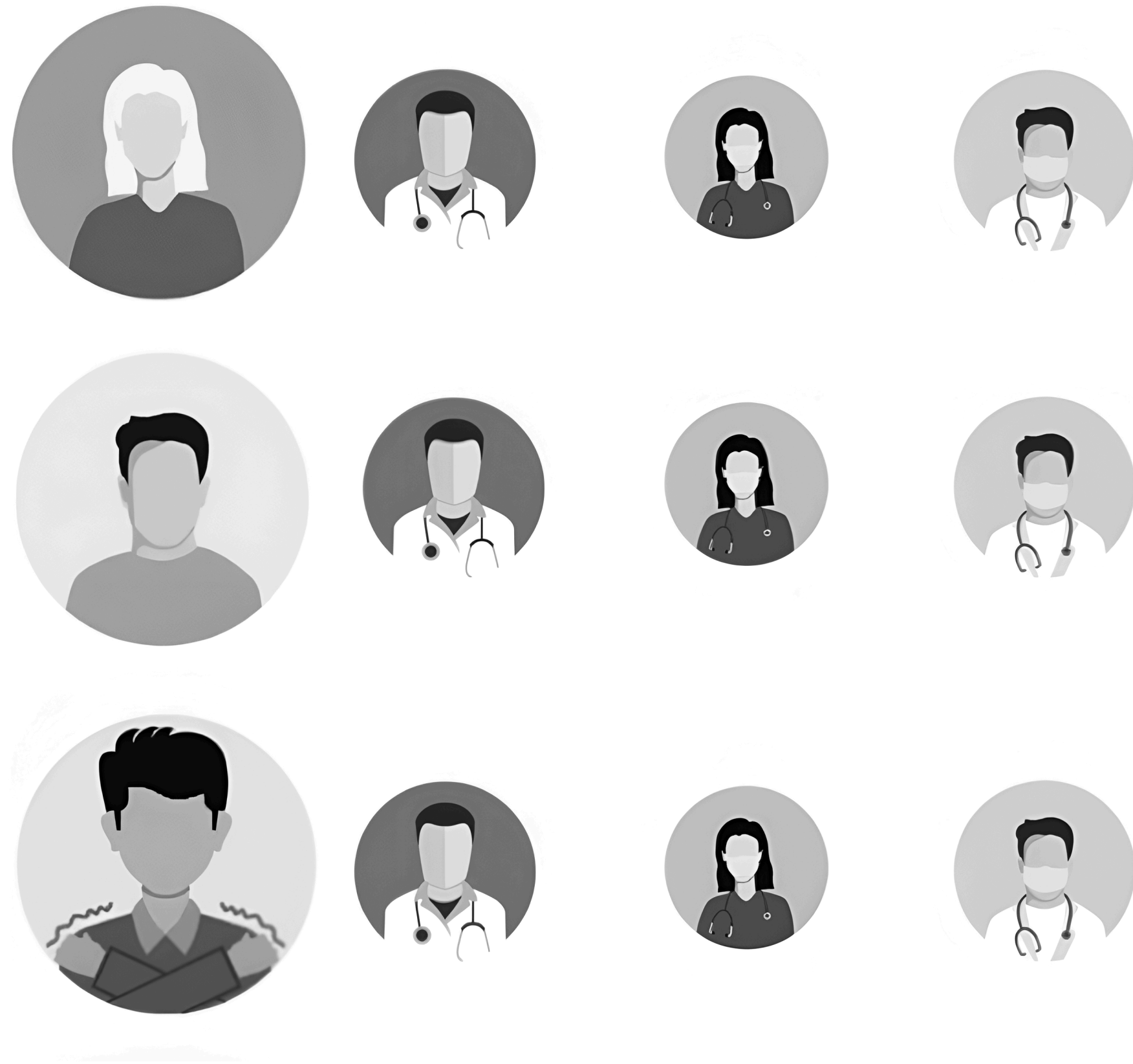


Greedy

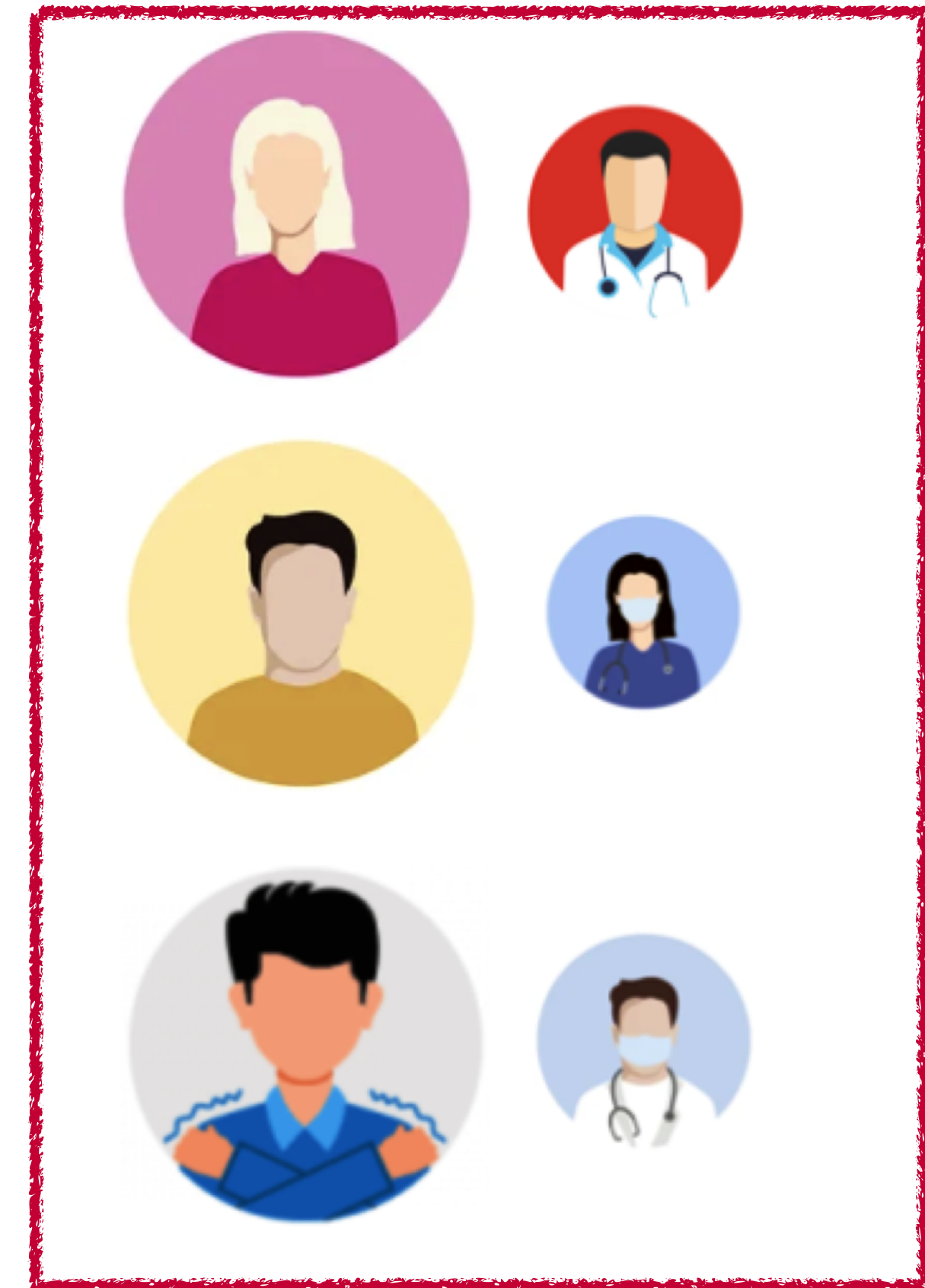


Pairwise

Two Extreme Policies



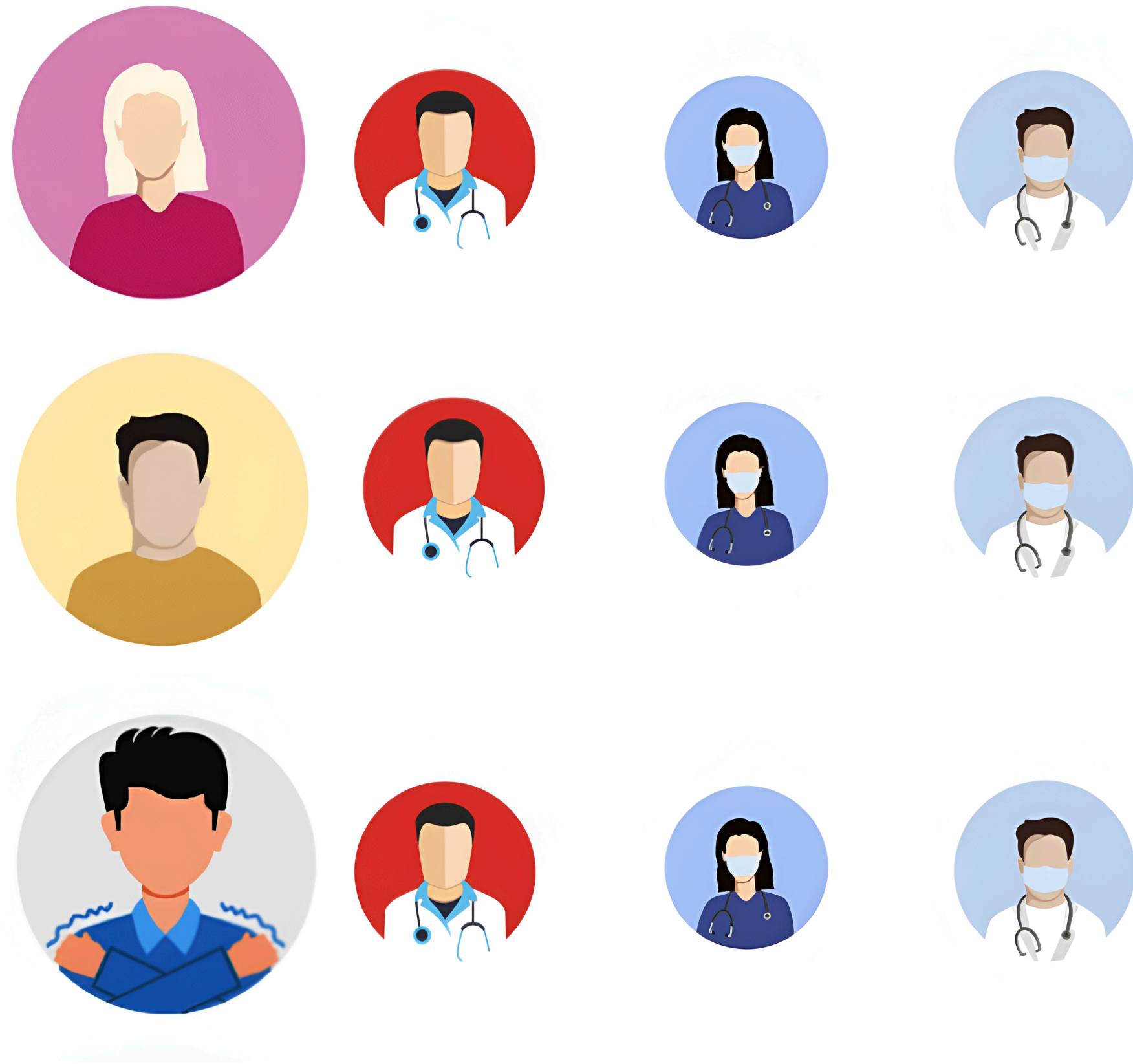
Greedy



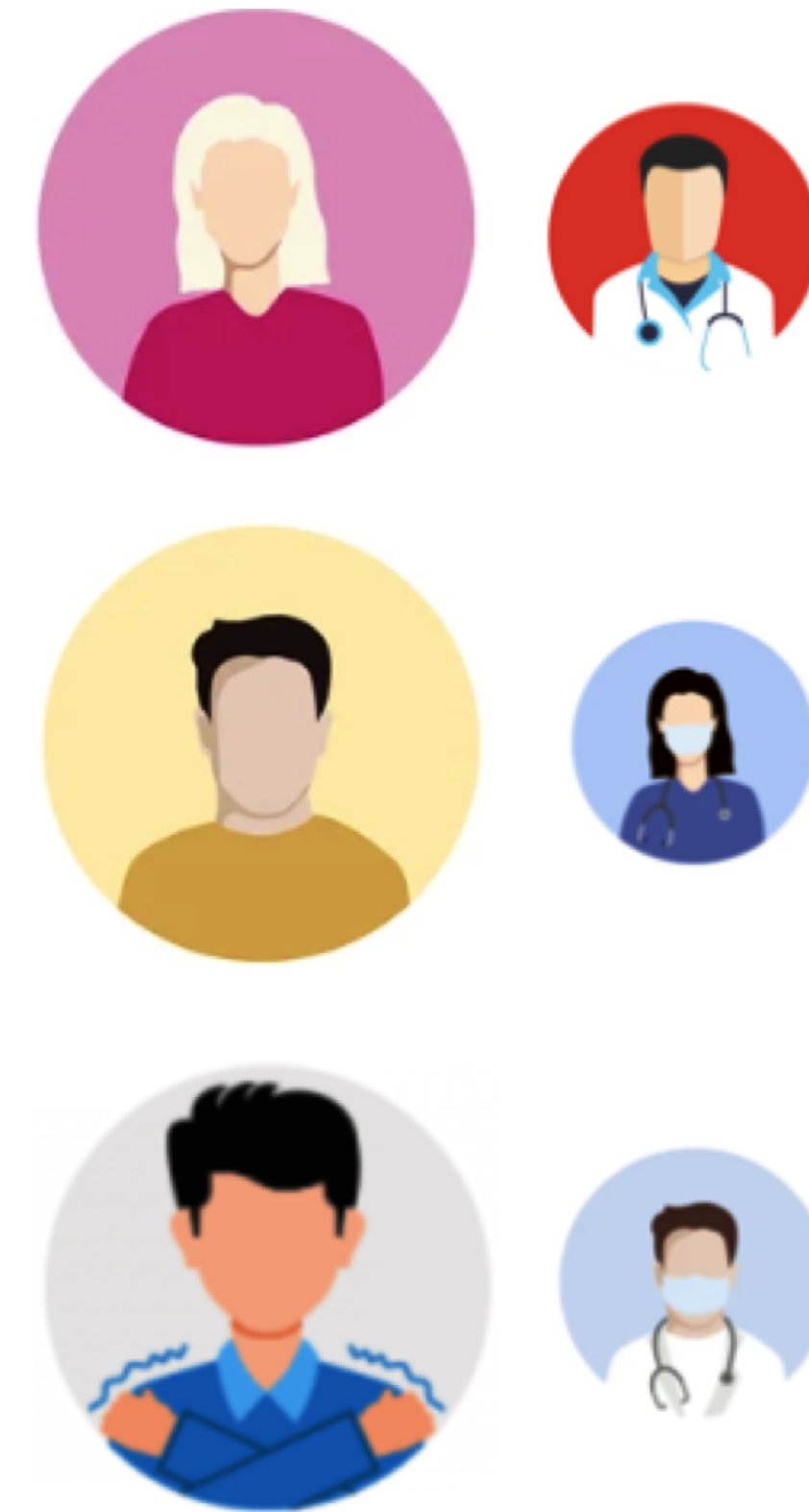
Pairwise

Beneficial when patient choices
are known & deterministic

Two Extreme Policies

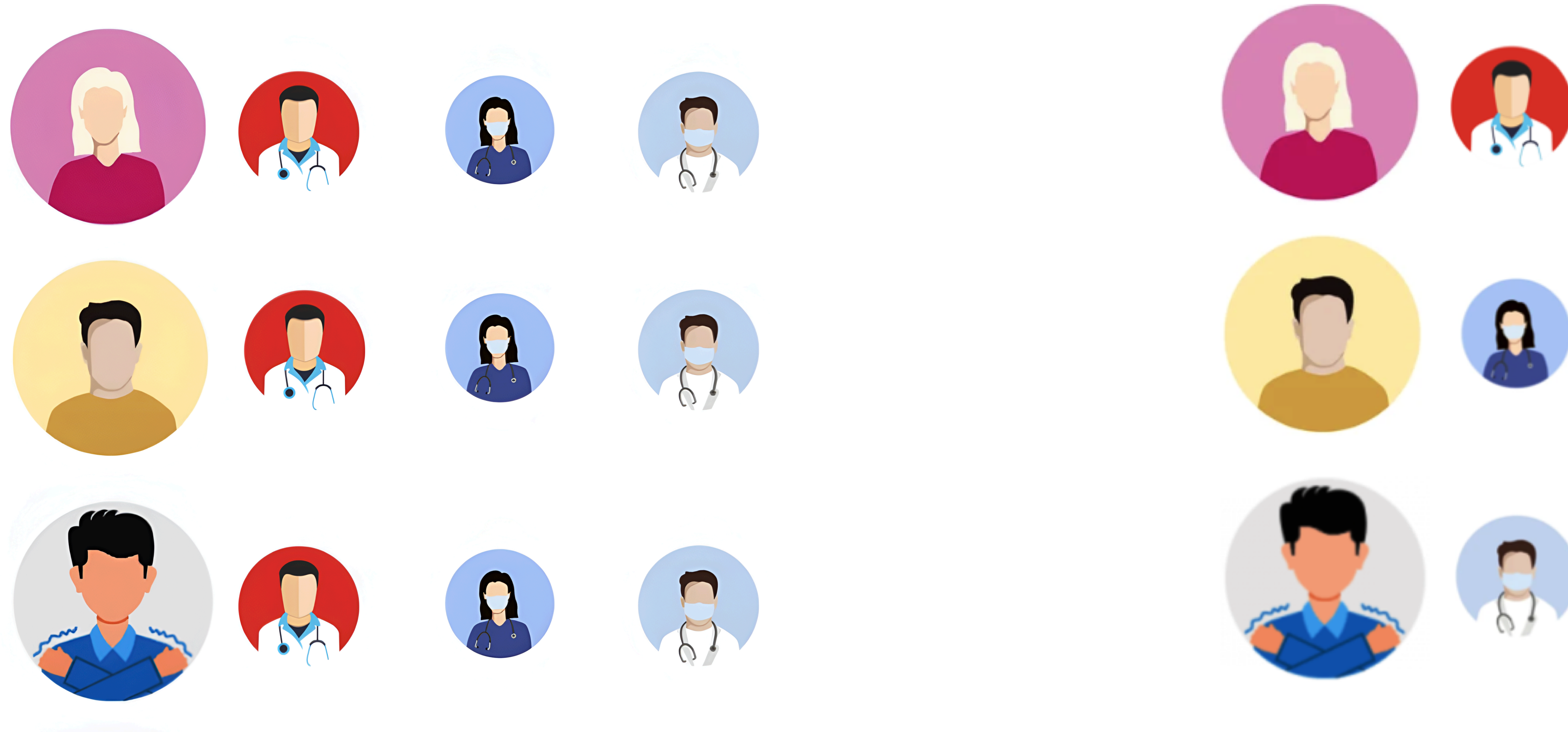


Greedy



Pairwise

Two Extreme Policies

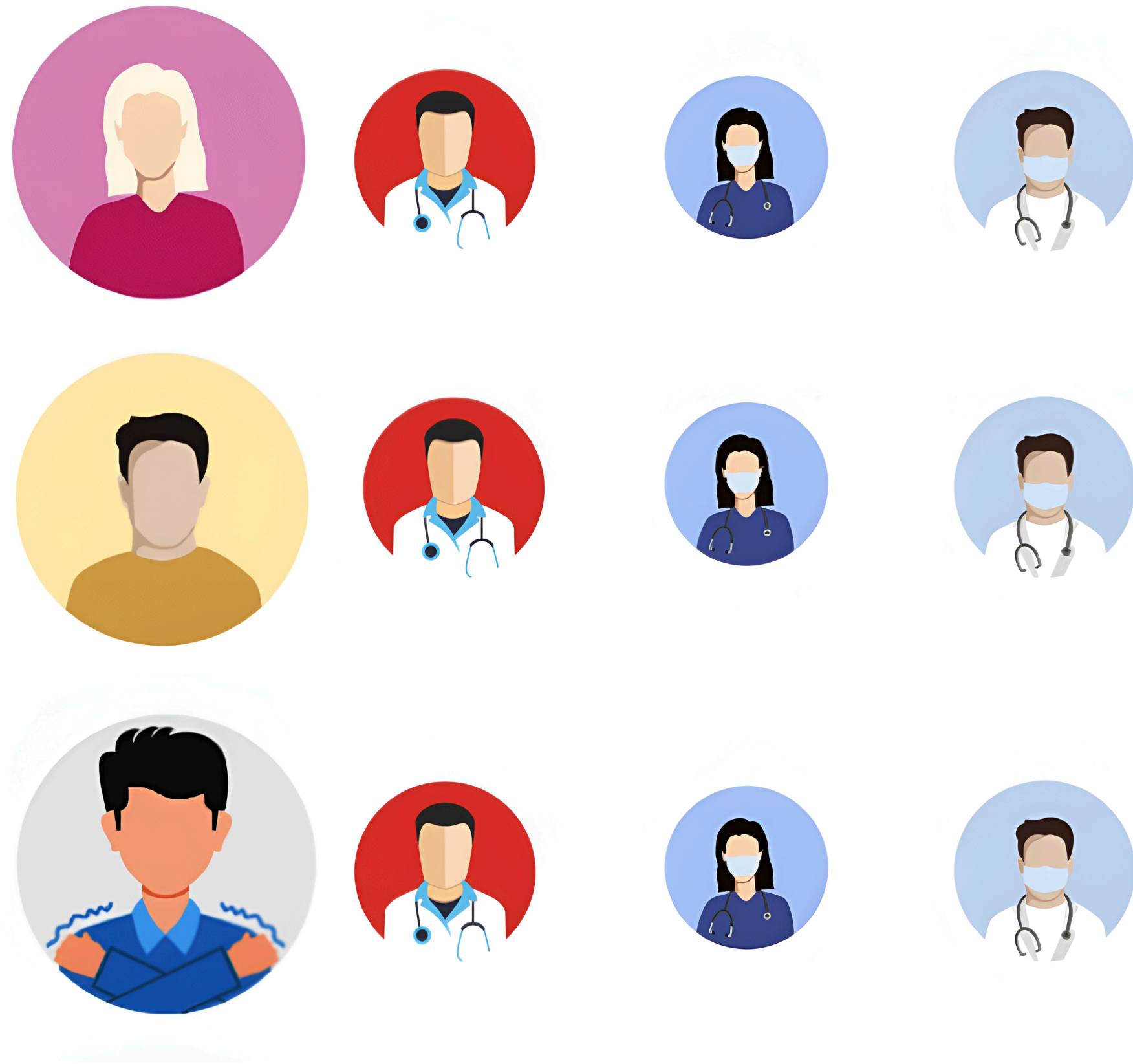


Greedy

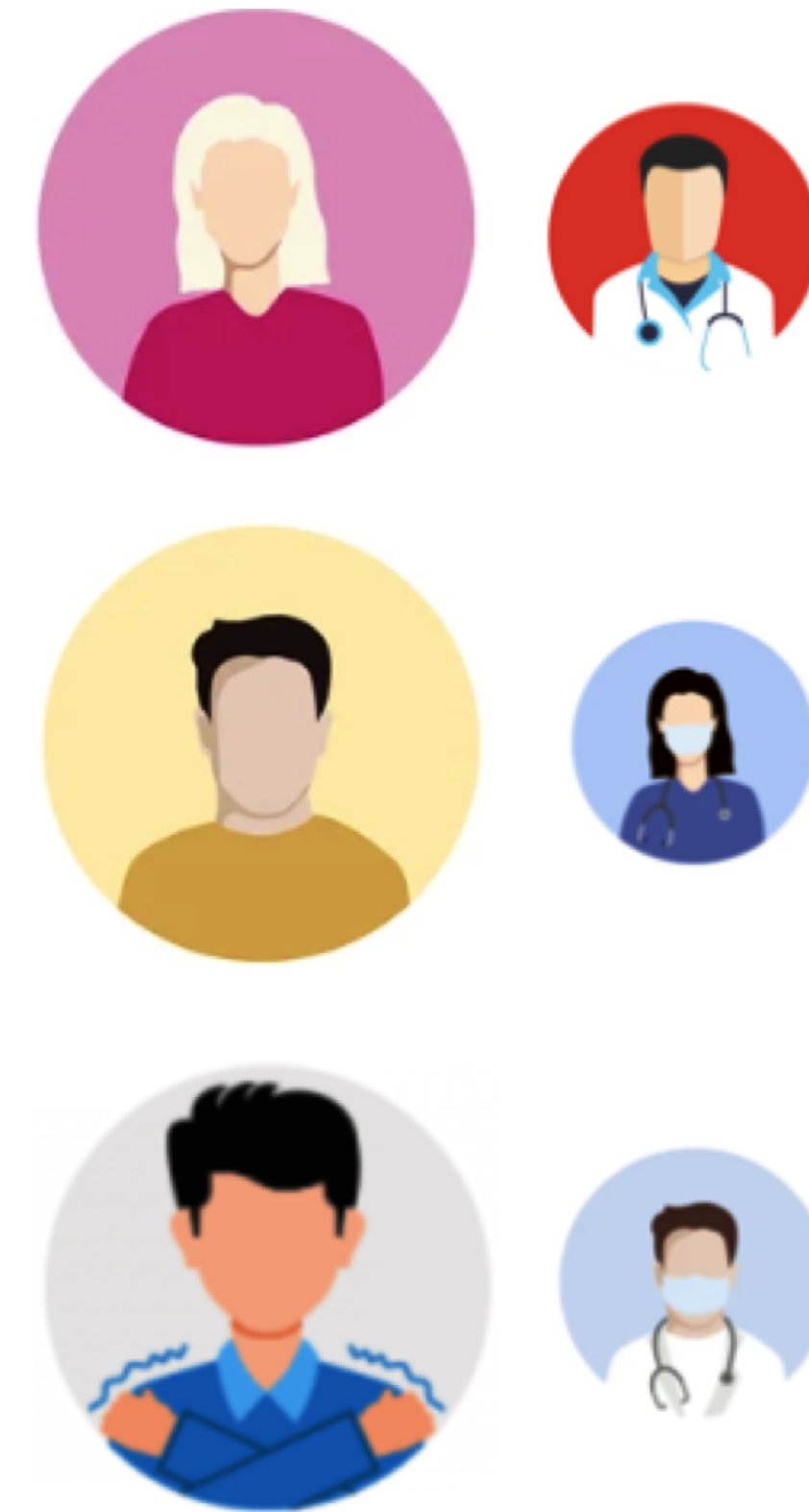
Pairwise

Choice allows us to overcome patient uncertainty during matching

Going beyond the Extremes

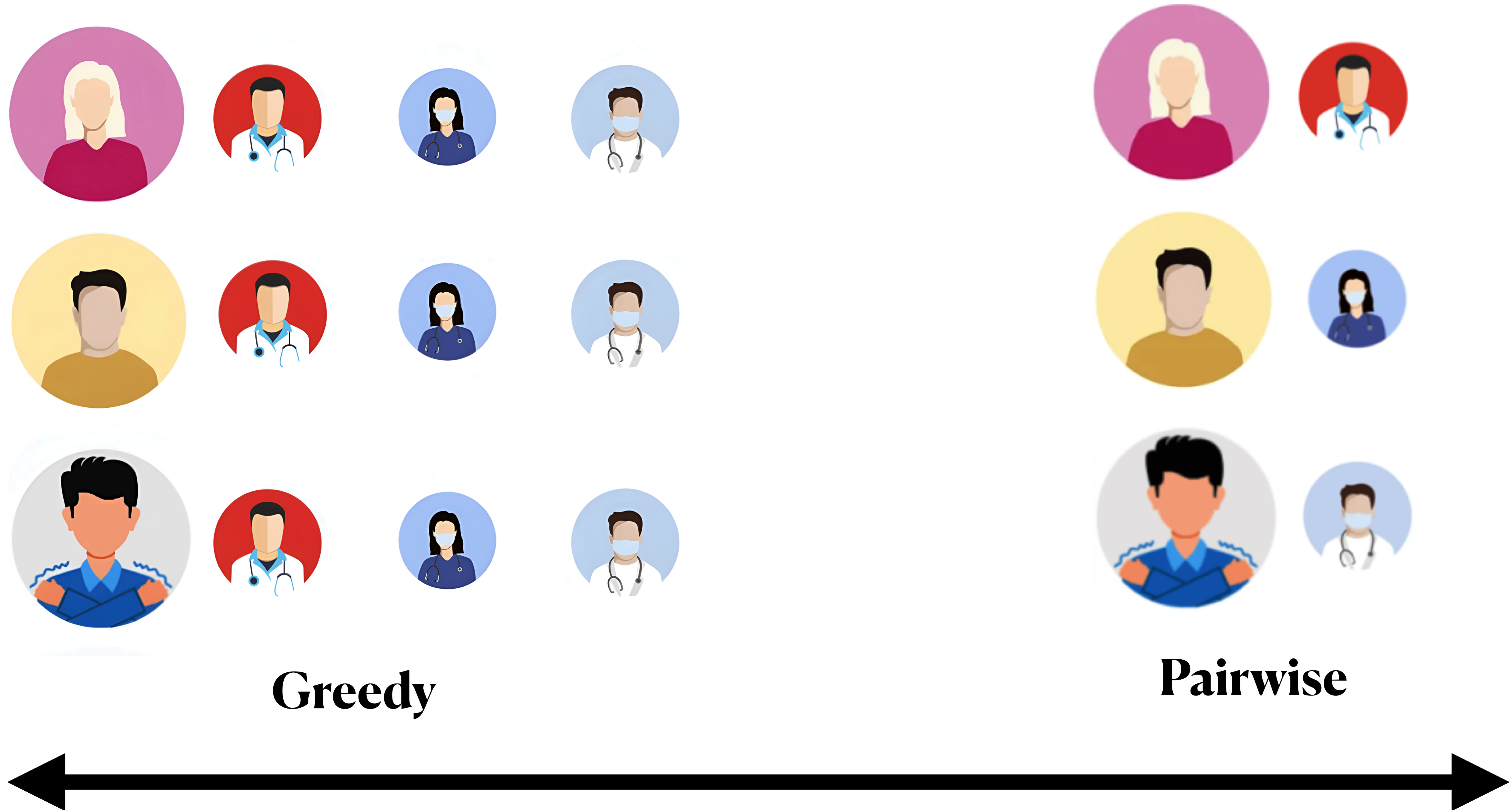


Greedy



Pairwise

Going beyond the Extremes



Greedy and pairwise lie on a spectrum of patient choice

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

$\Pr[j \text{ available}]$

Availability Probability

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

$\Pr[j \text{ available}]$

Availability Probability

Depends on number of
patients offered per provider

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

$\Pr[j \text{ available}]$

Availability Probability

Depends on number of
patients offered per provider

$\Pr[i \text{ selects } j | j \text{ available}]$

Selection Probability

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

$\Pr[j \text{ available}]$

Availability Probability

Depends on number of
patients offered per provider

$\Pr[i \text{ selects } j | j \text{ available}]$

Selection Probability

Depends on patient i's
ranking of providers

Optimization Problem

Heuristic lower
bounds utility

We optimize a heuristic approximation for match quality with two components

$$h(\mathbf{X}) = \sum_{\text{Patient } i} \sum_{\text{Provider } j} \text{Utility}(i, j) \Pr[j \text{ available}] \Pr[i \text{ selects } j | j \text{ available}]$$

$\Pr[j \text{ available}]$

Availability Probability

Depends on number of
patients offered per provider

$\Pr[i \text{ selects } j | j \text{ available}]$

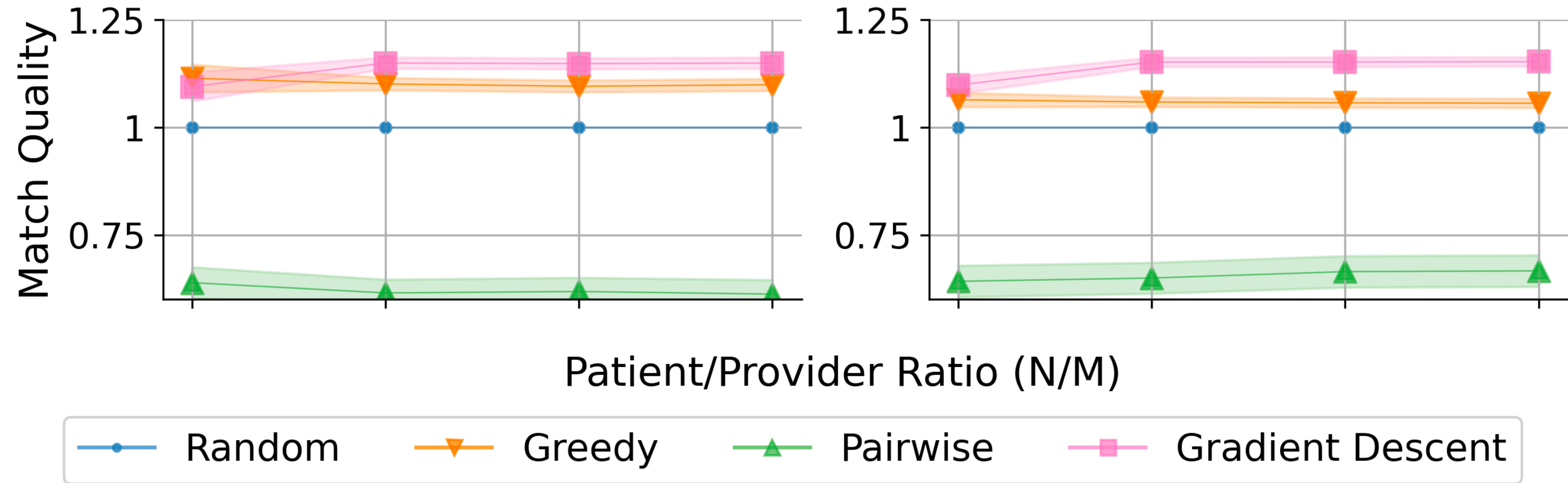
Selection Probability

Depends on patient i's
ranking of providers

Find the assortment $\mathbf{X}$ that maximizes the heuristic

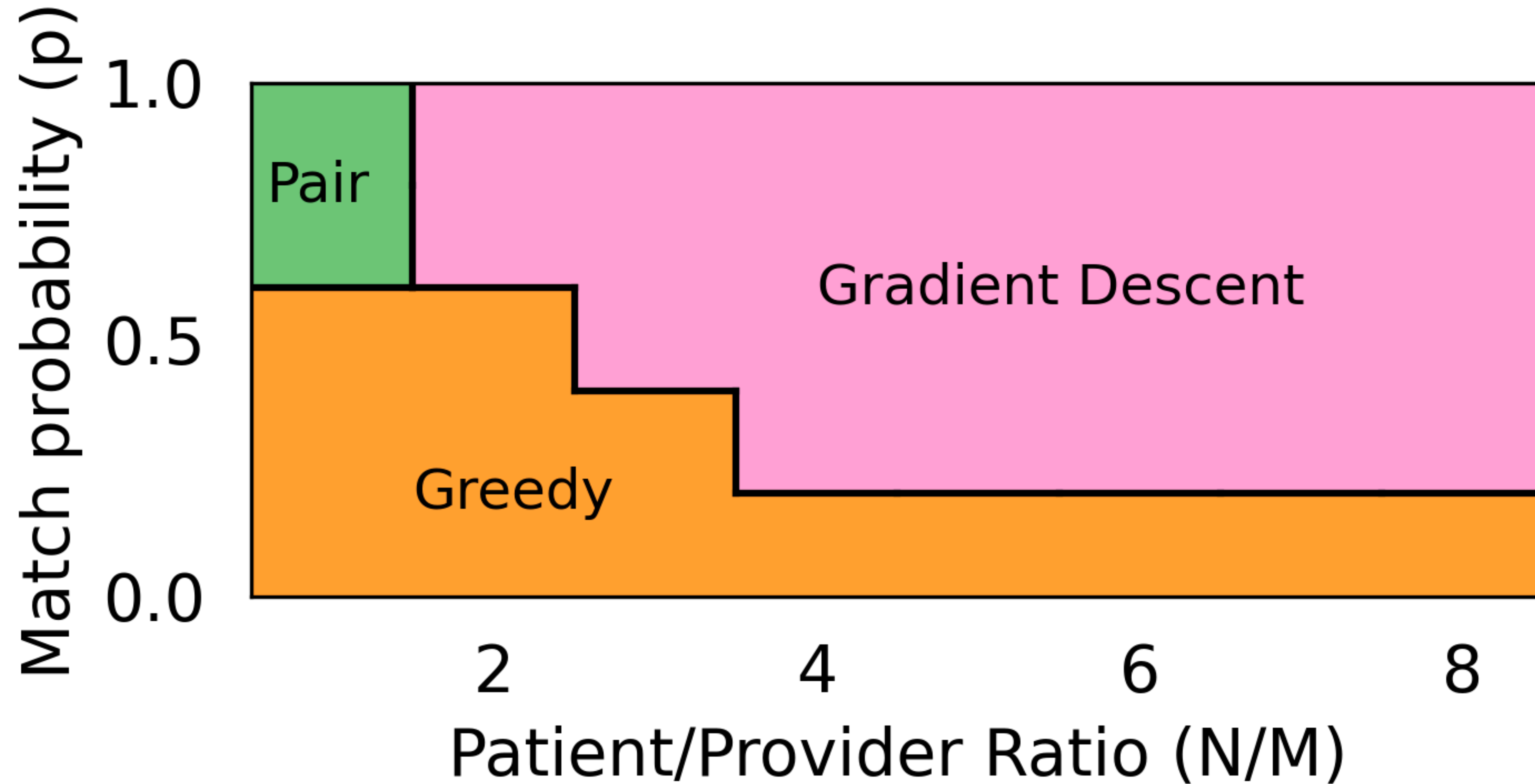
Impact of Patient/Provider Ratio

Impact of Patient/Provider Ratio



Impact of Match Probability

Impact of Match Probability



Constructing a Semi-Synthetic Dataset

We build a dataset
mimicking the Hartford
Healthcare system



Constructing a Semi-Synthetic Dataset

We build a dataset
mimicking the Hartford
Healthcare system



#Patients/Providers (N/M)

1225 patients and 700
providers; mimics the
effects of one provider
dropping out

Constructing a Semi-Synthetic Dataset

We build a dataset
mimicking the Hartford
Healthcare system



#Patients/Providers (N/M)

1225 patients and 700
providers; mimics the
effects of one provider
dropping out

Choice Model

Patients have a fixed
probability of
matching after utility
reaches a threshold

Constructing a Semi-Synthetic Dataset

We build a dataset mimicking the Hartford Healthcare system



#Patients/Providers (N/M)

1225 patients and 700 providers; mimics the effects of one provider dropping out

Choice Model

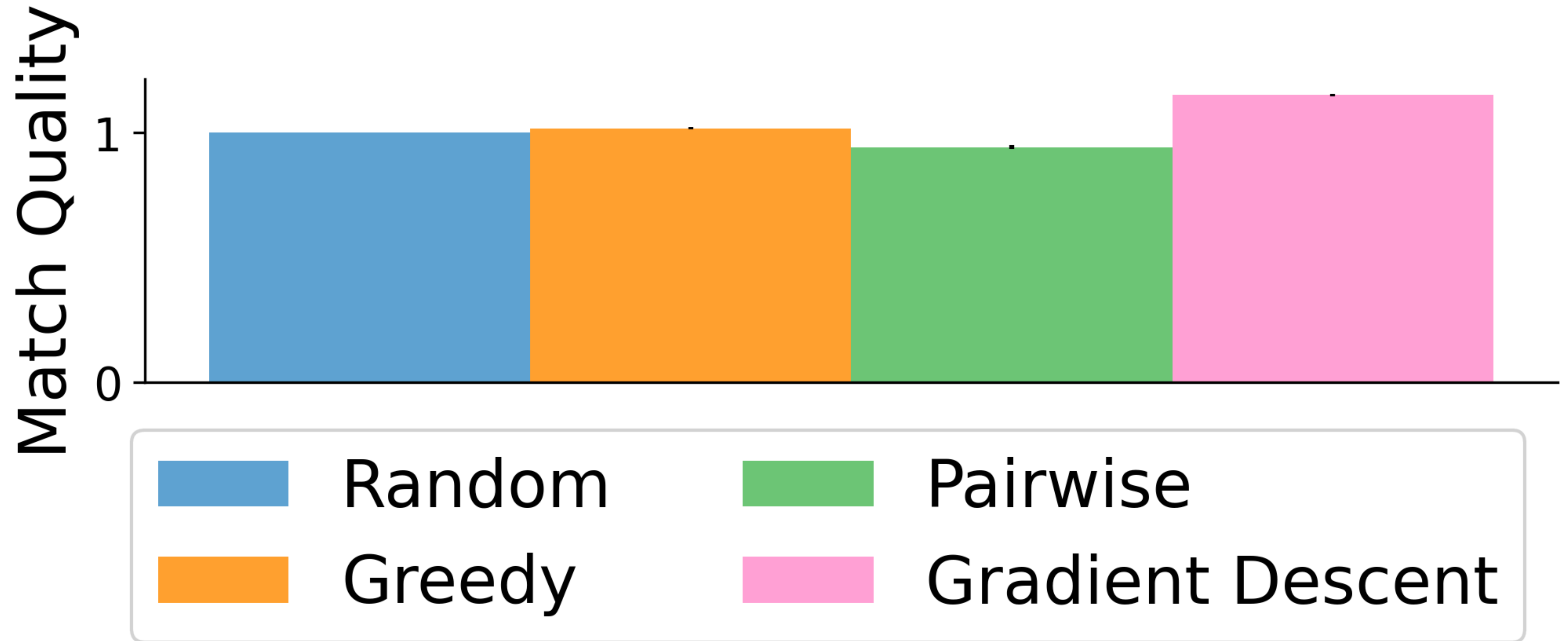
Patients have a fixed probability of matching after utility reaches a threshold

Match Quality

Incorporates provider proximity and comorbidities present

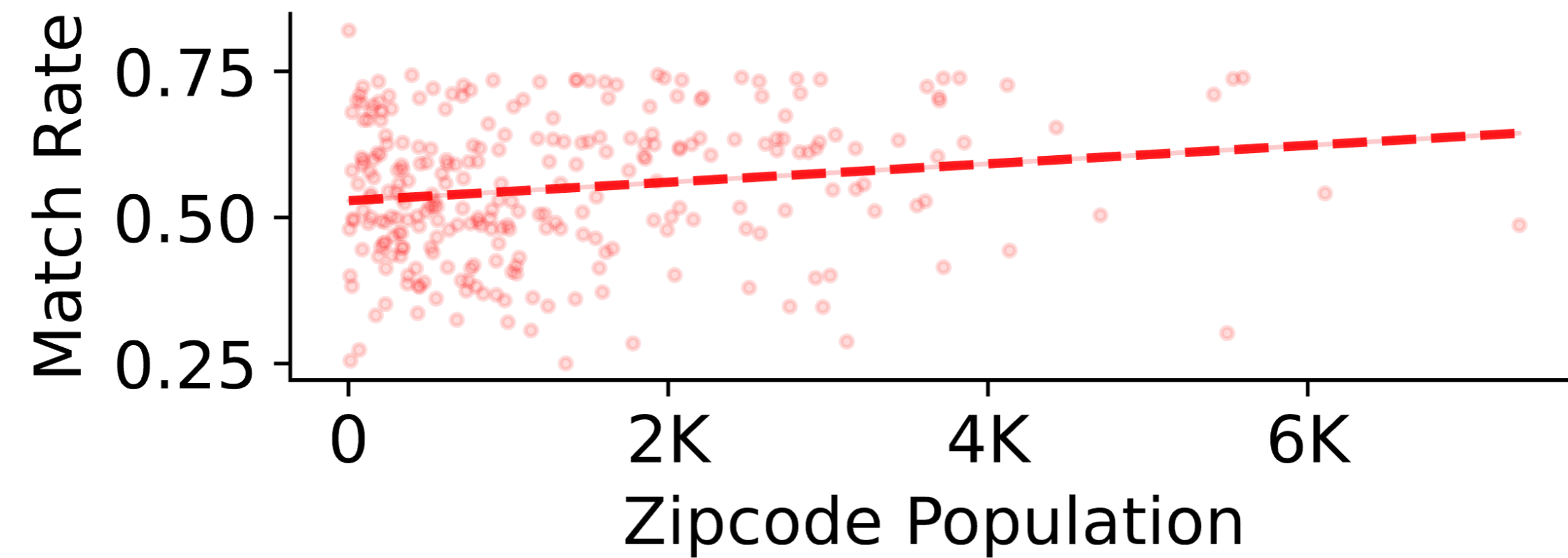
Match Quality Comparison

Match Quality Comparison



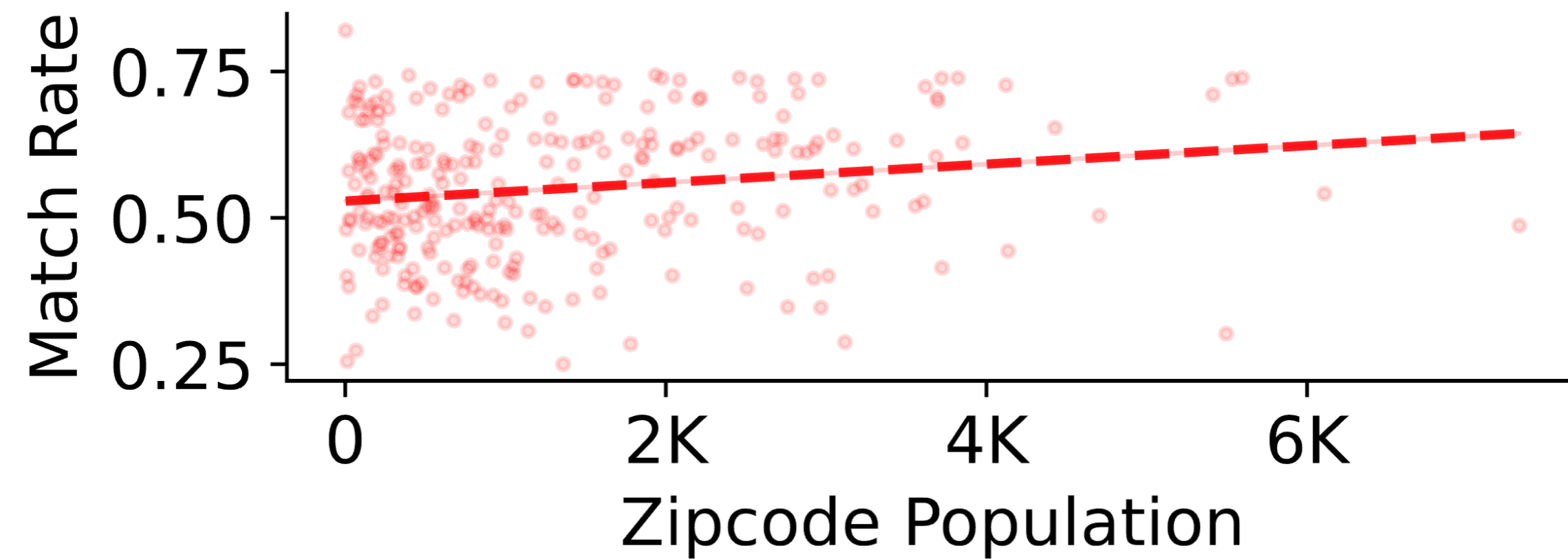
Who actually gets Matched?

Who actually gets Matched?



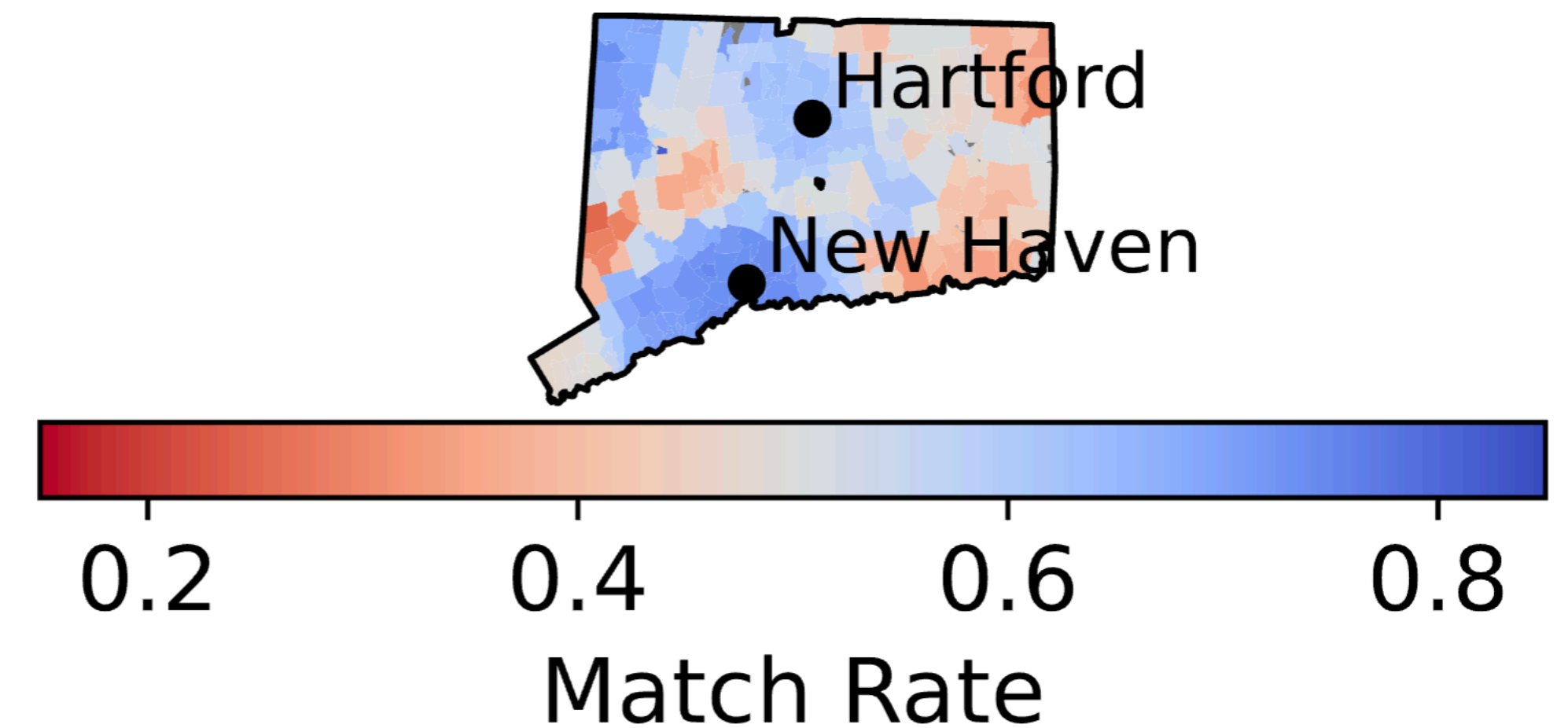
People from populated areas

Who actually gets Matched?

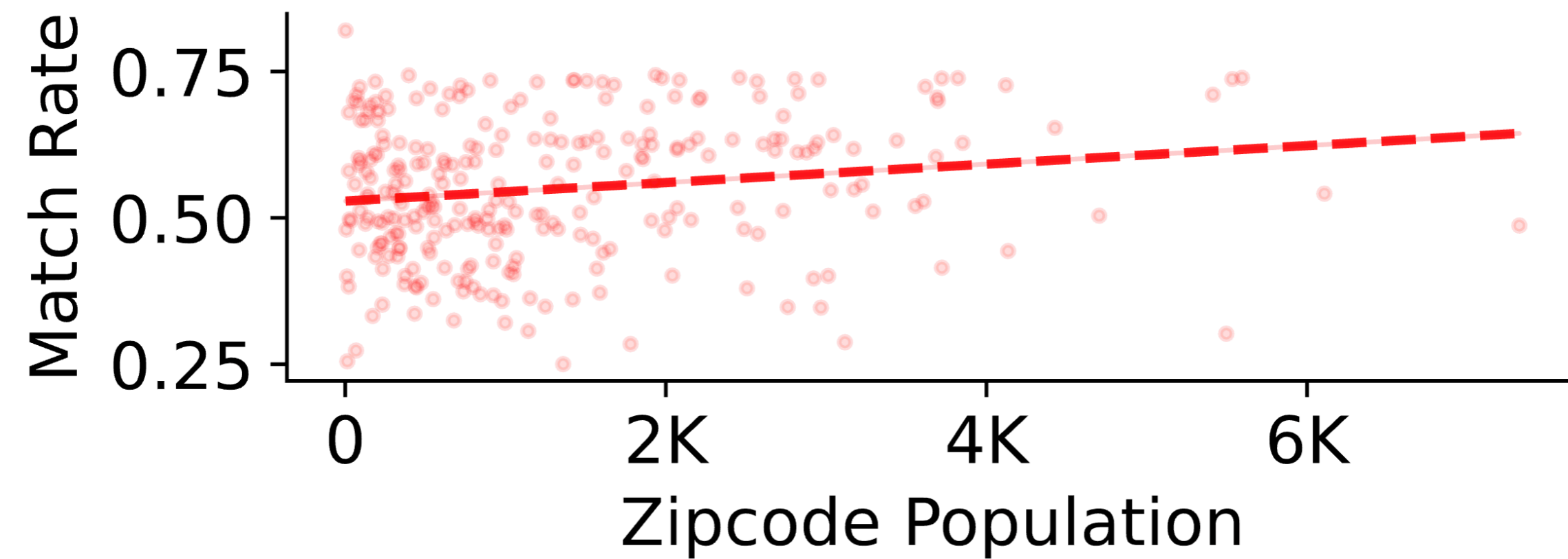


People near big cities

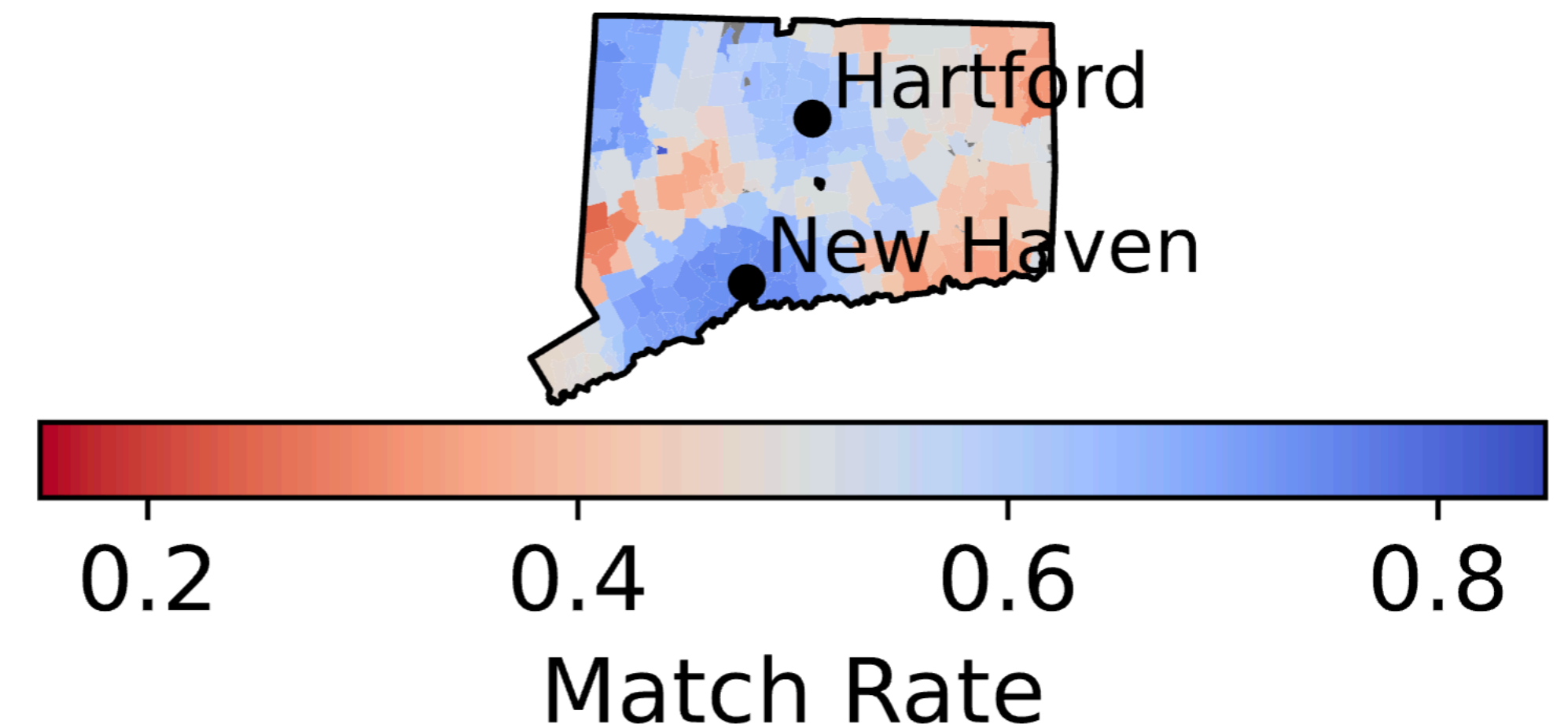
People from populated areas



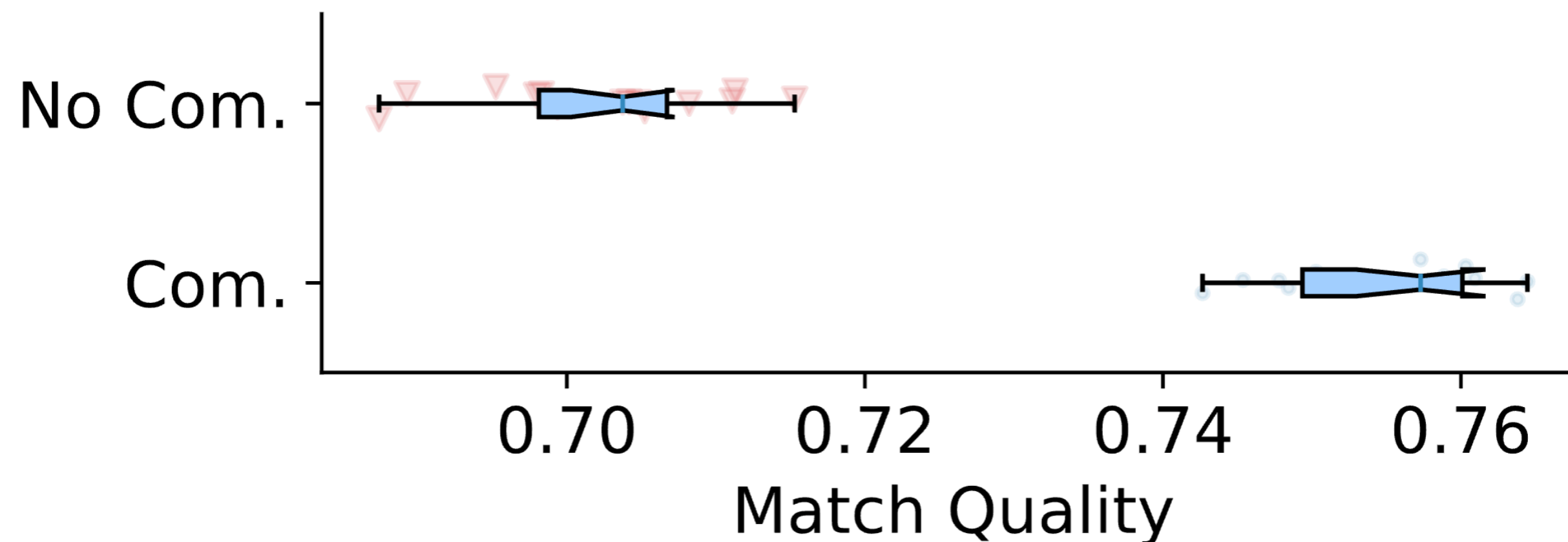
Who actually gets Matched?



People from populated areas



People near big cities



People with Comorbidities

Tension between Fairness and Match Rate/Quality

Tension between Fairness and Match Rate/Quality



Takeaways

Tailoring policies improves match quality. However, high match quality can lead to poor performance on other outcomes of interest, such as fairness.



Insights for Practitioners



Insights for Practitioners

Patient choice becomes more useful under uncertainty



Insights for Practitioners



Patient choice becomes more useful under uncertainty

Metrics such as fairness and match quality can be in tension

Insights for Practitioners



Patient choice becomes more useful under uncertainty

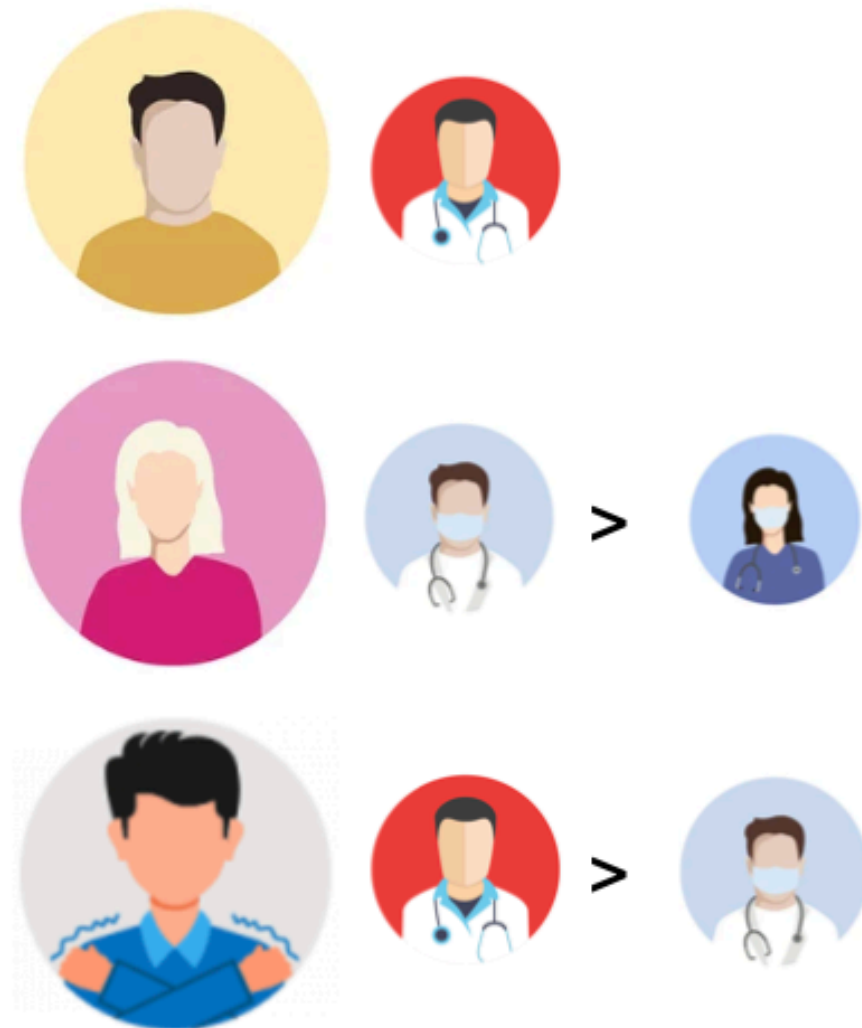
Metrics such as fairness and match quality can be in tension

Underlying factors might impact *who* gets matched

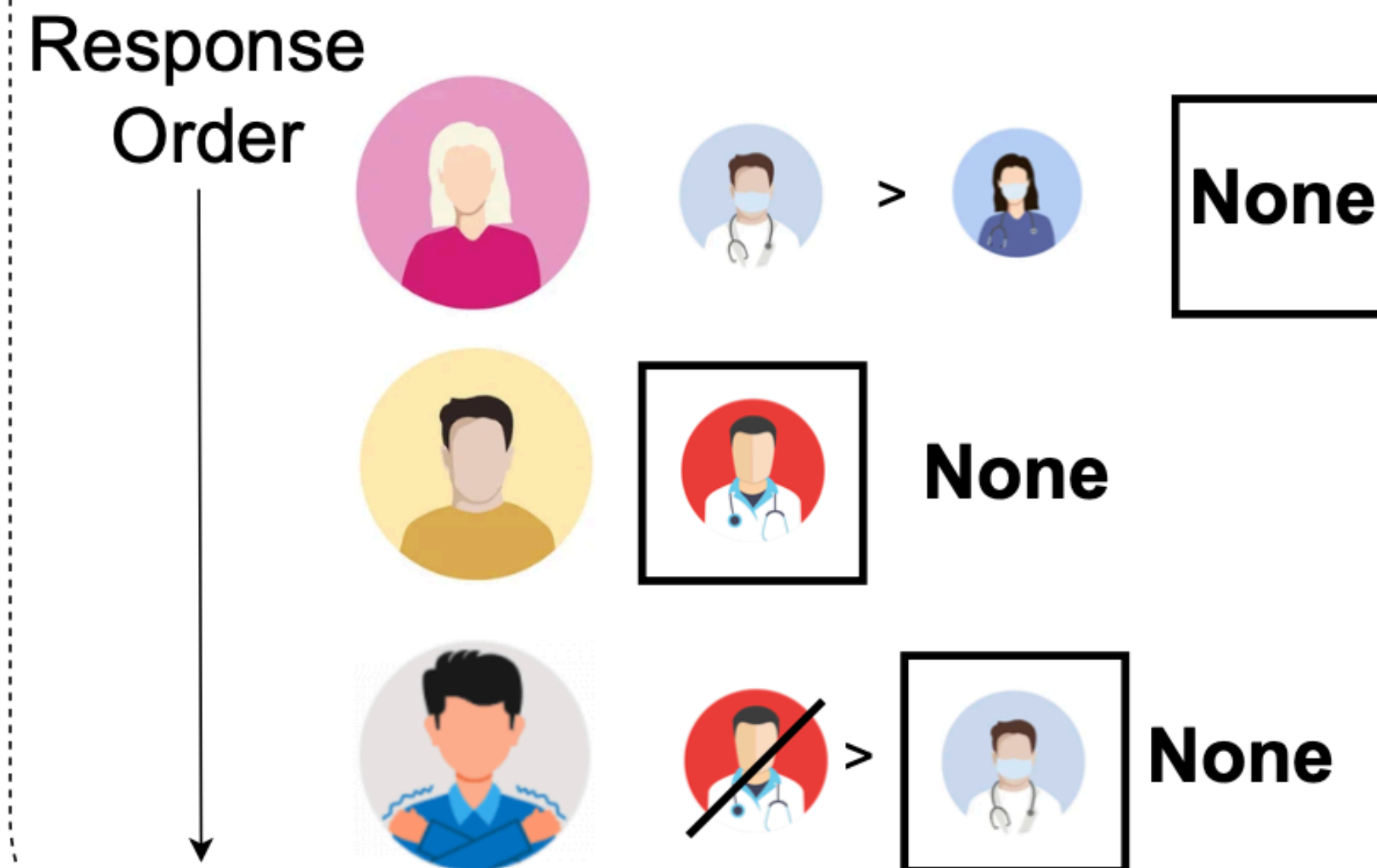


Patient-Provider Matching

Upfront Menu Offering



Patient Response



Final Matches

