Global demand for donated blood far exceeds supply, and unmet need is greatest in low- and middle-income countries. Large-scale coordination is necessary to alleviate demand. Using the Facebook Blood Donations tool, we conduct a large-scale algorithmic matching of blood donors with donation opportunities. While measuring actual donation rates remains a challenge, we measure donor action (for example, making a donation appointment) as a proxy for actual donation. We develop automated policies for matching patients and donors, based on an online matching model. We provide theoretical guarantees for these policies, both regarding the number of expected donations and the equitable treatment of blood recipients. In simulations, a simple matching strategy increases the number of donations by 5–10%; a pilot experiment with real donors shows a 5% relative increase in donor action rate (from 3.7% to 3.9%). When scaled to the global Blood Donations tool user base, this corresponds to an increase of around 100,000 users taking action toward donation. Further, observing donor action on a social network can shed light on donor behaviour and response to incentives. Our initial findings align with several observations made in the medical and social science literature regarding donor behaviour.

Blood is a scarce resource; its donation saves the lives of those in need. Countries approach blood donation in different ways, running the gamut from privately run to state-run programs, with or without monetary compensation, and with varying levels of public campaigns for action. Some examples follow. China maintains state control of its donation centres, which take a mix of captive-, quota- and voluntary-based donations. The United States mixes state- and private-run donation that is primarily sourced via voluntary donations. Brazil has seen a recent shift from remunerated to non-remunerated (that is, voluntary) donation at its initially state-run, and now federally run, centres. As such, blood donation rates differ across different countries; for example, approximately 3.2%, 1.5%, 0.8% and 0.5% of the population donates in high-, upper-middle-, lower-middle- and low-income countries, with varying rates of voluntary versus paid donors. Yet demand for blood still far exceeds supply, and unmet need is greatest in low- and middle-income countries. Thus, experts suggest that the blood supply chain—collection, testing, processing, storage and distribution—be managed at a national level.

Optimization-based approaches to blood supply chain management have a rich history in the operations research and healthcare management literature. Reference reviews over 100 publications in this space since 1963 (Fig. 1). The supply chain is roughly split into collection, testing and processing, storage and inventory, and distribution and transfusion. Substantial research effort has gone into each of these segments. Yet, we note that most optimization-based research in the initial collection stage of the blood supply chain has focused on prediction of blood supply (for example, during a crisis). In this work, we instead focus on the creation and coordination of blood supply via automated social prompts, subject to the expressed preferences and constraints of potential donors and the overall donation system. That is, we focus on the donor recruitment stage of the blood supply chain (Fig. 2).

Donor recruitment has also been a topic of study for decades. Factors such as social pressure, empathetic messaging and non-monetary incentives can increase donation rates. Negative past experiences, and real or perceived barriers to donation, can however...
impede donation rates\textsuperscript{15–17}. Most importantly, this body of work suggests that different donors are motivated by different factors. In other words, personalized recruitment strategies—which respect diverse donor motivations, preferences and perceived barriers to donation—should be more effective than a uniform recruitment strategy.

Our work leverages the widespread use of web-based applications (apps) and social media platforms, which already play a substantial role in blood donor recruitment. The American Red Cross, which provides about 40% of transfused blood in the United States\textsuperscript{18}, recently launched an app to connect blood donors with donation opportunities\textsuperscript{20}. A review\textsuperscript{20} identifies 169 free mobile apps for blood donation, though many of these apps have usability and privacy issues that may prevent widespread use. In a survey of donors at a German hospital, ref. \textsuperscript{21} finds that social media platforms Jodel and Facebook are a major motivation for donation—especially for first-time donors. Similar studies find that WhatsApp and Twitter help promote donation in Saudi Arabia\textsuperscript{22} and India\textsuperscript{23}.

Herein we propose a personalized donor recruitment strategy using the recently developed Facebook Blood Donations tool (https://socialgood.fb.com/health/blood-donations/), which connects millions of potential blood donors with opportunities to donate in several countries around the world. Users of this tool can opt in to receive notifications about nearby donation opportunities. We study algorithms for automatically notifying donors, with the dual goals of (1) maximizing the overall number of donations and (2) ensuring that recipients receive their ‘fair share’ of all notifications. Treating recipients fairly is especially important in our setting: for example, if a recipient is ignored by our algorithm (no notifications are sent about this recipient), then they may choose to leave the Blood Donations platform, which is an unfavourable outcome for all participants. To express this concept mathematically, we formally define what a recipient’s fair share of notifications is, and we analyse which fraction of this fair share is achieved for each recipient under different algorithms.

We frame this notification scenario as an online bipartite matching problem\textsuperscript{24}—a well studied paradigm, which has been applied to a variety of settings including online advertising\textsuperscript{25} and rideshare services\textsuperscript{26–28}. Online matching algorithms have recently been developed for volunteer crowdsourcing platforms: similar to our setting, these algorithms balance fairness with an efficiency objective\textsuperscript{25}. We demonstrate, both in computational simulations and in a real A/B test, that even a simple matching policy can substantially increase the likelihood of donor action.

**Measuring donation: meaningful action**

To design notifications that effectively encourage blood donation, it is necessary to know when donor action occurs. However, social networking platforms such as Facebook cannot directly observe a user’s actions outside the platform. As a proxy, we instead observe when a donor takes meaningful action (MA) toward donation after being notified. We say that a user takes MA in response to a notification if they take specific actions on the Facebook platform within a reasonable amount of time after receiving a notification (usually around one week). In our context, MAs might include creating a reminder to donate, or calling a blood bank. In practice we represent MA as a binary variable for each notification: 1 if the user takes action after being notified and 0 otherwise.

It is beyond the scope of this study to validate MA as a proxy for actual donation; however, initial results indicate that MA is a reliable indicator. For example, a 2018 Facebook study with its partner donation sites in India and Brazil found that 20% of donors said that Facebook influenced their decision to donate blood\textsuperscript{15}. In the remainder of this paper, we focus on investigating the number of donor MAs as a proxy for increasing the number of donations. Our goal is to design a notification policy that chooses both (1) when to notify a donor and (2) which donation opportunity to notify them about. The next step in designing this policy is to understand which notifications are likely to prompt
donor MA. For this, we created a dataset of all notifications sent to donors using the Facebook Blood Donations tool; for each notification we determine whether the donor took MA within one week after being notified. In Supplementary Information Section 1 we discuss high-level observations of a subset of this dataset. For the remainder of our analysis we use a machine learning (ML) model trained on this dataset to predict MA.

**ML model for donor action**
To develop an ML model of donor action we use all previous notifications sent by the Facebook Blood Donations tool. This model takes an individual notification as input, and predicts the probability that the donor will take action. Each notification is represented by a set of features of both the donor and the donation opportunity (that is, the independent variables); the dependent variable is binary (that is, whether or not the donor took MA). Before being deployed, this ML model and application passed through Facebook’s internal review process to protect user privacy.

Before training this model, we use industry-standard feature selection techniques to identify the most important features for predicting donor MA. These features are selected according to the frequency with which they appear in a boosted decision tree ensemble, trained on the entire dataset; this frequency is expressed as a percentage of all trees in the ensemble. The most important features are in decreasing order of importance, with importance in parenthesis: (1) whether the donor recently took MA (18%), (2) donor age (8.5%), (3) donor city (7.5%), (4) the number of Facebook friends the donor has (7.3%), (5) the distance between donor and recipient (6.8%). Other relevant features include the number of local donors (6.5%), number of times a donor has viewed the hub in the last 30 days and number of days since the donor’s last notification.

Using the selected features, we train a gradient boosted decision tree model. We use standard parameter-sweep techniques to obtain a learning rate of 0.1, 120 trees, a maximum tree depth of 5 and a maximum number of leaves of 120. This model is trained using tenfold cross-validation on 80% of the the training data and an additional 10% for validation; it achieves an area under the receiver operating characteristic curve of 0.66 and logistic loss of 0.45, averaged over all training folds. Training this model is particularly challenging because of the small number of ‘positive’ examples (that is, number of donor MAs). Figure 3 shows the density of prediction scores returned from this model, over all training data. Most prediction scores are between 0 and 10%, with an average of 3.43%—quite close to the observed likelihood of MA.

We use this model to estimate how likely it is that a donor will take action when notified about a particular donation opportunity. Next we describe how this model is used to design a notification policy: by framing blood donor recruitment as a matching problem.

**Matching framework for blood donation**
We represent a blood donation problem as a weighted bipartite donation graph $G = (U, V, E)$, with donors $u \in U$ and donation opportunities (or recipients) $v \in V$. We use the terms ‘donors’ and ‘recipients’ as shorthand for prospective donors and recipients. Facebook does not make any determination about a person’s eligibility to donate blood; these are potential donors who sign up to receive notifications of blood donation opportunities. Each vertex has a set of attributes (for example, blood type, geographical location and so on), and these attributes determine whether a donor $u$ can donate to a recipient $v$—that is, whether $u$ and $v$ are compatible. Compatible pairs $(u, v)$ are connected by edges $e = (u, v) \in E$; we denote all edges adjacent to vertices $u \in U$ ($v \in V$) as $E_u (E_v)$.

If an edge $e = (u, v)$ exists, then donor $u$ can be notified about $v$. In this work, we assume that the set of potential donors and donation centres do not change, although this longer-term dynamism is certainly interesting to consider as future research. We discretize time into days $t \in \mathcal{T} = \{1, \ldots, \mathcal{T}\}$ with a finite time horizon $\mathcal{T}$. In our setting both donors and recipients are dynamic, in the sense that some donors and recipients are available at certain time steps. This notion of dynamism is designed specifically to represent a blood donation setting.

We assume that donors may receive only one notification at each time step; however, any number of donors may be notified about the same recipient on any time step. Thus, our setting more closely resembles $b$-matching than traditional bipartite matching.

**Edge weights**
Each edge $(u, v)$ has weight equal to the probability that donor $u$ donates to recipient $v$ once notified (that is, the predicted MA likelihood, ‘ML model for donor action’); we assume that edge weights $w_{uv}$ are indexed by edge $e$ and time step $t$. In other words, some edges (notifications) are more likely than others to result in donation: for example, certain people may be more likely than others to donate (for example, people who have donated frequently in the past, as observed in ref. 33) and people may prefer to donate on specific days more than others.
Recipients

We consider both static recipients \( S \subseteq V \), such as blood banks and hospitals, and dynamic recipients (or events) \( D \subseteq V \), such as blood drives or emergency requests. Static recipients are available during all time steps, and edges into these recipients are always available. Events arrive in an online manner, and are available only during certain time steps. We assume that the distribution of recipient availability is known and defined by \( \mathcal{P}_r \in [0, 1] \): the probability that recipient \( v \) is available at time \( t \). This is a primary input to our matching algorithms. In practice, this distribution can be estimated by the matching platform from observations of previous demand. For example, we may observe that a particular high school tends to host blood drives at the beginning of each school year. The matching platform might also estimate this distribution by eliciting demand directly from recipients, for example using a survey or online form. We use \( \mathcal{P}_{rt} \) to denote a realization of recipient arrivals, which is 1 if recipient \( v \) is available at time \( t \) and 0 otherwise. We assume that realized recipient arrivals \( \mathcal{P}_{rt} \) are revealed at each time step \( t \). In other words, at time step \( t' \) all realized arrivals \( \mathcal{P}_{rt} \) are known for time steps \( t \) with \( 1 \leq t \leq t' \).

Donors

After a donor signs up with the Facebook Blood Donations tool, we say that they are available to receive notifications (that is, to be matched) at any time. While there is essentially no limit on the number of notifications that can be sent on via online platform, there is a legal limit on how often people can donate blood. This limit is meant to protect donor health, and is often set by local governments or health authorities, typically 5 weeks or longer. Thus, due to legal and health considerations, and out of respect for donors’ time and attention, we limit how often each donor is notified: this limit is one notification every \( K \in \mathbb{Z}^+ \) days. Since not all notifications lead to donation, it is reasonable to set \( K \) to 7 or 14 days—much shorter than the donation rate limit.

Balancing priorities

In general there are several priorities when matching blood donors and recipients: we aim to increase the number of active blood donors, maximize the number of donations, respect donor privacy and preferences, satisfy recipients’ needs and so on. Deciding which of these is most important is a matter of policy, and is beyond the scope of this paper. Here we consider two priorities that we believe are relevant to any blood donor matching platform: (1) increasing the overall number of donations from a fixed donor pool and (2) treating recipients equitably. While the justification for priority (1) is perhaps obvious, priority (2) requires more discussion.

Equitable treatment of recipients

In an online blood donor matching platform, notification policies have a far greater potential to impact recipients than donors. From a donor’s perspective, a change in notification policy might mean that they receive notifications at a slightly different rate, or that they are encouraged to donate to a different recipient. (Recall that donors can always browse for opportunities using the Blood Donations tool; they need not pay attention to notifications.) However, from a recipient’s perspective a change in notification policy can markedly impact the number of notifications encouraging donors to visit their facility. For example if predictive models suggest that edge weights to centrally located hospitals are high, while edge weights to rural hospitals are near zero, then a simple edge-weight maximizing policy would never notify donors about rural hospitals (indeed we report a similar distance-based effect in Results). Furthermore, two-sided matching platforms—such as the Facebook Blood Donations tool—are most effective when both sides of the market benefit from participating. If donors are never notified about rural recipients then these recipients might choose to leave the platform, which is a strictly worse outcome for everyone. For these reasons we consider the fairness of different notification policies. Our approach is inspired by the problem of fair division in economics. Approaches to fair division problems are typically inspired by axiom, such as envy-free allocation (no recipient should prefer another recipient’s allocation over their allocation) and proportionality (if there are \( N \) recipients, each should receive \( 1/N \) of the goods). Some approaches are based on economic equilibrium, where goods are assigned artificial prices and recipients start with an ‘endowment’ of artificial currency; each recipient is assigned the most desirable bundle of goods they can afford.

Since recipients in our setting cannot easily exchange ‘goods’ (notifications), and there is no notion of endowment or currency, the fair division principles of envy and economic equilibrium are not obviously applicable here. Instead, our approach is based on an axiomatic approach: each recipient should receive a proportion of notifications (measured in edge weight) that is at least a fraction \( \gamma \) of the allocation of any other recipient. Recent developments in online matching have taken a similar approach to balancing efficiency, in scarce resource allocation settings motivated by the COVID-19 pandemic and volunteer crowdsourcing. We also take a matching approach, with similar goals of fairness and efficiency. However our setting is sufficiently different that we cannot directly apply their methodology to our blood donation scenario.

Next we formalize this notion of proportionality; we emphasize that this is a design choice, and that other approaches to fairness and fair division may also be appropriate.

Weighted proportionality

In weighted proportional fair division, a finite set of resources is divided among agents such that each agent values their allocation proportionally to their ‘weight’ or ‘score’—where higher score represents greater endowment or priority. In our setting, different recipients have different numbers of compatible donors (for example, due to their location), or different edge weights (for example, due to donor preferences or recipient accessibility); it may not be reasonable to, for example, guarantee that each recipient is matched with the same total edge weight. Instead we endeavour to match each recipient with edge weight proportional to their normalization score, which is assigned ahead of time by the matching platform. Larger normalization score indicates that the recipient should be matched with more edge weight. Furthermore, since individual edges cannot be divided between recipients, it is not always possible to guarantee exact proportionality for all recipients. Instead we use a relaxed notion of proportionality, based on the normalized edge weight matched with each recipient.

Definition 1. (\( \gamma \)-proportional matching). Let \( Y_v \) be the total weight matched with recipient \( v \) over time horizon \( T \), and let \( m_v \) be the normalization score for \( v \). This matching is \( \gamma \)-proportional for \( \gamma \in (0, 1) \) if

\[
\frac{Y_v}{m_v} \leq \frac{Y_{v'}}{m_{v'}}
\]

for each \( v, v' \in V \).
In other words, a matching is $\gamma$-proportional if the normalized matched weight for recipient $v$ is at least fraction $y \in (0, 1]$ of the normalized matched weight for all other recipients. Note that with $y = 1$ all recipients receive the same normalized matched weight.

**Matching policies**

We aim to match donors with recipients such that we maximize edge weight (maximize the number of MASs), and such that the outcome is $\gamma$-proportional for recipients. Here we define matching policies that trade off between these two goals. These policies assume that donor availability is fixed, that is, we are given as input the time steps at which each donor can be notified. This is a natural constraint for fielded notification systems, which may only notify donors, for example, on certain days of the week. All proofs of our theoretical statements are given in Supplementary Information Section 3.

We begin by analysing an offline version of this problem, where all recipient availability is known ahead of time. While unrealistic, solutions to the offline problem can be used to guide sophisticated stochastic matching policies. We then analyse two simple matching policies, Rand and Max, which represent two ends of a spectrum: Rand is completely proportional (or fair) to recipients and does not optimize matched weight, while Max maximizes matched weight but can allocate notifications very unequally across donors.

In ‘Non-adaptive policies’ and ‘Adaptive policies’ we define two classes of policies using solutions to the offline optimal problem—the first policy class makes all matching decisions ahead of time (non-adaptive), and the second makes matching decisions adaptively, using all available information.

Each matching policy takes as input a bipartite graph $G = (U, V, E)$ with edge weights $w_{uv}$, normalization scores $m_v$, recipient arrival distribution $P_v$, and time horizon $\mathcal{T}$. At each $t$, all observed demand realizations $P^t_v$ for all $t \leq t$ are ‘revealed’ to the policy, and may be used as input.

We use parameters $a_{uv}$ to denote the (exogenous) donor availability on each time step: donor $u$ may be matched on time step $t$ only if $a_{uv} = 1$. We denote the set of available edges for recipient $u$ on time $t$ by $E^t_u \equiv \{(u', v') \in E | u = a_{uv} = 1\}$. To benchmark practical matching policies, we compare them with an unrealistic offline optimal policy, which has complete knowledge of the ‘true’ demand realization $P^t_v$. The offline optimal policy is defined using any optimal solution to problem (1). This problem uses the following variables and constants.

- $x_{et} \in \{0, 1\}$. Binary variable, which is 1 if edge $e$ is matched at time $t$ and 0 otherwise.
- $s_v \in \mathbb{R}$. Auxiliary variable that represents the normalized matched weight for recipient $v$.
- $\gamma \in (0, 1)$ (constant). Proportionality constant, chosen by the optimizer ahead of time.
- $w_{et} \in \mathbb{R}$ (constant). Edge weight for edge $e$ at time $t$.
- $P^t_v \in \{0, 1\}$ (constant). 1 if recipient $v$ is available at time $t$ and 0 otherwise.
- $m_v \in \mathbb{R}$ (constant). Normalization score for recipient $v$.
- $a_{uv} \in \{0, 1\}$ (constant). 1 if donor $u$ can be notified at time $t$ and 0 otherwise.

There are four sets of constraints, which can be interpreted as follows.

- $x_{et} \leq \hat{P}^t_v a_{uv}$: the probability that $e$ is matched at time $t$ can be no greater than the probability that the recipient is available, and must be zero if the donor is unavailable.
- $\sum_{e \in E_t} x_{et} \leq a_{vt}$: the probability that donor $u$ is matched at time $t$ must be no greater than 1 if $u$ is available, and must be 0 if $u$ is unavailable.
- $s_v = \frac{1}{m_v} \sum_{e \in E_t} \sum_{v' \in \gamma} x_{et} w_{et}$: this defines the normalized matched weight $s_v$ for recipient $v$.
- $\gamma s_v \leq s_v$: this enforces a $\gamma$-proportional matching.

Combining these variables and constraints yields

$$
\max \sum_{e \in E_t} w_{et} x_{et} \\
\text{s.t. } x_{et} \in \{0, 1\} \quad \forall e \in \mathcal{T}, t \in \mathcal{T} \\
\quad s_v \in \mathbb{R} \quad \forall v \in V \\
\quad x_{et} \leq \hat{P}^t_v a_{ut} \quad \forall e \in (u, v) \in E, t \in \mathcal{T} \\
\quad \sum_{e \in E_t} x_{et} \leq a_{vt} \quad \forall v \in V, t \in \mathcal{T} \\
\quad s_v = \frac{1}{m_v} \sum_{e \in E_t} X_{et} w_{et} \quad \forall v \in V \\
\quad \gamma s_v \leq s_v \quad \forall v, v' \in V, v \neq v'.
$$

An offline optimal policy is defined using an optimal solution to problem (1).

**Definition 2.** (Offline optimal policy OPT($\gamma$)). Let $x^*_{et}$ be an optimal solution to problem (1), for demand realization $P^t_v$. At each time $t \in \mathcal{T}$, OPT($\gamma$) matches all edges $e \in E$ such that $x^*_{et} = 1$. Policy OPT(0) refers to the offline optimal matching policy without proportionality constraints.

We compare all matching policies with OPT($\gamma$) using the following two evaluation metrics.

**Competitive ratio.** Let $E[OPT(0)]$ be the expected weight matched by OPT(0), over all demand realizations. Let $E[ALG]$ be the expected weight matched by matching policy ALG, over all demand realizations and (if ALG is stochastic) all policy realizations. The competitive ratio is

$$
\text{CR} \equiv \min_{G, \gamma, t} \frac{E[ALG]}{E[OPT(0)]},
$$

where the minimization is over all possible matching graphs, demand distributions and donor availability. In other words, CR is the worst-case ratio of expected matching weight over all possible matching scenarios.

**Expected proportionality.** Let $E[Y_v]$ be the expected weight matched by a matching policy, over all demand realizations and (if ALG is stochastic) all policy realizations. The expected proportionality of policy ALG is

$$
E_P \equiv \min_{G, \gamma, t} \max_{m_v \in \mathbb{R}} \{y \in [0, 1] \mid E[Y_v] / m_v \leq E[Y_{v'}] / m_v \quad \forall (u, v') \in V, v \neq v'.\}
$$

where as before $m_v$ is a fixed normalization score for recipient $v$, and the minimization is over all possible graphs, demand distributions and donor availabilities. In other words, if policy ALG is guaranteed to be $\gamma$-proportional in expectation, then $E_P = \gamma$. Note that $E_P$ may be 0, meaning that there is no $\gamma > 0$ such that the expected outcome is $\gamma$-proportional.

For the remainder of this section we assume that agent normalization scores are determined by a uniform random notification policy, defined below.

**Definition 3.** (Uniform random policy Rand). At each time step $t \in \mathcal{T}$, for each available donor $u$: Rand matches $u$ using an edge in $E^t_u$, chosen uniformly at random.
Definition 4. (Normalization score $m_\gamma$). Let $E[Y]$ be the expected weight matched with recipient $v$, over all recipient demand realizations and (for randomized policies) over all policy realizations. The scaling factor for recipient $v$ is $m_{\gamma} = E[Y]$. Using these normalization scores we imply that policy Rand, and its outcome, are fair; we emphasize that this is only one choice of normalization scores, and in practice the notion of fairness/proportionality should be defined by stakeholders.

Metrics CR and EP help us characterize the expected performance of fixed-time matching algorithms. In the following two sections we analyse two classes of policies: myopic policies use only information from the current time step to make matching decisions (this includes both policies implemented in our online experiments); non-myopic policies take into account the demand distribution for future time steps.

Myopic policies
We consider two simple baseline myopic policies, Rand (defined above) and Max. Policy Max is defined below.

Definition 5. (Max-weight policy Max). At each time step $t \in T$, for each available donor $u$, let $W \equiv \max_{e \in \mathcal{E}_t} w_{ue}$ be the maximum edge weight for any of $u$’s available edges at time $t$. Max matches $u$ using any edge in $\mathcal{E}_t$ with edge weight $W$, and if multiple edges have weight $W$ then one is chosen randomly.

First, note that Rand has $EP = 1$ by definition. On the other hand, Max always maximizes matched weight.

Lemma 1. Max is $EP = O$; that is, in the worst case Max is $O$-proportional in expectation.

Intuitively Max ignores $m_u$, meaning that it does not guarantee proportionality. In the worst case, Max can leave some recipients unmatched, meaning that $EP = 0$. On the other hand, Max always maximizes matched weight.

Lemma 2. Max achieves $CR = 1$. Further, without proportionality constraints ($\gamma = 0$), Max is equivalent to an offline optimal policy (OPT(0)). On the other hand, since Rand ignores edge weight, its worst-case competitive ratio is low.

Lemma 3. Rand achieves a competitive ratio of at most $CR = 1/N$ when there are $N$ recipients.

Baseline policies Max and Rand represent two ends of a spectrum: on one side, Max prioritizes maximizing edge weight, at the cost of proportionality for recipients; on the other side, Rand treats all recipients fairly (for one specific notion of fairness), but does not prioritize edge weights. To balance these objectives we propose a class of stochastic policies with moderate guarantees on CR and EP, though their performance is far better than these guarantees in computational experiments.

The policies introduced in this section are based on the optimal solution to a linear programming (LP) formulation of our matching problem. As a baseline for these policies we use an LP relaxation of the offline optimal mixed-integer LP, problem (1). We refer to this relaxation as problem (1)-LP (not stated explicitly). This problem is nearly identical to problem (1), with two differences: (1) variables $x_{et}$ are continuous (on interval $[0, 1]$) rather than binary, and (2) demand realization $P_{et}$ is replaced by demand distribution $\mathcal{P}_{et}$.

Before defining matching policies based on problem (1)-LP, we make some important observations. First, problem (1)-LP yields a valid upper bound for problem (1).

Lemma 4. Let $Z_{LP}$ denote the optimal objective of problem (1)-LP for a matching problem defined by $U, V, E, m_\gamma, P_{et}$ and $\gamma \in [0, 1]$. Let $E[OPT(\gamma)]$ be the expected objective of the offline optimal policy, over all demand realizations. Then, $Z_{LP} \geq E[OPT(\gamma)]$.

This result lets us use problem (1)-LP as an upper bound on the matched weight for any matching policy; we use this as a baseline with which to compare other matching policies.

We consider two classes of LP-based policies: non-adaptive policies (which pre-commit to a set of edges that may be matched), and adaptive policies (which may change their matching decisions at each time step).

Non-adaptive policies
We consider a class of non-adaptive policies which pre-match at most one edge for each donor at each time step—that is, matching decisions may not adapt at each time step as new information is revealed. At each time step, if the donor is pre-matched to an edge and the edge’s recipient is available, then this edge is matched; otherwise, the donor remains unmatched during this time step. Of course, this does not guarantee that all donors are matched at each time step—and therefore the competitive ratio can be quite low.

Warm-up: policies based on problem (1). First we consider a non-adaptive policy based on an optimal solution for problem (1)-LP.

Definition 6. (NAdapLP($\alpha, \gamma$)). Let $x_{et}^*$ denote an optimal solution to problem (1)-LP with proportionality parameter $\gamma \in [0, 1]$ and $\alpha \geq 0$. For each time step $t \in T$ and each donor $u \in U$, edge $e \in \mathcal{E}_t$ is pre-matched with probability $ax_{et}^*/P_{et}$, and the donor is not pre-matched with probability $1 - a\sum_{e \in \mathcal{E}_t} x_{et}^*/P_{et}$. At each time step, all donors are matched using their pre-matched edge, if the pre-matched donor is available.

In this policy, parameter $\alpha$ is a scaling factor used to ensure that each edge assignment distribution is valid—that is, that $\alpha\sum_{e \in \mathcal{E}_t} x_{et}^*/P_{et} \leq 1$ for all $u \in U$. Note that this policy can only be implemented if each of these distributions are valid. Conveniently, the probability that any edge is matched by NAdapLP($\alpha, \gamma$) is expressible in terms of the optimal solution to problem (1)-LP used to define this policy.

Lemma 5. Let $x_{et}^*$ be the optimal solution used in policy NAdapLP($\alpha, \gamma$). The unconditional probability that edge $e$ is matched at time $t$ by policy NAdapLP($\alpha, \gamma$) is $\alpha x_{et}^*$.

Lemma 5 leads to some additional observations about this policy.

Corollary 1. NAdapLP($\alpha, \gamma$) has CR = $\alpha$ and is $\gamma$-proportional in expectation; that is, $EP = \gamma$.

Both corollaries follow directly from Lemma 5 and the constraints of Problem (1)-LP. These results suggest that we can arbitrarily increase the weight matched by NAdapLP($\alpha, \gamma$) by increasing $\alpha$; however, these policies are not guaranteed to be valid. This policy can only be implemented if $\alpha$ is small enough that each edge assignment distribution is valid.

Lemma 6. Policy NAdapLP($1/D$, $\gamma$) is always valid and achieves $CR = 1/D$ and $EP = \gamma$ for all $\gamma \in [0, 1]$, where $D$ is the maximum degree of any donor: $D = \max_{u \in U} |\mathcal{E}_u|$. In other words, Policy NAdapLP($1/D$, $\gamma$) is always implementable; thus there always exists a non-adaptive policy that achieves $EP = \gamma$ and $CR = 1/D$ for all $\gamma \in [0, 1]$. This competitive ratio guarantee is quite weak, and we might ask whether a better non-adaptive policy exists. Indeed it does, and we discuss this policy next.

Optimal $\gamma$-fair non-adaptive policies. Here we aim to identify a policy that is $\gamma$-proportional in expectation ($EP = \gamma$), and also maximizes matched weight (and thus CR); we refer to this as an optimal $\gamma$-proportional non-adaptive policy. To identify this policy, we first observe that any non-adaptive policy can be characterized by the probability that it pre-matches edge $e$ at time $t$, $\gamma_e \in [0, 1]$; using these statistics, the unconditional probability that $e$ is matched at time $t$ is...
t is y, p,
Note that, for any non-adaptive policy, the probability that donor u is pre-matched at time t is at most 1 if u is available and 0 otherwise; thus, statistics y, must satisfy conditions ∑e∈E,y, ≤ a, for all u ∈ U, and t ∈ T. If a non-adaptive policy is γ-proportional, then y, must satisfy conditions
γ, ≤ s, ∀u, v ∈ V
with
s, = 1/m, ∑ e∈E,y, ∈ e v ew, ∀v ∈ V.

Aggregating these conditions, we observe that the statistics y, of any γ-proportional non-adaptive policy are a feasible solution to the following LP.

max ∑ e∈E,y, ∈ e ew
s.t. y, ∈ [0, 1] ∀e ∈ E t ∈ T
s, ∈ R ∀v ∈ V
∑ e∈E,y, ∈ e u ≤ a, ∀u ∈ U, t ∈ T (2)
sv = 1/m, ∑ e∈E,y, ∈ e v ew, ∀v ∈ V
γ, ≤ s, ∀v, v′ ∈ V, v ≠ v′.

Furthermore, a solution to problem (2) corresponds to a non-adaptive policy; we use an optimal solution to this problem to define a γ-proportional non-adaptive policy.

Definition 7. (NAdapOpt(γ)). Let y, be an optimal solution to problem (2). For each time step t ∈ T and each donor u ∈ U, a pre-matched edge is drawn with probability y, with probability 1 − ∑e∈E,y, ∈ e u, no edge is pre-matched. At each time step t and for each available donor u, if the donor is pre-matched with an available recipient, then the pre-matched edge is matched.

Lemma 7. NAdapOpt(γ) achieves EP = γ and maximal competitive ratio over all non-adaptive policies, with CR ≥ 1/D.

Both non-adaptive policies described in this section are γ-proportional in expectation (EP = γ), though their competitive ratio guarantee is somewhat weak. This is expected, since non-adaptive policies cannot change their matching decisions between time steps—they pre-match at most one edge for each donor at each time step. Some pre-matched edges will in fact be unavailable, depending on the particular demand realization (which is not known in advance).

Adaptive policies
Adaptive policies can use any available information to make matching decisions—including observed demand realizations, previous matching decisions and the distribution of future demand. We leave a general characterization of adaptive policies to future work; here we consider a simple class of adaptive policies that naturally extends the non-adaptive policies from the previous section. This policy class, AdaptMatch, takes as input the set of edges pre-matched by a non-adaptive policy, denoted by M, where M, = e ∈ E if u is pre-matched along edge e at time t, and M, = ∅ if u remains unmatched at time t. AdaptMatch uses pre-matched edges when possible, and if a pre-matched edge is not available it matches donors using either Rand (with probability γ) or Max (with probability 1 − γ). Algorithm 1 gives a pseudocode description of this matching algorithm.

Algorithm 1: AdaptMatch: Adaptive matching policy

Input: donors V, recipients U, edges E, time steps T, donor availability, pre-matched edges M, parameter γ ∈ [0, 1].
Output: Matched edges at each time step.
1 for each time step t ∈ T do
2 for each available donor, u do
3 if u has a pre-matched edge M, and this edge is available then
4 Match u using pre-matched edge M,;
5 else
6 Flip a weighted coin with ‘heads’ probability γ;
7 if heads then
8 Match u with policy Rand;
9 else
10 Match u with policy Max;

Note that this adaptive policy matches strictly more edges (in expectation) than do its non-adaptive counterparts. Thus, expected matched weight (and CR) is strictly larger for AdaptMatch than for the non-adaptive policy on which it is based.

While competitive ratio is at least as large for these policies (CR ≥ 1/D) as for their non-adaptive counterparts, there is no meaningful guarantee on expected proportionality. We leave more sophisticated adaptive policies to future work. However, while these approximate adaptive policies do not have strong guarantees on CR or EP, they perform far better than these guarantees in computational experiments (‘Computational simulations’).

Results
Before deploying new matching policies in an online setting, it is important to assess their performance in simulations. ‘Computational simulations’ outlines computational simulations with real data from the Facebook Blood Donation Tool, using our proposed matching policies; ‘Online experiments’ describes our online experiment with the Facebook blood donation tool. In the Supplementary Information Section 2 we also present results using synthetic, publicly available data (Supplementary Fig. 1).

Computational simulations
We conduct computational simulations that implement each of our proposed policies; details of these simulations are discussed in Supplementary Information Section 2. All code and data used in these simulations are available in Supplementary Software and on GitHub40. We test each matching policy from the previous section using data from the Facebook Blood Donations tool, and we run separate simulations for 12 major cities around the world. For each city we create a blood donation graph, consisting of donors V and recipients U registered with the Blood Donations tool; edges are created between donors and recipients within 15 km of each other, and edge weights are calculated using the gradient-boosted decision tree (GBTD) models described in ‘ML model for donor action’. Each of these cities has of the order of 1,000 donors, 100 recipients and 100,000 edges; to protect user privacy we cannot share additional information about these data.

We require that donors are notified exactly once every K = 14 d, and the first day each donor is notified is chosen randomly from t ∈ [1, ..., 13]; P, are determined from past notifications. The realized recipient availability used in these experiments is randomly drawn using parameters P, and this realization is fixed for the remainder of the experiment. Each simulation runs for 60 d, so each donor is notified exactly four times. Since policies Rand and AdaptMatch are random, we run 50 independent trials with these policies. We define recipient normalization scores m, as the average weight matched to v over all 50 trials of Rand.
For policy Max we calculate the total matched weight, and for Rand and AdaptMatch we calculate the average matched weight over all trials. We also calculate the (average) weight matched to each recipient, $Y_r$. Using the recipient weights we calculate a measure of proportionality, $\Gamma$, defined as

$$\Gamma(y) = \max\{y \in [0,1] | y_{Y_r'}/m_Y \leq y_{Y'}/m_Y', \forall v, v' \in V\}.$$ 

**Simulation results.** Simulation results for all 12 cities are shown in Fig. 4. For each city we simulate matching using policies Max, Rand and AdaptMatch. We implement several versions of AdaptMatch: each uses a fixed parameter $\gamma \in \{0.0, 0.1, \ldots, 1.0\}$, and pre-matched edges $M = N_{\text{AdapOpt}}(y)$. These plots in Fig. 4 illustrate the trade-off between overall matched weight and proportionality (or fairness) for recipients. While Max maximizes matched weight in this setting, it does not guarantee a proportional outcome: in all cities except for City 1 and City 9, Gamma is zero for Max, meaning that some recipients are never matched by this policy. On the other hand, Rand is proportional by definition (and $\Gamma = 1$), though this policy does not maximize matched weight. However, Rand always matches at least 90% of the maximum possible matched weight in all simulations, and more than 95% in five out of the 12 cities.

While policy AdaptMatch does not have strong guarantees on matched weight or proportionality, it mediates smoothly between the extremes of Rand and Max, according to parameter $y$. In some cases, this policy matches more weight than Rand, while still achieving a nearly proportional outcome ($\Gamma = 1$), as in Cities 3, 5 and 7.

**Online experiments.** As a proof of concept, we compare the max-weight matching policy (Max) with the random baseline policy (Rand, which is similar in behaviour to the notification policy currently used by the Facebook Blood Donations tool), in an online experiment. The goal of this experiment is to answer the question of whether we can increase the overall number of donor MAs by carefully selecting which recipient to notify each donor about. Both of these policies notify donors once every 14 d; they only differ in which recipient each donor is notified about. Rand selects a nearby recipient at random, while Max selects a nearby recipient with the greatest likelihood of donor MA—according to our predictive model.

To compare these policies we design a randomized online experiment, including hundreds of thousands of donors registered with the Facebook Blood Donations tool. We randomly partition these donors into a control group (who were notified using policy Rand) and a test group (who were notified using policy Max). As in our simulations, we include only static recipients (for example, hospitals and large blood banks) that are always available to receive donations. Donors and recipients are considered compatible (and connected by an edge) if they are located within 15 km of each other.

**Potential impact on donors and recipients.** This experiment was approved by an internal review board. We emphasize that the impact of these experiments is minimal: the only difference between the test and control groups is which donor is notified about. The impact on blood recipients is less clear: due to our experimental design we cannot effectively measure the proportionality of each notification policy in a meaningful way. However it is possible that any optimization-based matching policy (for example, Max or AdaptMatch) prioritizes certain recipients over others. This may marginalize recipients in rural areas or those with a limited Facebook presence. More thorough analysis of these impacts is necessary before more widespread adoption of these policies.

**Online experiment results.** This experiment ran from 23 November to 17 December 2019 (25 d). In total, 1,359,980 donors were notified using either policy Rand or Max; to protect user privacy we cannot share additional details of this experiment. In this experiment many donors had only one compatible recipient—in this case, the donor was always notified about this recipient, regardless of the notification policy. For clarity, we distinguish between notifications sent to donors who had only one compatible recipient (1R) and those sent to donors with two or more compatible recipients (+2R). Thus we only expect to observe a difference between control and test groups for +2R notifications; we expect the same outcome for (1R) notifications.

Table 1 shows the number of notifications and MAs for notifications of each type (1R and +2R), in both the test and control groups. Note that only +2R notifications are relevant for comparing the test and control groups, though we report both for transparency. The key result in these tables is the percentage of notifications that led to meaningful action (%MA, a number on [0, 100]). We report the Wilson score interval for %MA as $C \pm R/2$, where $[C - R/2, C + R/2]$ is the 95% confidence interval.

In the remaining discussion we consider only the +2R notifications, as there is no difference between the test and control groups for 1R notifications. For the overall experiment, %MA is about 5% higher for Max than for Rand. To better understand the differences between the control and test groups, we use two statistical tests to compare the notifications sent by Rand and Max.

**Overall comparison.** We use both a two-sided and one-sided Chi-square test to compare %MA (+2R notifications only) for the control and test groups, over all notifications sent during this experiment. Let $P_{\text{Rand}}$ and $P_{\text{Max}}$ represent %MA for the control (Rand) and test (Max) groups, respectively. The two-sided test checks the null hypothesis $H_0$: $P_{\text{Rand}} = P_{\text{Max}}$ with alternative $P_{\text{Rand}} \neq P_{\text{Max}}$, the one-sided test checks null hypothesis $H_0$: $P_{\text{Rand}} = P_{\text{Max}}$ with alternative $P_{\text{Rand}} < P_{\text{Max}}$. We can
We introduce the problem of connecting blood donors with demand centres in a time-dependent setting, with uncertain demand. We formalize this as an online matching problem, with the priorities of efficiency (maximizing the number of donations) and fairness (proportionality) for recipients. We propose a class of stochastic policies for this setting, with which we compare a realistic randomized baseline. In simulations we see a clear trade-off between the overall number of donations and proportionality (Fig. 4); the particular trade-off between these objectives depends on the notification policy used. Policy Max (which maximizes edge weight/expected donations) results in a 5–10% increase in the overall number of expected donations, compared with a random baseline (Rand). However, Max tends to favour certain recipients over others. In our simulations, Max completely ignores some recipients in 11 out of the 12 cities tested—presumably because these recipients are already unlikely to recruit donors, which we expect is the case. Of course, this potential injustice is exactly the motivation for our stochastic policy AdaptMatch.

Blood donation is a global challenge, and has been the focus of many dedicated organizations and researchers for decades. In this paper we investigate a new opportunity to recruit and coordinate a massive network of blood donors and recipients, enabled by the widespread use of social networks. We formalize a matching problem around matching blood donors with recipients, and test these policies in both offline simulations and an online experiment using the Facebook Blood Donations tool. Our findings suggest that a matching paradigm can significantly increase the overall number of donations, though it remains a challenge to do so while treating recipients equitably.

As a proof of concept we run an online experiment via the Facebook Blood Donations tool, comparing notification policies Rand and Max. We find that Max results in about 5% more MAs (a proxy for donations) than Rand. In relative terms this improvement seems small; however, the implications are quite meaningful. This experiment investigated one small improvement to the notification strategy used by the Facebook Blood Donations tool: that is, whether the donor is notified about a nearby donation opportunity at random (Rand) or notified about a particular opportunity selected by a predictive model (Max). Several other modifications to the notification policy might yield similar improvements: for example, by changing how often each donor is notified, by more carefully planning for future donation needs or by tailoring notifications to each donor’s unique preferences and values.

The potential impact of this work is considerable. Indeed, if our observed results generalize to the entire community of Facebook blood donors, then a 5% increase in donor action corresponds to at about 200,000 more donors taking MA toward donation when notified. Our results reported in Table 1 suggest that policy Max has an MA rate of 3.9%, compared with 3.7% for policy Rand. The difference is 0.2 percentage points—or 200,000 of the estimated 100 million donors registered with the Blood Donations tool.

Even if few of these MAs lead to actual donation, the increase is still substantial.

Before implementing these policies at a large scale in practice, it is important to understand their potential impacts on both blood donors and recipients. In this study impact on donors is minimal; the only difference between notification policies is which donation opportunity they are notified about. However our simulation results indicate that blood recipients may face substantial impacts from changes in notification policy. For example, policies that prioritize edges with a high likelihood of MA (for example, policy Max) may ignore certain recipients—such as rural hospitals or small donation centres with a limited web presence. This observation is particularly troubling if low-weight recipients are already unlikely to recruit donors, which we expect is the case.

We reject both of these null hypotheses with \( P \ll 0.01 \). In light of the results presented in Table 1, these statistical tests suggest that Max achieves a small (−5%) but significant improvement over Rand in terms of overall %MA. In the next set of statistical tests we compare each day of the experiment as a separate trial.

**Daily paired comparison.** Next we treat day of the experiment as a set of paired measurements of both \( P_{\text{Rand}} \) and \( P_{\text{Max}} \). For each day of the experiment (26 in total) we calculate sample estimates of \( P_{\text{Rand}} \) and \( P_{\text{Max}} \)—that is, the 100 times the ratio of MAs to overall notifications. Note that donors are notified once every 14 days, meaning that the set of donors notified on any particular day is nearly disjoint from the donors notified on any other day of the experiment; for this reason we treat the measurements of \( P_{\text{Rand}} \) and \( P_{\text{Max}} \) on different days as independent.

We use a two-sided Wilcoxon signed-rank test to check the null hypothesis \( H_0 \): the median difference between daily \( P_{\text{Max}} \) and \( P_{\text{Rand}} \) is zero. We reject this null hypothesis (\( P \ll 0.01 \)), further confirming that notification policy Max yields a higher MA rate than Rand. For illustration, Fig. 5 shows the 95% confidence intervals for \( P_{\text{Rand}} \) and \( P_{\text{Max}} \), using the aggregated number of notifications and MAs for each day of the experiment. In Supplementary Information Section 2.1 we show the results for each individual day, as well as the cumulative rates (Supplementary Fig. 2).

**Discussion**

Before implementing these policies at a large scale in practice, it is important to understand their potential impacts on both blood donors and recipients. In this study impact on donors is minimal; the only difference between notification policies is which donation opportunity they are notified about. However our simulation results indicate that blood recipients may face substantial impacts from changes in notification policy. For example, policies that prioritize edges with a high likelihood of MA (for example, policy Max) may ignore certain recipients—such as rural hospitals or small donation centres with a limited web presence. This observation is particularly troubling if low-weight recipients are already unlikely to recruit donors, which we expect is the case. Of course, this potential injustice is exactly the motivation for our stochastic policy AdaptMatch.

Blood donation is a global challenge, and has been the focus of many dedicated organizations and researchers for decades. In this paper we investigate a new opportunity to recruit and coordinate a massive network of blood donors and recipients, enabled by the widespread use of social networks. We formalize a matching problem around matching blood donors with recipients, and test these policies in both offline simulations and an online experiment using the Facebook Blood Donations tool. Our findings suggest that a matching paradigm can significantly increase the overall number of donations, though it remains a challenge to do so while treating recipients equitably.

**Methods**

All code for our simulations is available online, and is included in Supplementary Software. All simulations were run on a personal computer (16 GB RAM, four CPUs), and used Python 3.6.10 and Gurobi, with packages gurobipy 9.0.3, Pyomo 5.7.1, NumPy 1.19.5 and pandas 1.1.3.

Datasets related to Facebook user information are not publicly available due to privacy concerns. All data used to create plots are available from the corresponding author on reasonable request. Datasets used for simulations (Supplementary Information Section 2) are publicly available from the Socioeconomic Data and Applications Center (SEDAC) and can be found online (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

**Data availability**

The datasets related to Facebook user information are not publicly available due to privacy concerns. All data used to create plots are available from the corresponding author on reasonable request. Datasets used for simulations (Supplementary Information Section 2) are
publicly available from the Socioeconomic Data and Applications Center (SEDAC)\textsuperscript{[40]}, and can be found online (http://sedac.ciesin.columbia.edu/data/collection/gpw-v4).

**Code availability**

All code used for our simulations is available online\textsuperscript{41}, and is included in Supplementary Software.

**References**

1. Guan, Y. When voluntary donations meet the state monopoly: understanding blood shortages in China. *China Q.* **236**, 1111–1130 (2018).

2. Osorio, A. F., Brailsford, S. C. & Smith, H. K. A structured review of quantitative models in the blood supply chain: a taxonomic framework for decision-making. *Int. J. Prod. Res.* **53**, 7191–7212 (2015).

3. Carneiro-Proietti, A. B. et al. Demographic profile of blood donors at three major Brazilian blood centers: results from the international REDS-II study 2007 to 2008. *Transfusion* **50**, 918–925 (2010).

4. World Health Organization. *The importance of the blood supply and availability* (2006).

5. Roberts, N., James, S., Delaney, M. & Fitzmaurice, C. The global need and availability of blood products: a modelling study. *Lancet Haematol.* **6**, e606–e615 (2019).

6. Prastacos, G. P. & Brodheim, E. PBDS: a decision support system for regional blood management. *Manag. Sci.* **26**, 451–463 (1980).

7. Sojka, B. N. & Sojka, P. The blood donation experience: self-reported motives and obstacles for donating blood. *Vox Sang.* **94**, 56–63 (2008).

8. Reich, P. et al. A randomized trial of blood donor recruitment strategies. *Transfusion* **46**, 1090–1096 (2006).

9. Chell, K., Davison, T. E., Masser, B. & Jensen, K. A systematic review of incentives in blood donation. *Transfusion* **58**, 242–254 (2018).

10. Godin, G. et al. Factors explaining the intention to give blood among the general population. *Vox Sang.* **89**, 140–149 (2005).

11. Craig, A. C., Garbarino, E., Heger, S. A. & Slonim, R. Waiting to give: stated and revealed preferences. *Manag. Sci.* **63**, 3672–3690 (2017).

12. American Red Cross. *Importance of the Blood Supply* (2023). https://www.redcrossblood.org/donate-blood/how-to-donate/how-blood-donations-help/blood-needs-blood-supply.html

13. American Red Cross *Blood Donor App* (2022). https://www.redcrossblood.org/blood-donor-app.html

14. Ouhbi, S., Fernández-Alemán, J. L., Toval, A., Idri, A. & Pozo, J. R. Free blood donation mobile applications. *J. Med. Syst.* **39**, 52 (2015).

15. Sümüg, A., Feig, M., Greinacher, A. & Thiele, T. The role of social media for blood donor motivation and recruitment. *Transfusion* **58**, 2257–2259 (2018).

16. Ouhbi, S., Fernández-Alemán, J. L., Toval, A., Idri, A. & Pozo, J. R. Free blood donation mobile applications. *J. Med. Syst.* **39**, 52 (2015).

17. Godin, G. et al. Factors explaining the intention to give blood among the general population. *Vox Sang.* **89**, 821–827 (2014).

18. Godin, G., Conner, M., Sheeran, P., Bélanger-Gravel, A. & Germain, M. Determinants of repeated blood donation among new and experienced blood donors. *Transfusion* **47**, 1607–1615 (2007).

19. American Red Cross *Blood Safety and Availability* (2023). https://www.redcrossblood.org/faq.html

20. Steinhaus, H. The problem of fair division. *Econometrica* **16**, 101–104 (1948).

21. Brams, S. J. & Taylor, A. D. An envy-free cake division protocol. *Am. Math. Mon.* **102**, 9–18 (1995).

22. Budish, E. The combinatorial assignment problem: approximate competitive equilibrium from equal incomes. *J. Political Econ.* **119**, 1061–1083 (2011).

23. Arrow, K. J. An extension of the basic theorems of classical welfare economics. In *Proc. Second Berkeley Symposium on Mathematical Statistics and Probability* **2**, 507–533 (University of California Press, 1951).

24. Manshadi, V., Niazadeh, R. & Rodilitz, S. Online Policies for Efficient Volunteer Crowdsourcing. *Manag. Sci.* **68**, 6572–6590 (2022).

25. Mehta, A., Saberi, A., Vazirani, U. & Vazirani, V. A randomized trial of blood donor recruitment strategies. *Transfusion* **56**, 548–564 (2007).

26. Katsalaki, K. & Brailsford, S. C. Using simulation to improve the blood supply chain. *J. Oper. Res. Soc.* **58**, 219–227 (2007).

27. Cederberg, W. & Haverkort, B. Simulation-optimization model for regional blood management. *Trans. Sci.* **52**, 548–564 (2017).

28. Wang, X., Agatz, N. & Erera, A. Stable matching for dynamic ride-sharing systems. *Oper. Res.* **55**, 571–587 (2017).

29. Manshadi, V. & Rodilitz, S. Online Policies for Efficient Volunteer Crowdsourcing. *Manag. Sci.* **58**, 7191–7212 (2015).

30. Jin, K.-X. Over 100 million people have signed up for local blood donation notifications. *Facebook* (14 June 2021). https://about.fb.com/news/2021/06/100-million-people-signed-up-for-blood-donation-notifications/

31. Budaraju, H. Helping increase blood donations in the US. *Facebook* (12 June 2019). https://about.fb.com/news/2019/06/us-blood-donations/

32. Anstee, R. P. A polynomial algorithm for b-matchings: an alternative approach. *Inf. Process. Lett.* **24**, 153 (1987).

33. Godin, G., Conner, M., Sheeran, P., Bélanger-Gravel, A. & Germain, M. Determinants of repeated blood donation among new and experienced blood donors. *Transfusion* **47**, 1607–1615 (2007).

34. American Red Cross *Blood Safety and Availability* (2023). https://www.redcrossblood.org/faq.html

35. Arrow, K. J. An extension of the basic theorems of classical welfare economics. In *Proc. Second Berkeley Symposium on Mathematical Statistics and Probability* **2**, 507–533 (University of California Press, 1951).

36. Manshadi, V., Niazadeh, R. & Rodilitz, S. Fair Dynamic Rationing. *Manag. Sci.* **55**, 7191–7212 (2015).

37. Budish, E. The combinatorial assignment problem: approximate competitive equilibrium from equal incomes. *J. Political Econ.* **119**, 1061–1083 (2011).

38. Arrow, K. J. An extension of the basic theorems of classical welfare economics. In *Proc. Second Berkeley Symposium on Mathematical Statistics and Probability* **2**, 507–533 (University of California Press, 1951).

39. Manshadi, V., Niazadeh, R. & Rodilitz, S. Fair Dynamic Rationing. *Manag. Sci.* **55**, 7191–7212 (2015).

40. Manshadi, V., Niazadeh, R. & Rodilitz, S. Online Policies for Efficient Volunteer Crowdsourcing. *Manag. Sci.* **58**, 6572–6590 (2022).

41. Jin, K.-X. Over 100 million people have signed up for local blood donation notifications. *Facebook* (14 June 2021). https://about.fb.com/news/2021/06/100-million-people-signed-up-for-blood-donation-notifications/

42. Yuan, S., Chang, S., Uyeno, K., Almquist, G. & Wang, S. Blood donation mobile applications: are donors ready? *Transfusion* **56**, 614–621 (2016).
Acknowledgements
All authors were employed by Facebook while contributing to this project.

Author contributions
D.C.M. led manuscript preparation, coding, data analysis and theoretical analysis. S.P. provided mentorship and contributed to coding and data analysis. K.S. contributed to ML experiments. N.D. and Z.C. contributed to data analysis and software engineering. C.K. and J.P.D. provided mentorship and contributed to theoretical analysis. All authors contributed to shaping discussions and manuscript preparation. E.S., J.P.D., C.K. and D.C.M. conceived of the idea.

Competing interests
All authors were employed by Facebook (now Meta) during this project. No authors will benefit financially from the Facebook Blood Donations tool, or from blood donations facilitated by this platform.

Additional information
Supplementary information The online version contains supplementary material available at https://doi.org/10.1038/s42256-023-00722-5.

Correspondence and requests for materials should be addressed to Duncan C. McElfresh.

Peer review information Nature Machine Intelligence thanks Arpita Biswas and the other, anonymous, reviewer(s) for their contribution to the peer review of this work. Primary Handling Editor: Liesbeth Venema, in collaboration with the Nature Machine Intelligence team.

Reprints and permissions information is available at www.nature.com/reprints.

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations. This is a U.S. Government work and not under copyright protection in the US; foreign copyright protection may apply 2023