

## RESEARCH ARTICLE

# Finding Receptive Donors: Unpacking the Dynamics of Social Influence in Large-Scale Political Donor Networks

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## ABSTRACT

Although previous studies tend to emphasize the role of influencers in donation campaigns, this study shifts attention to focus on influencees, namely donors who are highly receptive to the influence of others within local social networks. We integrated insights from social influence research with that of the COM-B model and examined the distribution of influencees in eight donor populations. In addition, we examined how donors' capabilities, opportunities, and motivations influence their propensity to be influencees. We found that across eight mutually exclusive donor networks, about 10% of donors can be classified as influencees and they, on average, donate two to 10 times more than other donors. Our analysis consistently demonstrated that donors with extensive connections and those associated with tightly interconnected clusters were more inclined to be influencees. Social influence was clearly present and played a large role for these influencees. Additionally, both the capability and motivation of donors played crucial roles in accurately pinpointing the most receptive individuals to social influence. Notably, disparities were observed among different racial groups. Overall, models that integrated all three sets of COM-B factors exhibited superior predictive performance.

## 1 | Introduction

Revenue from donations plays a critical role in sustaining nonprofit organizations (Romero and Abril 2024). There is growing interest in exploring how social influence affects individuals' decisions to engage in collective actions, support cause-related marketing initiatives, and contribute to charitable causes (Aral 2011; Aral and Walker 2012; Chung et al. 2021; Iyengar et al. 2011; Yang and Taylor 2021). This need for new approaches for fundraising, combined with increasing recognition of social influence mechanisms, creates opportunities for developing novel tools and theory-based insights.

Social influence manifests within a social network when an individual's behaviors or opinions are shaped by others within that network. While social influence takes many forms, in the context of donation behavior, we focus specifically on how donors influence one another—a form of peer influence (Meer 2011).

This phenomenon requires both influencers and influencees, with the latter being individuals who are more susceptible to influence from others through various mechanisms (Aral and Walker 2012).

Peer-to-peer fundraising is a key mechanism in nonprofit donation management (Hesse and Boenigk 2025). However, past research has predominantly examined influencers (Jin et al. 2019). However, as Christakis and Fowler (2011) note, successful marketing campaigns can benefit significantly from identifying not only who holds influence but also who is receptive to it. Furthermore, Aral and Walker (2012) argue that the traditional influencer model, which assumes that influential individuals drive the spread of opinions and behaviors, is overly simplistic. Instead, mounting evidence indicates that “susceptibility, not influence, is the key trait that drives social contagions” (Aral and Walker 2012, 337). Research based on large-scale social media data similarly demonstrates that the success of social contagion

depends largely on the presence of highly receptive individuals (Chung et al. 2019).

In this study, our focus lies in identifying and studying influencees, defined here as individuals highly receptive to the influence of others within local social networks. Understanding influencees is crucial, as they represent a vital yet underexplored element in social influence dynamics. Unleashing their potential could enhance the effectiveness of behavioral interventions, as well as marketing and fundraising campaigns (Hoffmann and Broekhuizen 2009; Chung et al. 2019; Watts and Dodds 2007; Zhang and Gong 2020).

To gain insights into influencees, we conduct a review of the literature on social influence, with a specific focus on studies investigating receptive individuals within massive social networks (Aral and Walker 2012; Hoffmann and Broekhuizen 2009; Chung et al. 2019; Watts and Dodds 2007; Zhang and Gong 2020). Additionally, we integrate insights from the COM-B model (Michie et al. 2011), which explains how capabilities, opportunities, and motivations either facilitate or impede individuals' behaviors. We adapt the COM-B model's concept of behavior to include the nuance of behavior caused by others, that is, someone's receptivity to social influence. The value of the COM-B model is that it allows us to theoretically frame, and then operationalize, the factors that lead individuals to adopt the behaviors of others.

We do this in the context of political non-profit fundraising. Utilizing a new machine-learning algorithm (Williams et al. 2023) called "Social Value Algorithm," we estimate donors' receptivity. The algorithm uses the timing and proximity of others to first establish potential connections between donors and then to model and estimate their effects on each other. This approach incorporates both network and longitudinal behavioral data in machine learning models to estimate links between donors and quantify the degree of influence (explained in methods). Our analysis focused on eight donor populations, comprising 247,119 individuals of different racial backgrounds who contributed to US political causes across the ideological spectrum in 2016, a presidential election year.

Using Social Value Algorithm, we identified a subset of political donors significantly more prone to social influence, labeling them as "influencees," along with the amount of their spending attributable to others. This measurement enabled us to systematically map the distribution of influencees across various demographic groups and served as the main outcome variable of the study. Subsequently, we used theory to select predictors for these outcomes and tested these with machine-learning models. These included the three COM-B precursors: measures of donors' opportunity (measured by their network position matrices and network embedding), capability (assessed via education and financial status), and motivation (measured by past donation patterns across different causes). These models aimed to discern which factors most accurately predict the likelihood of donors being classified as influencees using observational data and the amount of receptivity at play.

We found that across eight mutually exclusive political donor networks, about 10% of donors can be classified as influencees

and they on average donate two to 10 times more than other donors. Our analysis consistently demonstrated that donors with extensive connections and those associated with tightly connected clusters were more inclined to be influencees. Additionally, both the capability and motivation of donors played crucial roles in accurately pinpointing the most receptive individuals to social influence. Notably, disparities were observed among different racial groups. Overall, models that integrated all three sets of COM-B factors exhibited superior predictive performance. These findings prompt a re-conceptualization of influencees within social networks, offering highly reliable and practical methods for identifying such influencees across various contexts and opening the door to subsequent tests of new fundraising and marketing strategies.

## 2 | Social Influence and the Power of Donor-To-Donor Networks

The success of fundraising and philanthropic initiatives often hinges on the dynamics within donor-to-donor networks. A critical factor in these networks is their capacity for social influence (Aral 2011; Aral and Walker 2012). Social influence, defined as the process by which attitudes, opinions, and behaviors are shaped, is a fundamental driver in various social processes, including socialization, product adoption, and, crucially, donation (Friedkin 1998). In interactive social contexts, this influence propagates through established social networks (Katz et al. 1955; Watts and Dodds 2007), allowing interconnected individuals to observe, adapt to, and even amplify the behaviors of others, potentially leading to cascading effects (Chung et al. 2019).

The pervasive impact of social influence is evident across diverse fields. It plays a pivotal role in the diffusion of innovations (Iyengar et al. 2011, 2015), catalyzes broader social changes (Earl and Kimport 2011), and significantly shapes outcomes in both marketing and fundraising efforts (Chapman et al. 2022). Specifically within the realm of philanthropy, extensive research highlights the profound effect of social influence on donor behaviors. For instance, Hong et al. (2018) observed that Kickstarter campaigns initiated by highly interconnected donors achieved significantly higher success rates, underscoring the power of network position. Similarly, in medical donations, Hur et al. (2023) demonstrated that the donation behaviors of an individual's friends substantially influence their own donation intentions.

Given the undeniable importance of social influence in driving philanthropic outcomes, understanding the underlying mechanisms that accelerate this process is of considerable practical value for maximizing impact. In the following sections, we delve into two distinct theoretical models that offer complementary perspectives on how social influence operates within donor networks. The first model highlights the well-recognized role and impact of influencers—individuals who actively shape the opinions and behaviors of others. The second model, however, sheds light on the often-overlooked contributions of influencees—those who are receptive to and act upon the influence of others and whose collective actions

are equally vital for the propagation of donation behaviors. By examining both facets, we aim to provide a more comprehensive understanding of effective social influence strategies in fundraising.

## 2.1 | Two-Step Flow and Influencers

In their seminal research, Lazarsfeld and colleagues introduced the concept of a two-step flow process of social influence, explaining why, across various contexts, individuals' decisions are often shaped more by interpersonal interactions than by direct media exposure (Katz et al. 1955; Lazarsfeld et al. 1968). According to this model, a small group of influencers, also known as opinion leaders, initially absorb information from media channels and subsequently disseminate it, in some form, to their followers. This sequential transmission of information—from media to influencers and then to their followers—delineates the “two-step flow” of communication.

This model accords influencers a central and powerful role in social influence dynamics, portraying them as catalysts for widespread cascading effects. Indeed, the two-step flow theory has dominated research for decades. As observed by Watts and Dodds (2007), thousands of studies spanning diverse social scientific disciplines have, since its inception, sought to identify these key influencers. Many of these efforts are motivated by the deeply held belief that these individuals singularly drive the process of social influence and are thus instrumental in the success of interventions and campaigns.

However, while the concept of influencers intuitively appears logical, significant critiques have emerged. Burt (1999) noted that the precise mechanism through which influencers exert influence on their immediate connections was never clearly specified within the two-step flow model itself. Furthermore, the overall contribution of such direct influence to the broader social influence process remains ambiguous (Watts and Dodds 2007). Another critical limitation of the original two-step flow studies (Katz et al. 1955; Lazarsfeld et al. 1968) is their minimal utilization of social network analysis, despite the model's inherent assumption of existing social networks. Consequently, the often-emphasized role of influencers in the diffusion process within real, large-scale social networks remains more of a theoretical presumption than a consistently supported empirical finding.

## 2.2 | Influencees as an Alternative Lens

Recent decades have seen studies utilizing simulated social networks and massive datasets reveal a far more complex process of social influence than previously understood (Aral and Walker 2012; Watts and Dodds 2007). Many of these studies highlight the significant role of influencees as an alternative explanation to the social influence process depicted by the two-step flow theory (Chung et al. 2019; Hoffmann and Broekhuizen 2009; Zhang and Gong 2020).

Watts and Dodds (2007) notably employed simulated network models to investigate the role of influencers in social influence. Across a spectrum of models, they observed that influencers

often wielded negligible power over the diffusion process, whether as catalysts for large cascades or as early adopters. Exceptions were rare, with discernible impact from influencers appearing only in specific circumstances. Their analysis led them to conclude that focusing on influencers—which emphasizes the significance of a select few—is, in many respects, a misleading framework for understanding how social influence diffuses in large populations. Instead, they argued that “cascades do not succeed because of a few highly influential individuals influencing everyone else but rather on account of a critical mass of easily influenced individuals influencing other easy-to-influence people” (Watts and Dodds 2007, 454). In essence, they contend that influencees, who are more numerous, may better explain social influence at scale. Moreover, they suggest that influencers and influencees are not necessarily distinct individuals; these characteristics can coexist within some people.

In another study, Chung et al. (2019) utilized mathematical models of social contagion to illuminate the distinct roles of influencers and influencees in social scenarios. For passive social influence—where an individual's decision to adopt a product or message is influenced by peer adoption—they observed that both influential and receptive individuals contributed progressively and fairly to the contagion's spread. In contrast, their analysis revealed a different dynamic for active social influence—where actors actively seek to influence peers, for example, by directly endorsing a new behavior or product. Here, receptive individuals initially facilitated rapid contagion, but the sustained growth required the involvement of influencers. Similarly, Aral and Walker's (2012) experiment involving 1.3 million Facebook users found that the joint effect of influencers, receptive individuals, and the likelihood of spontaneous adoption together shaped the propagation of behaviors in massive social networks.

Katona et al. (2011) also explored how social influence spreads in online networks. They modeled adoption decisions as a binary choice influenced by three factors: (1) the network structure of adopted neighbors, (2) the characteristics of these influencers, and (3) the traits of potential influencees. Their study identified two key effects: individuals with more influencee connections are more likely to adopt (a degree effect), and denser connections among influencees increase the likelihood of adoption by those linked to them (a clustering effect). Influencers' and influencees' characteristics, such as network position and demographics, also predicted adoption. Interestingly, as individuals gained more contacts, their individual influential power decreased. These findings hold significant implications for viral marketing, particularly for platforms leveraging user network data.

Taken together, previous research strongly suggests that individuals termed “influencees” are a critical component of social influence flow, regardless of whether it aligns with a two-step model or not. However, a significant gap persists in the literature regarding the precise scale of this influencee demographic. We assume there are more influencees than influencers, but how common are they in large social networks? Specifically, within the context of charitable giving, what proportion of donors can be categorized as influencees? Do they exhibit distinct patterns of donation behavior? To address these inquiries, we pose the following research question:

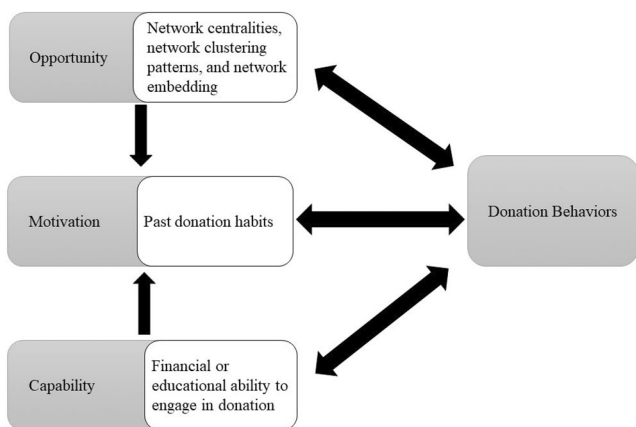
**RQ1.** What proportion of donors within a donation network can be classified as influencees?

Another critical gap in influencee research lies in its theoretical underpinnings. In contrast to the extensive exploration of influencer dynamics guided by the two-step flow model, few studies have delved into a comprehensive theoretical framework for understanding influencees. Specifically, we have limited understanding of the mechanisms through which individuals in large social networks become highly receptive to social influence. This study aims to address this gap by introducing the COM-B model as a conceptual framework. The COM-B model offers a structured approach to comprehending the variables.

### 2.3 | The COM-B Model for Understanding Influencees' Behavior

The COM-B model underscores the critical roles of capability, opportunity, and motivation in determining an individual's behavior, which we are extending to the portion of behaviors caused by their receptivity to social influence. Note that our approach below allows for the separation and measurement of behaviors into those caused by the original source and those caused by the influence of others. So, we are taking the broader term "behavior" as used in the COM-B model, and splitting it into two observable parts. This is a nuance for the COM-B model that extends its theoretical power and applications. Originating from the observation that behavior occurs when a person possesses the capability and opportunity and is motivated to engage in that behavior over others (Michie et al. 2011), the COM-B model is particularly apt for understanding influencees, as social influence relies on individuals' willingness and receptivity to change.

According to Michie et al. (2011), capability encompasses psychological (e.g., knowledge) and physical (e.g., skills) aspects, while opportunity pertains to social (e.g., social norms) and physical (e.g., environmental resources) factors. Motivation can be automatic (e.g., habits) or reflective (e.g., beliefs, intentions). Capability and opportunity serve as logical gates influencing motivation, while behavior feeds back to all precursors, fostering either positive or negative feedback cycles. Figure 1



**FIGURE 1** | The conceptual COM-B model.

visualizes these factors and their relationships with the target behavior, acting either as barriers or enablers.

Although primarily applied in public health behavioral interventions (Willmott et al. 2021), the COM-B model has also been utilized to understand environmentally and socially beneficial behaviors such as recycling, water consumption, and blood donation (Nabil et al. 2020). Moreover, research has demonstrated that the COM-B model specifically aids in understanding the receptivity of individuals when making decisions about donation (Allison et al. 2022; Manika et al. 2022). Building upon this framework, our study investigates whether donors' receptivity to influence is affected by their capability, opportunity, and motivation.

When applying the COM-B model to examine individuals' receptivity in social networks, the first step involves conceptualizing the role of networks in the COM-B model. The concept of opportunity encompasses social and physical contexts enabling specific behaviors (Michie et al. 2011). Social networks present a type of opportunity for social influences to occur in that we must be connected to others for influence to be possible. Mapping those networks is therefore a necessary condition for studying influence at scale. Previous network research has documented how different network positions provide varying opportunities for exposure to diverse levels and types of social influence (Chung et al. 2019; Hoffmann and Broekhuizen 2009; Zhang and Gong 2020). In this study, we further differentiate opportunities associated with three types of network positions: network centrality, network clustering, and network embedding.

### 2.4 | Network Centrality as Opportunity

Scholars in network science have extensively explored the correlation between network position and individuals' capacity to exert influence or receptivity to social influence (Friedkin and Johnsen 1997; Friedkin 2001). In essence, a person's centrality within the network structure reflects their power and receptivity to influence, while similarity in network relations indicates shared social positions, including attitudes and opinions. Friedkin (2001) further demonstrated that receptivity to influence correlates with centrality in communication networks, where greater degree centrality offers more opportunities for interaction.

Subsequent studies have highlighted disparities in network positions between influentials and influencees (Zhang and Gong 2019). Zhang and Gong (2019) investigated the network positions of these two groups, finding that individuals with high degree centrality (referred to as hubs) and high betweenness centrality (termed bridges) exhibit diminished sensitivity to social influence. Conversely, those with moderate levels of centrality are more receptive to normative influence and status competition. These findings suggest an inverse-U relationship, consistent with the concept of middle-status conformity and anxiety.

These findings indicate that while higher degree centrality generally correlates with increased receptivity, there are nuanced distinctions based on the specific type of centrality

being examined. Donors with high degree centrality (connected to many others) tend to interact with a larger number of peers, thereby potentially being more susceptible to influence (Zhang and Gong 2019). Moreover, research suggests that individuals with high betweenness centrality, indicative of diverse connections, may also be exposed to a wide array of influences (Friedkin and Johnsen 1997). Additionally, research proposes that closeness centrality, reflecting proximity to peers, could serve as a more accurate predictor of susceptibility to social influences (Zagenczyk et al. 2015). Building on this existing research, and given that most research suggests that there is a linear relationship between different network measures and donors' likelihood to be influenced, we hypothesize that various network centralities—namely, degree centrality, betweenness centrality, and closeness centrality—significantly impact a donor's likelihood of being categorized as influencee:

**H1.** *Donors' network centralities highly correlate with their likelihood of being influencees.*

## 2.5 | Network Clustering as Opportunity

In addition to individuals' network positions, their membership in small clusters may also shape their receptivity to social influence. This is because densely connected clusters within a larger social network intensify opportunities for interaction, facilitating the formation of group norms (Flache et al. 2017).

Chung et al. (2019) demonstrated that, unlike influencers, the clustering of influencees plays a particularly significant role in the propagation of social influence. Influential and receptive individuals act as catalysts for the diffusion of social contagion through distinct mechanisms. Influential individuals exert a direct and impactful influence over their peers, while receptive individuals possess the trait of easy activation. They are especially influential among peers when present in enough numbers. Thus, their findings underscore the pivotal role of clustering patterns for influencees in driving the spread of social influence. When influencees are clustered together, they are far more likely to significantly drive the diffusion of social influence through large social networks. Consequently, we propose that donors' clustering coefficient (e.g., measure such as triangle and clustering coefficient assess the degree to which donors belong to tightly connected clusters) may positively correlate with their receptivity.

**H2.** *Donors' clustering coefficient highly correlate with their likelihood of being influencees.*

## 2.6 | Capability and Motivation

In addition to opportunities, we also operationalize and investigate the impact of individuals' capability and motivation on their susceptibility to influence. In the context of donations, capability may be contingent upon factors such as donors' educational background and economic resources.

Specifically, education and financial resources are widely recognized as core indicators of individuals' capability to engage in

charitable giving. Education, in particular, has been consistently associated with increased philanthropic behavior. Wiepking and Maas (2009) found that higher levels of education are robustly and consistently linked to greater generosity, potentially due to increased awareness of societal needs, enhanced critical thinking, and broader social networks. Similarly, Bekkers and Wiepking (2011) identify education as a fundamental mechanism underlying philanthropic behavior, proposing that it enhances the cognitive ability to evaluate charitable appeals and increases social responsibility.

Financial resources also play a critical role in shaping philanthropic capability. Numerous studies have found that income, wealth, and financial stability strongly predict charitable giving (Havens et al. 2007; Rooney et al. 2005). Lee and Kim (2023) found that perceived behavioral control increases donation intention. Financial capability provides donors with the discretionary resources needed to give and may increase their psychological sense of security, which in turn facilitates generosity (Meer 2011). Furthermore, individuals with greater residential permanence—an indicator of economic stability—are more embedded in their communities and thus more likely to contribute to local causes (Grønbjerg and Paarlberg 2001).

Moreover, political donations are often conceptualized as motivated by both consumption (i.e., expressive or ideological alignment) and investment (i.e., strategic or instrumental returns) considerations (Fink 2017; Gordon et al. 2007). Liu and Li (2025) found that emotional, rational, and perception-related motivations play key roles in donation decisions. Higher income enables individuals to absorb the financial costs associated with political donations, while higher education levels are linked to increased political awareness, civic engagement, and ideological consistency—each of which has been shown to increase the likelihood and frequency of giving. Taken together, both education and financial resources serve as key enablers of giving. Therefore, we propose:

**H3.** *Donors' capability (in terms of education and financial resources) highly correlate with their likelihood of being influencees.*

In terms of motivation, Michie et al. (2011) note motivation can be reflected in automatic (e.g., habits) or reflective (e.g., beliefs, intentions) behaviors. Previous studies have tended to utilize questionnaires to ask for individuals' motivation for donation, which may subject to self-reporting errors (Allison et al. 2022; Manika et al. 2022). Instead, the current study operationalizes motivation as reflected by donors' past donation habits: people who have done something once are likely to do it again, due to either the force of psychological commitment and consistency (Cialdini 2009), or as a proxy for interest. Indeed, fundraisers make this assumption in their regular practices as well, looking at previous donation habits in fields such as environmental causes, political causes, and charity and religious causes as demonstrating a level of caring and motivation for those issues (Sargeant 2014). Moreover, we explore how such motivations lead donors to be receptive to social influence. Based on COM-B model, we propose that higher levels of motivations should correlate with a higher likelihood for a donor to be classified as influencees. As such, we propose:

**H4.** *Donors' motivation (in terms of donation habits) highly correlate with their likelihood of being influencees.*

### 3 | Methods

#### 3.1 | Sample

We obtained our data through Moore (<https://wearemoore.com/>), a nonprofit data management company that specializes in nonprofit fundraising, donor acquisition, branding, and marketing. The Moore database contains records of millions of individual donors in the United States and over 1 billion donation incidents to hundreds of nonprofits dating back over three decades (1990–2024).

For the current analysis, we utilized political donation data from the year 2016, which was a presidential election year in the U.S. Donations to political organizations tend to soar in such years (Mummalaneni et al. 2024). Specifically, we have donation records to 88 political nonprofits in the dataset, among them, based on self-identified labels, civil rights social movement organizations and liberal political organizations were classified as left-leaning nonprofits; and Republican political campaigns, conservative political organizations, and conservative judicial & patriotic political organizations were classified as right-leaning nonprofits. Overall, there were 36,564,614.55 USD ( $M = 101.46$ ,  $SD = 2277.12$ ) donations made to left-leaning nonprofits and 117,908,674 USD ( $M = 44.92$ ,  $SD = 228.37$ ) donation to right-leaning nonprofits in 2016. The unequal size of donations reflect the nature of our nonprofit sample because Moore has more right-leaning clients than left-leaning ones. Subsequently, our analysis does not attempt to generalize or compare totals between left and right, instead focusing on per-capita measures to standardize and allow comparisons. We therefore analyzed left-leaning and right-leaning datasets separately and used standardized measures for all variables that adjust to different sample sizes. Within the left-leaning sample, there were a total of 360,357 donation records. We removed negative values, which were a negligible set of donations resulting from refunds and errors. We set the minimum donation amount to \$10 to eliminate extremely small donations especially negative donation records (reflecting refunds), which reduced the donation records to 266,323. We used the same procedures for the right, and the total donation records dropped from 2,624,597 to 2,040,292.

#### 3.2 | Social Value Algorithm Logic and Source Data

The Social Value Algorithm is conceptually analogous to an experimental design in which the two conditions are: (1) what a donor does when their network contact donates, and (2) what they do when that contact does not. If a donor's behavior systematically differs across these conditions over time, this suggests a causal relationship—though not one as definitive as in a controlled experiment. Specifically, it estimates the portion of a donor's activity that is attributable to the activity of their connected peers. In classical causal inference, three criteria are necessary: correlation, temporal precedence, and elimination of alternative explanations (Hume 2007). Observing that donor

A's contribution increases when donor B donates satisfies the correlation criterion. In addition, we also need to observe what happens when donor B's behavior changes—particularly when it declines or ceases—requiring variation in behavior over time. In our case, this variation comes from longitudinal donation records: when donor A donates, how does donor B respond across multiple instances?

To make such estimation meaningful, we included only donors who gave at least twice during the 2016 election cycle, with many donors contributing multiple times. This repeated behavior over time allows us to detect consistent patterns of influence and estimate a directional relationship—offering stronger support for causal inference than a single time point alone.

The other challenge is identifying which donors may be connected to one another. Because individual-level data rarely include direct relational ties, we rely on the logic of the Social Value Algorithm, which evaluates whether donor behavior is temporally patterned in response to another's activity. When presented with a pair of donors who are not connected (i.e., strangers), the algorithm simply returns a value of zero—indicating no detectable influence—rather than falsely imputing a connection. Therefore, the risk of false positives is minimal.

Ideally, we would test all possible donor pairs to ensure complete coverage. However, due to computational constraints and the combinatorial explosion of potential pairs, this is impractical at scale. To manage this, we restrict the input to pairs that are more likely to be socially or behaviorally connected—such as those who donate to the same campaign or live in close geographic proximity. This filtering may lead to some false negatives (i.e., missed true connections), but we prefer this conservative approach over risking inflated estimates of influence due to over-inclusion. In this sense, we construct a potential—not definitive—network, and the algorithm then identifies the subset of pairs that exhibit consistent, directional influence over time.

#### 3.3 | Network Construction

The Social Value Algorithm tracks pairs of individuals over time to build potential donor networks. We constructed ties between donors based on three main criteria: shared racial identity (categorized as African American, Asian, Hispanic, or White), mutual contributions to the same political orientation (left-leaning or right-leaning) during the 2016 election cycle, and residence within the same geographic area. To define geographic proximity, we used the first four digits of each donor's ZIP code to allow for a broader regional scope while maintaining local relevance. A tie was established between two donors if they satisfied all three criteria and made their donations within the same calendar week. This approach approximates potential channels of social exposure by capturing racial, ideological, spatial, and temporal proximity in the donation process.

This method of constructing influence networks based on geolocation, political, and racial homophily rests on two foundational assumptions. First, prior research highlights the powerful role of homophily in social influence: individuals with similar characteristics—such as race or political

orientation—are more likely to interact and influence one another (Aral 2011; Christakis and Fowler 2011). Second, geographic proximity facilitates social influence, as individuals who live near one another are more likely to share local experiences—such as attending the same schools, events, or establishments—which provide opportunities for interaction and influence.

To advance understanding of donor influence within political philanthropy, it is critical to account for geographic, political, and ethno-racial homophily in network construction. The spatial and ideological clustering of U.S. communities—often referred to as the “big sort”—has significant implications for how nonprofits emerge and attract support. Lecy et al. (2019) demonstrate that nonprofit missions tend to align with the political ideologies of the communities they serve, indicating that geographic proximity often reinforces shared values and facilitates donor alignment around common causes. Similarly, Ben-Ner (2022) argues that the nonprofit sector is predominantly in-group oriented, with organizations often serving culturally or ideologically cohesive communities—contributing to fragmentation and, at times, polarization. These dynamics suggest that donor influence is more likely to occur within racially, politically, and geographically aligned groups. Supporting this, Rolf et al. (2023) show that the racial and political composition of local communities shapes nonprofit leadership diversity, underscoring how community-level demographics influence the structure and orientation of nonprofits.

Incorporating homophily and geolocation into network design thus not only increases the realism of influence modeling but also helps capture the structural inequalities and identity-based clustering that characterize philanthropic behavior in a polarized society.

We established four distinct networks for left-leaning donors, with one network dedicated to each racial group, alongside an additional four networks based on right-leaning donors. These eight networks are temporal, weighted, and non-directional, reflecting the dynamic and nuanced nature of repeated political donations throughout an election year. These mutually exclusive networks offer us opportunities to independently execute models within each sample and to compare and validate results across samples.

### 3.4 | Influence Classification

To classify “influencees” among donors, we followed a two-step process. First, we calculated each donor’s receptivity, which is the amount of their donations that the algorithm attributes not to their behaviors but to their friends’. From the starting analogy, it is what you do only when your friends do it. Next, we classified donors whose receptivity was one standard deviation above the mean as influencees. A donor with receptivity one standard deviation above the mean demonstrates a statistically significant tendency to follow others’ donation behaviors within their social networks.

To measure receptivity, we utilized the open-source software developed by Williams et al. (2023) to calculate dollar-based

values (for codes and data structure, please visit <https://github.com/eunakhan/social-value>). For each network, we took several steps to build models to calculate Social Values for all actors (see Appendix A for a flowchart illustration). First, we build models that used data up to time  $t$  to predict actors’ total donation amount in interval  $\tau = (t, t + \tau)$ . This step essentially records actors’ performance at each time point, makes an estimation about how they would perform at the next time points, and then compares the observation from  $t + \tau$  against the prediction to record errors. Second, based on each network, we found all actors ( $U$ ) whose neighbors were absent in this interval  $\tau$  and considered the pairwise social influence each of these users had on their neighbors. This step uses the network information to consider who could have the chance to exert networked influence on a given actor. In addition, it utilizes the timestamp associated with each donation. Next, we predicted actors’ donation amount at  $\tau$  for each actor  $u \in U$ , using the models from step 1. This step brings the network information into the model estimation at step 1 to further record errors and make model estimations. At this point, fitted models are ready to produce estimations of social influence, as further explained below.

At the last step, for each donor  $u \in U$ , we subtracted the sum of pairwise social influence value of all absent neighbors on actor  $u$ , forming the total donation amount estimate of the previous step, to get the networked influence adjusted value amount:  $AdjTotalDonation_u^\tau(t) = TotalDonation_u^\tau(t) - \sum_{y \in N(u) \& y \text{ churmed in } \tau} SocialValue_{yu}^\tau(t)$ . In addition, we compared  $AdjTotalDonation_u^\tau(t)$  with the actual observed data. It was expected that  $AdjTotalDonation_u^\tau(t)$  would be more accurate than  $TotalDonation_u^\tau(t)$ .

Through this procedure, the models generate multiple value estimations that decompose observed behavior into social and nonsocial components. Nonsocial value captures donor behavior that is not attributable to social influence, representing the level of activity a donor would be expected to exhibit independently of their network. Conceptually, nonsocial activity is analogous to loyalty in marketing research, insofar as it reflects behavior driven primarily by the relationship between the individual and the organization or cause rather than by peer influence.

To illustrate, consider donor A. If A participates for 1 h regardless of whether donor B is present, A has no following value with respect to B, and the full hour is attributed to A’s nonsocial activity. However, if A’s presence induces B to participate for an additional 30 min, this increment is attributed to A’s Social Value on B, reflecting A’s outward influence within the network. Importantly, influence attributed to outgoing ties and incoming ties is conserved: the framework does not create new behavior but reallocates observed behavior to the actors most plausibly responsible for it. This example represents an idealized case. In practice, unobserved contextual factors—such as weather or scheduling constraints—may also shape participation and are not fully captured in the model, introducing attribution error. As a result, estimated social value should be interpreted as conservative, in that it is more likely to understate than overstate the true extent of social influence.

In contrast to social value, receptivity captures the degree to which a donor's own behavior is shaped by others in the network (Williams et al. 2023). Taken together, a donor's social value reflects the aggregate behavioral change in the network that can be attributed to that donor's presence, operationalized as the additional activity of others that is most plausibly induced by the donor. High receptivity suggests that when many donors within a focal donor's network contribute to a particular campaign, that donor is also more likely to donate to the same campaign shortly thereafter, indicating a strong likelihood of following others' behaviors. The validity of this measure is confirmed through repeated observation and system-level aggregation.

For repeated observation, a donor's receptivity would not score high if they followed others' donation patterns only once. For each observation, the algorithm also compares the observed value to a simulated value in which others are removed from the network. Only when a pattern persists over time and significant differences exist between the observed and simulated values is a donor assigned a high receptivity score. System-level aggregation involves tracking the social influence each donor exerts on others, as well as the receptivity each donor receives. At the system level, the total amount of social influence equals the total amount of receptivity, though individual levels of influence and receptivity may vary. In other words, in our networks with hundreds or thousands of donors, although each varying in social influence and receptivity, the total social influence and receptivity remain balanced. When the algorithm calculates that the total social influence equals the total receptivity, it confirms that the algorithm can accurately assess both how much influence Person A has on their network and how much receptivity they experience from others.

Once we obtained the receptivity measure for every donor in each network, we further calculated the mean and standard deviations in each network and classified influences.

## 3.5 | Measures

### 3.5.1 | Network Centrality Measures

In this study, we employed four distinct network centrality measures: degree centrality, betweenness centrality, closeness centrality, and PageRank. Degree centrality quantifies a node's significance within a network based on its total number of connections, essentially gauging its level of interconnectedness. In this context, a donor with high degree centrality has many connections to others who have donated to similar political causes around the same time. Betweenness centrality assesses the extent to which a node acts as a bridge or intermediary between other nodes along the shortest paths within the network, highlighting nodes that facilitate the flow of information, influence, or resources. A donor with high betweenness centrality occupies a key position between other donors who have contributed to similar causes. Closeness centrality measures how close a node is to all others in the network, offering insights into its efficiency in communication and interaction. Here, donors with high closeness centrality are closely associated with many others who have donated to similar causes. Finally, PageRank, developed by Larry

Page and Sergey Brin, assigns scores to nodes based on the quality and quantity of their inbound links, reflecting a node's relative importance within the network. A donor with high PageRank is likely connected to many other central or influential donors. While each of these measures evaluates network centrality from a different perspective, they tend to be highly correlated. We leveraged the *NetworkX* library in Python to compute these metrics.

### 3.5.2 | Network Clustering Measures

To evaluate the extent of donor integration into their local clusters, we employed two metrics: local clustering coefficient and triangles. The local clustering coefficient assesses the clustering tendency of individual nodes by computing the ratio of edges between a node's neighbors to the total possible edges among them. It quantifies the proportion of a node's neighbors that are interconnected. A "triangle" signifies a specific arrangement of connections among three nodes in a network. This configuration emerges when each node is linked to the other two, forming a closed loop. Nodes belonging to numerous triangles indicate highly interconnected neighbors, suggesting significant local cohesion or clustering around the node. We utilized the *NetworkX* library to compute these metrics.

### 3.5.3 | Capability (Education)

Education level was measured at four intervals: 1 = completed high school, 2 = completed college, 3 = completed graduate school, and 4 = attended vocational/technical.

### 3.5.4 | Capability (Financial Resources)

In this category, we include donors' net worth (1 = less than or equal to \$0, 2 = \$1–\$4999, 3 = \$5000–\$9999, 4 = \$10,000–\$24,999, 5 = \$25,000–\$49,999, 6 = \$50,000–\$99,999, 7 = \$100,000–\$249,999, 8 = \$250,000–\$499,999, 9 = \$500,000–\$999,999, 10 = \$1,000,000–\$1,999,999, 11 = \$2,000,000+), economic stability indicators (measured on a 30-point scale by Moore, with 1 indicating the highest level of economic stability and 30 indicating the lowest level of economic stability), home ownership (1 = home owner, 2 = renter), length of home ownership (00 = less than 1 year, 01 = 1 year, 02 = 2 years, 03 = 3 years, 04 = 4 years, 05 = 5 years, 06 = 6 years, 07 = 7 years, 08 = 8 years, 09 = 9 years, 10 = 10 years, 11 = 11 years, 12 = 12 years, 13 = 13 years, 14 = 14 years, 15 = greater than 14 years), and investment portfolio (which consists of three types of investment options: personal investment, real estate, and stock and bond. The value indicates the number of those three investment options the donor possesses, whereas 0 indicates no investment options).

### 3.5.5 | Motivation (Donation Habits)

We differentiate four types of donation habits: (1) health causes (1 = yes, 0 = no). (2) Donations to environmental causes (including contributions to animal welfare, environmental or wildlife causes), where higher values indicate a habit of donating to more

environmental causes. (3) Donations to charity and religious causes (including contributions to churches, international aid, art and cultural causes, and veteran's causes), where higher values indicate a habit of donating to more charitable causes. And (4) donations to political causes (including contributions to general politics, political-conservative, and political-liberal causes), where higher values indicate a habit of donating to more political causes.

### 3.5.6 | Basic Demographics

Previous research shows that donors of different demographics tend to have different priorities in their donation (Gillespie and Xie 2025). In this category, we have included donors' age, gender (1 = male, 2 = female, 3 = unisex), marital status (0 = married, 1 = single). For political leaning, we have donors' party registration: 1 = no party, 2 = Republican, 3 = Democrat, 4 = independent, 5 = others.

## 3.6 | Model Estimation

We selected the random forest algorithm for this study due to its strong performance in handling complex, high-dimensional classification problems (Hastie et al. 2005), its robustness to overfitting through ensemble averaging and out-of-bag error estimation (Breiman 2001), and its ability to model nonlinear relationships and interactions between variables (Breiman 2001; Liaw and Wiener 2002). Random forest has also been shown to be effective or adaptable in contexts with class imbalance when combined with cost-sensitive approaches or sampling strategies (O'Brien and Ishwaran 2019). To further justify this choice, we compared the performance of the random forest model with that of a multinomial logistic regression model, as the dependent variable in our study comprises three categories. The results, presented in Appendix B, show that the random forest model consistently outperformed multinomial regression across key metrics.

In addition, to address potential overfitting in the random forest model, we implemented a series of model tuning strategies aimed at improving generalization. Specifically, we constrained the maximum depth of individual trees to prevent the model from capturing noise in the training data. We also set minimum thresholds for the number of samples required to split a node and to remain at a leaf node, thereby avoiding overly specific partitions. In addition, we limited the number of features considered at each split to reduce model variance. The number of trees in the forest was also optimized to strike a balance between performance and computational efficiency. All hyperparameters were tuned using grid search with cross-validation on the training data, ensuring that model complexity was controlled based on validation performance (see Appendix C for learning curve visualization).

## 4 | Results

### 4.1 | Mapping Influencee Distribution

The research question aims to investigate the proportion of influenceable donors within a network. Table 1 depicts the percentage of influencee donors across eight networks. Across

samples, approximately 10% of donors are classified as influencees, a consistent figure observed among both left-leaning and right-leaning donors. Notably, the highest percentage of influencees is found among right-leaning Asian donors (13.90%) and left-leaning Asian donors (12.82%), while the lowest percentage is observed among right-leaning African American donors (7.55%). Additionally, we compared the average donation amounts between influencees and non-influencees (see Table 2). Across networks, influencees consistently contributed at least twice as much as non-influencees, with some instances showing a tenfold difference. For example, among left-leaning White donors, influencees contribute an average of \$657.57, compared to \$56.17 from non-influencees. This observed difference may be due to influencees' propensity to donate when others do and thus lead to a higher total donation amount over 1 year. Taken together, influencees constitute approximately 10% of donors displaying heightened receptivity to others' donation behaviors. Moreover, they significantly outspend their peers, highlighting the importance of identifying such donors for various purposes. Further exploration into mechanisms aiding in the identification of these influenceable donors is discussed below.

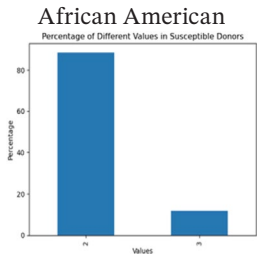
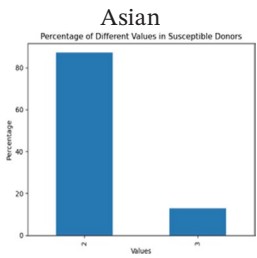
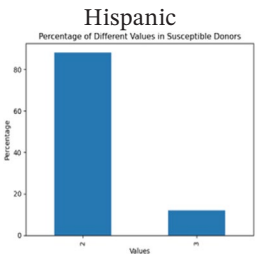
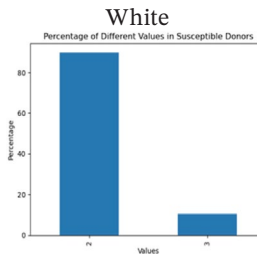
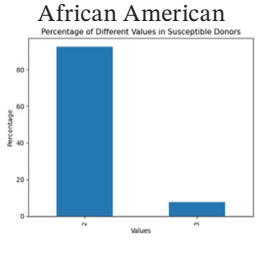
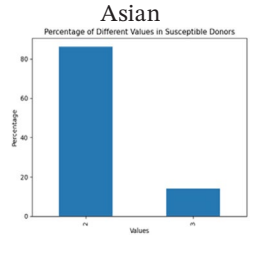
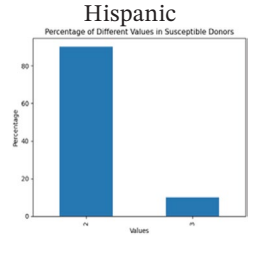
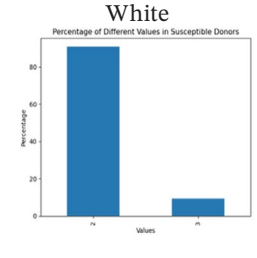
### 4.2 | Impact of Network as Opportunity

H1 and H2 aimed to investigate whether higher network centralities and clustering coefficients correlated with an increased likelihood of donors being classified as influencees. Furthermore, Research Question 2 asked whether network embedding enhances model accuracy in classifying influencees. To test these, eight machine-learning models were executed independently. The results of model fitting are presented in Appendix D, demonstrating consistent performance across all models. Additionally, Web Appendix E highlights the top features that significantly contributed to the identification of influencees.

In terms of model performances, all eight models achieved similar results, suggesting high reliability. For instance, considering African American donations to left-leaning organizations, the model demonstrates high accuracy in classifying non-influencees, with a precision of 0.88, recall of 0.95, and F1-score of 0.92, indicating its proficiency in correctly identifying true non-influencees while minimizing false positives. However, its performance in identifying influencees is notably weaker, with a precision of 0.13, recall of 0.05, and F1-score of 0.07, suggesting a significant proportion of false positives and negatives in this category. Despite achieving a high training accuracy of 0.99, the test accuracy of 0.85 reveals a slight drop in performance when applied to unseen data, emphasizing the need for further evaluation and potential refinement of the model to enhance its effectiveness in identifying influencees.

Moreover, in terms of the most important network features aiding model predictions, six out of the eight models identify network centrality measures such as closeness and degree centrality as the most important. Similarly, these six models also highlight triangles as a top measure. Only in the White donor network donating to right-leaning organizations was

**TABLE 1** | Distribution of influencees across eight networks.

Left-leaning donors				
	African American	Asian	Hispanic	White
				
% of Influencees	11.67	12.82	11.94	10.29
N	2126	663	1256	22,112
Right-leaning donors				
	African American	Asian	Hispanic	White
				
% of Influencees	7.55	13.90	9.88	9.25
N	6248	3547	9702	201,465

**TABLE 2** | Influenceable and non-influenceable donors' average donation amount.

	African American	Asian	Hispanic	White
Left-leaning donors				
Influencees' donation amount	M = \$110.36	M = \$132.39	M = \$167.78	M = \$657.57
Non-influenceable donation amount	M = \$ 34.36	M = \$ 33.66	M = \$ 35.04	M = \$ 56.168
Right-leaning donors				
Influencees' donation amount	M = \$89.02	M = \$126.93	M = \$110.78	M = \$114.64
Non-influencees' donation amount	M = \$ 43.02	M = \$ 44.49	M = \$ 40.86	M = \$ 44.48

PageRank among the most influential predictors. Among the eight models, two identified network embedding as significant predictors.

Taken together, the analysis provides strong support for **H1**, suggesting that network centrality measures highly correlate with the amount of receptivity. Specifically, being close to many other donors and having many ties are important for most donors to be classified as influencees. For White donors who donated to political-right organizations, ties with other highly central donors are also important. Partial support for **H2** was found, indicating that while being members of many clusters may not matter for a donor, being closely related to a small group of donors (triangles) heightens their likelihood of receptivity to social influence.

### 4.3 | The Impact of Capability and Motivation

**H3** and **H4** explored whether donors' capability and motivation significantly influenced their likelihood of being classified as influencees. To address this question, eight machine-learning models were executed independently. The results of model fitting are presented in Appendix F, demonstrating consistent and excellent overall performance across all models. Additionally, Appendix G highlights the top features that significantly contribute to the identification of influencees.

In terms of model performances, all eight models achieved similar results, exemplified by African American donations to left-leaning organizations, where the model demonstrates exceptional performance in classifying both influencees and

non-influencees, with precision, recall, and F1-scores of 0.99 for both categories. This suggests the model effectively identifies true positives while minimizing false positives and false negatives, showcasing its robustness in distinguishing between the two classes. Additionally, achieving a high training accuracy of 0.99 further validates the model's capability to generalize well on the training data. The equally impressive test accuracy of 0.99 indicates that the model maintains its high performance even when applied to unseen data, highlighting its reliability and potential for practical use in classifying influencees and non-influencees with a high degree of confidence.

Furthermore, regarding the most important features that shape model predictions, all eight models demonstrate strikingly similar results, with minor differences. In terms of capabilities, financial resources emerged as a top factor in all models, while donors' education was not significant in any, partially supporting H3. It is important to note that economic stability and net worth were the most important financial capabilities. Regarding motivation, all eight models identify donation habits as among the top five influential predictors. However, the specific type of important donation habit varies across racial networks. For left-leaning donors, past donations to charities and religious organizations topped the chart for African Americans and Hispanic donors, whereas past donations to political organizations were exceptionally important for Asians and Whites. For right-leaning donors, past donations to charity and religious organizations emerged as the most significant motivation across all racial groups. Overall, it appears that for left-leaning Asian and White donors, political engagement was a strong motivation leading them to be influencees, whereas for all other groups, their motivation may have stemmed from concerns for charities and religious causes, partially supporting H4.

#### 4.4 | Models With All Best-Performing Features

Finally, we ran eight models that included the best-performing features to assess which of all the COM-B factors are most important in terms of making a donor influenceable. The results of model fitting are included in Appendix H, and Appendix I showcases the top features that significantly contribute to the identification of influencees.

In terms of model performances, all eight models achieved similar results. Taking African American donations to left-leaning organizations as an example, the model demonstrates high accuracy and performance in classifying both influencees and non-influencees. With a precision of 0.95 for non-influencees and 0.86 for influencees, the model excels in accurately identifying instances of both classes, with a slight decrease in precision for influencees. The F1-scores further corroborate this, with scores of 0.96 for non-influencees and 0.70 for influencees, emphasizing the model's balanced ability to maintain precision and recall for both classes. Additionally, achieving a high training and test accuracy of 0.93 underscores the model's consistency and reliability in correctly classifying influencees and non-influencees, suggesting its potential utility in real-world applications with a high level of confidence.

These combined models also demonstrated dynamics unseen in previous models where we separated network measures and attribute measures. All eight models identified donors' financial capability as the most important feature shaping their likelihood of being classified as influencees. In addition, five models identified donors' motivation as also among the top influential factors. Interestingly, all models identified network embedding as among the top 10 predictors, but the significance of network measures is mediated in these combined models. It is likely that some of the donor capability measures (e.g., length of residence) may capture the effects of network measures. Taken together, these combined models largely confirm that donors' capability, network opportunities, and motivations all help to strongly predict a donor's receptivity to social influence.

## 5 | Discussion

Through the analysis of a large political donation dataset, our exploratory study unveiled a remarkably consistent distribution of highly receptive donors across eight networks. Moreover, our in-depth analysis offers a nuanced and comprehensive profile of these donors, further advancing our conceptualization of the socio-economic characteristics that render certain individuals receptive to social influence in the context of political donation.

### 5.1 | The COM-B Framework and a Theory-Driven Conceptualization of Influencees

The COM-B framework proposes that behavioral changes such as receptivity to social influence are shaped by individuals' opportunities, capabilities, and motivations. When applied to understanding influencees, it suggests that being receptive is not a blanket status. Rather, it is a nuanced outcome made possible by individuals' network positions and their individual capabilities and motivations.

Regarding capability, financial resources emerged as the most crucial factor in the context of political donation. This likely stems from the discretionary nature of political donations, where individuals with certain economic conditions are more inclined to donate when their peers do. Among various indicators of financial capability, economic stability and net worth consistently emerged as the most significant, followed by the size of their investment portfolio. Surprisingly, income was not highly significant across all models, potentially due to some high-income earners lacking economic stability or substantial net worth, especially among individuals with unstable jobs or significant financial obligations such as student loans or mortgages. These findings suggest that for a donor to be receptive, they require economic stability and high net worth, reflecting a level of economic freedom conducive to receptivity. Additionally, another important predictor, investment portfolios, may also indicate a considerable amount of disposable income.

The importance of disposable income highlights the notion that individuals categorized as "influencees" necessitate specific levels of capability in political donation. Future research endeavors aimed at identifying influencees in various contexts, such as marketing or behavioral changes, should also prioritize the

examination of the types of capabilities that serve as the initial criteria for qualifying individuals as influencees. In other settings, capability may be more appropriately operationalized as skill or economic mobility or something more contextually appropriate.

Our study extends the COM-B framework by extending it to the context of social network research. Our analysis underscores the significance of network positions in reflecting opportunities for social influence. Specifically, our findings indicate that being well-connected and closely linked within a network are key positions that facilitate receptivity to social influence. The diversity and proximity of connections within these positions provide ample opportunities for individuals to encounter and be influenced by others. Moreover, our analysis suggests that small clusters, such as triangles, may intensify the impact of social influence, creating enclaves of highly influenceable individuals within larger networks. Furthermore, our examination of network embedding reveals that conventional metrics alone do not fully capture the complexity of network positions that shape individuals' receptivity to influence. Future studies could leverage explainable AI methods to unpack the information embedded within these networks, thereby advancing our theoretical understanding of how different network structures offer diverse opportunities for shaping social influence.

In this study, our focus on motivation centered on habitual tendencies, as evidenced by individuals' past donation behaviors. Our findings indicate that charitable and religious donation habits largely drive individuals across various demographics to exhibit receptivity to influence in the realm of political donations (Mummalaneni et al. 2024). Notably, this pattern diverges for Asian and White left-leaning donors, whose past political donation activities emerge as the strongest motivational factor.

It is plausible that these past donation habits have facilitated interactions with fellow donors, allowed them to leave behind their contact information with fundraisers, or exposed them to specific social issues. Crucially, our research highlights the role of past charitable and religious donations in motivating African and Hispanic left-leaning donors, as well as all types of right-leaning donors, to engage in political contributions. We recommend that future research further explore the link between religion and political donation.

In conclusion, drawing from the COM-B model, we can conceptualize influencees as individuals whose actions are shaped by their capabilities and network positions. These individuals must also possess motivations that predispose them to adopt specific social influences. This theorization emphasizes that it is important to recognize that being influenceable is not solely a product of external circumstances or individual agency; rather, it necessitates a combination of internal and external factors that influence individuals' behaviors and decisions.

Our adaptation of the COM-B model also introduces a degree of nuance in that we have essentially split a behavior (donations) into two more nuanced components: the non-social portion that is driven directly by the source, and the receptivity portion that is driven by social influence mechanisms. The Social Value Algorithm (Williams et al. 2023) allows for this nuanced

measurement, and so opens up a wide range of theory-driven research on whether people are socially influenced in their actions. We highlight that this can be used in any context where a network can be formed and actions are time-stamped. The COM-B model can now be used as a theoretical frame to not only find individuals and study distributions, but can guide comparative analysis or longitudinal study. When used in the aggregate, the Social Value Algorithm allows the researcher to see what percentage of activity in a context is social, how that compares to other contexts, and how it varies over time. In turn, that allows for experimental and quasi-experimental designs to begin to explore the "how" questions that will further drive theory development. As computing power rises and costs drop, researchers will be able to use larger datasets and build models with fewer restrictions.

## 5.2 | Racial Group Level Patterns of Influenceable Distribution

A noteworthy discovery of this study is the remarkably consistent distribution patterns of influencees across racial groups, comprising approximately 10% of political donors. This group significantly outnumbers influencers, who, as indicated by previous studies (Aral and Walker 2012), constitute merely about 1% of donors. Moreover, our research reveals that influencees outspend non-influencees by anywhere from 2 to 10 times.

Collectively, these findings underscore the crucial role of influencees in social networks across various domains, including fundraising, marketing, and behavioral change campaigns. These individuals exhibit receptivity to social influence and consistently outperform their peers. Furthermore, both prior research and our findings indicate that they possess the potential to influence closely connected individuals. For any campaigns to achieve success in large populations, they cannot do so without leveraging the power of influencees.

Furthermore, our investigation revealed significant racial disparities. Notably, across four racial groups, Asians from left to right consistently exhibited the highest prevalence of influencees. This trend suggests a possible correlation with cultural values emphasizing collectivism, rendering individuals more receptive to social influence within Asian communities.

Future research should delve deeper into the intricate interplay between culture and social influence in the context of political donation and beyond. Such inquiries could shed light on how cultural dynamics shape behavioral tendencies. Moreover, integrating culture as an additional dimension within the COM-B model might offer valuable insights into individual propensities and their predisposition to adopt specific behavioral changes.

## 6 | Limitations and Future Research

This exploratory study is subject to several limitations. First, unlike many COM-B model-guided studies that rely on survey or experimental opinion data (Allison et al. 2022; Manika et al. 2022), our investigation exclusively utilized observational data. While this design enables examination of donation behaviors within

a large sample, it also necessitates certain assumptions. For instance, we presume that donors' past donation habits accurately reflect their motivations toward specific issues. However, other variables may influence their donation history. Future research should integrate observational data with survey or focus group methodologies to explore nuances comprehensively.

Second, because donors may respond to shared contextual factors—such as local political events, targeted campaign solicitations, or synchronized fundraising cycles—the observed clustering of donation behavior may partially reflect common exposure rather than direct interpersonal influence. Although the analytic strategy is designed to identify potential opportunities for influence, it cannot definitively disentangle interpersonal influence from correlated responses to shared stimuli. However, as the number of corresponding actions within a donor pair increases, the likelihood that such clustering is driven solely by shared contextual factors diminishes.

Third, the donor networks used in this study are inferred rather than directly observed. In the absence of comprehensive relational data, network ties are constructed from observable attributes that capture plausible opportunity structures for interaction rather than confirmed social relationships. Although this approach is consistent with prior large-scale research where ground-truth network data are unavailable, the inferred ties cannot be externally validated using surveys or known relational data at this scale. Collecting such validation data for millions of individuals would be prohibitively costly and subject to substantial nonresponse and recall bias. Accordingly, the networks should be interpreted as conservative, theory-informed approximations of relational opportunity, and the findings as indicative of coordinated behavior rather than definitive evidence of interpersonal influence. Because the estimation of offline networks necessarily relies on simplifying assumptions (see Section 3), this approach may understate the extent of social influence within donor communities. This trade-off reflects the scale of the data and the goal of minimizing speculative ties. Future research could address these limitations by combining large-scale behavioral data with smaller-scale surveys, interviews, administrative linkages, or experimental designs to more directly assess interpersonal influence. In online contexts, where social interactions are automatically recorded by digital platforms, network data may be observed with greater precision, allowing future studies to compare patterns of online and offline social influence.

Because social value is estimated by attributing observed behavioral changes within a network to individual donors, donors with higher levels of activity or more frequent participation may exert disproportionate influence on the resulting estimates. This sensitivity reflects the fact that frequent donors create more observable opportunities for potential social influence and attribution, rather than differences in predictive accuracy or model fit. Consequently, social value should be interpreted as capturing realized network impact conditional on observed activity, not as a normalized measure of influence potential independent of participation frequency. This property is inherent to attribution-based measures of social influence and should be considered when comparing donors with substantially different levels of activity.

One limitation of this study is the use of donor data from a single election cycle (2016). While more recent data are available, extending the analysis across multiple election cycles would require tracking the same individuals over time. However, because many donors do not contribute consistently across elections, such an approach would drastically reduce the sample size and may bias the analysis toward highly active or habitual donors. To preserve sample representativeness and analytic power, we focused on a single cycle that captures a broad cross-section of donor behavior. Future research could explore longitudinal patterns of political giving by focusing on repeat donors across multiple election cycles to better understand how influence dynamics evolve over time, particularly among persistent contributors. Such work would complement the present study by offering insights into the stability or change of influence roles within donor networks.

We acknowledge that geographic proximity between donors (or their communities) and the focal nonprofit organization may influence social transmission and engagement patterns. While this spatial dimension was not incorporated into the current analysis, it presents an important avenue for future work, particularly in understanding how local versus distant actors may differently shape influence dynamics and contribute to potential underreporting in network detection. In addition, due to privacy considerations, we did not retain identifiable information about the political nonprofit recipients, including organizational names or financial attributes. Consequently, we are unable to assess variation across nonprofits in terms of size, geographic scope, or other institutional characteristics. Future research could explore how differences among recipient organizations—such as national versus local reach or financial capacity—may interact with donor influence dynamics, if privacy-preserving access to such data can be ensured.

One striking pattern in our findings is that donors identified as influencees not only exhibit behavioral responsiveness to others, but also give significantly more, on average, than non-influencees. This difference—ranging from 2 to 10 times depending on the context—is nontrivial and suggests that influencees may represent a particularly valuable segment of the donor population in terms of both engagement and financial capacity. While the present study does not directly investigate the mechanisms underlying this pattern, it raises important questions for future research. Are influencees more embedded in social networks that reinforce giving? Do they have higher baseline interest in political engagement? Or do social cues from others activate deeper commitment in ways that translate to greater giving? For practitioners, this highlights the potential return on investment from targeting socially connected donors who are responsive to peer behaviors—not just in expanding donor pools, but in maximizing total contributions. Future studies should further unpack the attributes and motivations of influencees to better understand how social dynamics and donor capacity intersect.

In addition, with regard to how different network positions affect individuals' susceptibility to influence, some studies have identified a U-shaped relationship (Zhang and Gong 2019). Although our study did not reveal a similar pattern, future

research may explore different contexts and samples to uncover potential nuances in the relationship between network centrality and social influence.

Lastly, we did not examine the mechanism by which influence occurs. We know that some actors influenced others, but we do not know *how*. There are myriad pathways and theories to guide future analysis. This will require a combination of qualitative analysis to discover the potential relationships and experimental and quasi-experimental designs to find causal patterns of influence at larger scales. These approaches would add a great degree of nuance to the COM-B model, the study of influence using Social Value Algorithm, and would likely have outsized practical implications for both researchers and practitioners hoping to impact socially driven behaviors.

We note that there is a general gap in the literature about the *mechanisms* that lead to receptivity via networks. People are connected and behaviors spread, but precisely how is rarely known. In general, networks are a necessary but not sufficient condition for the question of “how?” We speculate that donations (and other forms of behavior) could be influenced by others via social dynamics such as envy, copying, admiration, friendship maintenance, or social pressure. There are several major theoretical models to address each of these, but capturing these various routes is beyond the scope of this paper, or our ability via the methods below. Still, we highlight it as a key area of need for a more nuanced theoretical model.

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### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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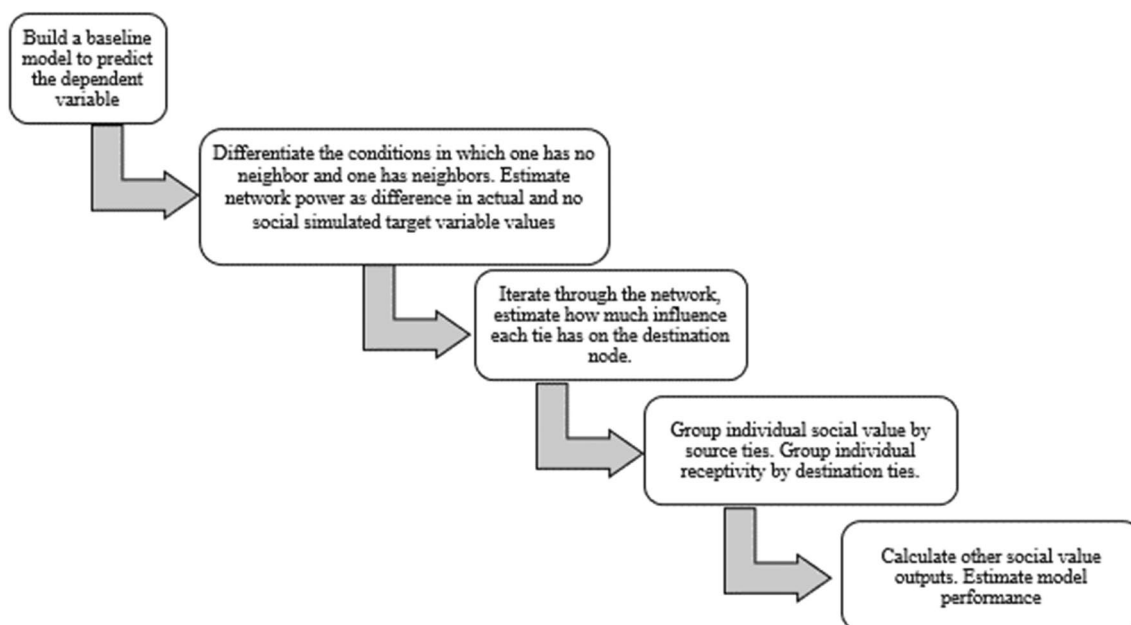
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## Appendix A

### Flowchart of Social Value Estimation

#### Process of Estimating Social Value



## Appendix B

### Model Performance Comparisons Between Random Forest and Multinomial Logistic Regression With Models Containing All the COM-B Factors

	Random forest models				Multinomial logistic regression models			
	Precision	Recall	F1score	Support	Precision	Recall	F1score	Support
Left-lean African American donors								
2	0.95	0.98	0.96	9872	0.88	0.61	0.72	9872
3	0.86	0.70	0.77	1795	0.20	0.53	0.29	1795
Accuracy			0.94	11,667			0.60	11,667
Macro ave	0.91	0.84	0.87	11,667	0.54	0.57	0.51	11,667
Weighted ave	0.93	0.94	0.93	11,667	0.77	0.60	0.65	11,667
Left-lean Asian donors								
2	0.95	0.96	0.96	3301	0.89	0.62	0.73	3301
3	0.82	0.80	0.81	767	0.29	0.68	0.41	767
Accuracy			0.93	4068			0.63	4068
Macro ave	0.89	0.88	0.88	4068	0.59	0.65	0.57	4068
Weighted ave	0.93	0.93	0.93	4068	0.78	0.63	0.67	4068
Left-lean Hispanic donors								
2	0.97	0.99	0.98	6964	0.90	0.56	0.69	6964
3	0.93	0.81	0.87	1176	0.20	0.64	0.30	1176
Accuracy			0.96	8140			0.57	8140
Macro ave	0.95	0.90	0.92	8140	0.55	0.60	0.50	8140
Weighted ave	0.96	0.96	0.96	8140	0.80	0.57	0.64	8140

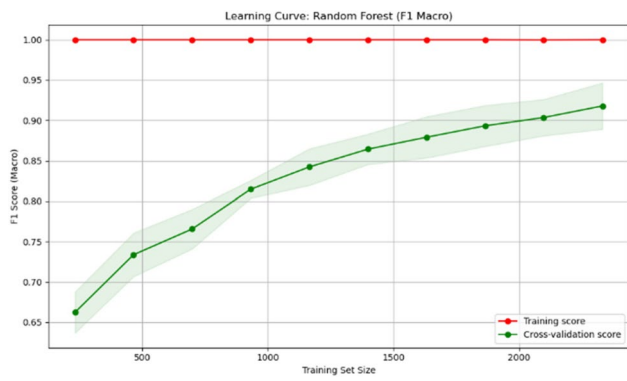
	Random forest models				Multinomial logistic regression models			
	Precision	Recall	F1score	Support	Precision	Recall	F1score	Support
Left-lean White donors								
2	0.91	0.86	0.88	147,434	0.83	0.58	0.68	147,434
3	0.57	0.70	0.63	39,822	0.27	0.56	0.36	39,822
Accuracy			0.82	187,256			0.58	187,256
Macro ave	0.74	0.78	0.76	187,256	0.55	0.57	0.52	187,256
Weighted ave	0.84	0.82	0.83	187,256	0.71	0.58	0.62	187,256
Right-lean African American donors								
2	0.99	0.92	0.95	66,566	0.99	0.60	0.74	66,566
3	0.63	0.79	0.35	2027	0.57	0.72	0.10	2027
Accuracy			0.91	68,593			0.60	68,593
Macro ave	0.61	0.85	0.65	68,593	0.52	0.66	0.42	68,593
Weighted ave	0.97	0.91	0.94	68,593	0.96	0.60	0.72	68,593
Right-lean Asian donors								
2	0.97	0.85	0.91	26,815	0.92	0.54	0.68	26,815
3	0.64	0.82	0.57	3786	0.57	0.67	0.27	3786
Accuracy			0.85	30,601			0.56	30,601
Macro ave	0.71	0.84	0.74	30,601	0.55	0.60	0.48	30,601
Weighted ave	0.91	0.85	0.87	30,601	0.83	0.56	0.63	30,601
Right-lean Hispanic donors								
2	0.99	0.89	0.94	90,395	0.97	0.59	0.73	90,395
3	0.62	0.82	0.46	5677	0.40	0.69	0.17	5677
Accuracy			0.89	96,072			0.59	96,072
Macro ave	0.66	0.86	0.70	96,072	0.53	0.64	0.45	96,072
Weighted ave	0.95	0.89	0.91	96,072	0.92	0.59	0.70	96,072
Right-lean White donors								
2	0.94	0.66	0.78	732,144	0.88	0.57	0.69	732,144
3	0.66	0.73	0.39	121,045	0.47	0.55	0.26	121,045
Accuracy			0.67	853,189			0.57	853,189
Macro ave	0.70	0.69	0.58	853,189	0.53	0.56	0.48	853,189
Weighted ave	0.84	0.67	0.72	853,189	0.78	0.57	0.63	853,189

Note: the three categories of donors are: 1 = difficult to influence, 2 = neutral non-influenceable, and 3 = influencees.

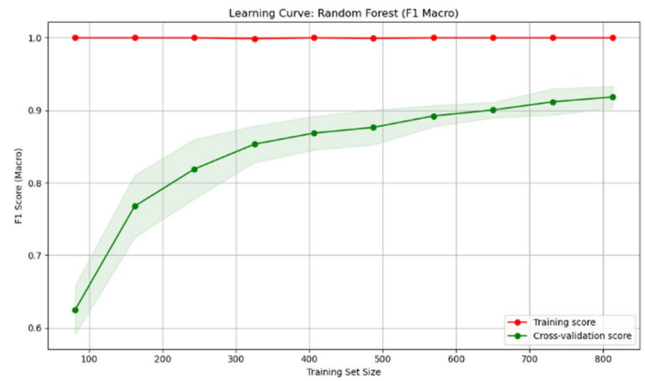
## Appendix C

### Learning Curve Comparisons

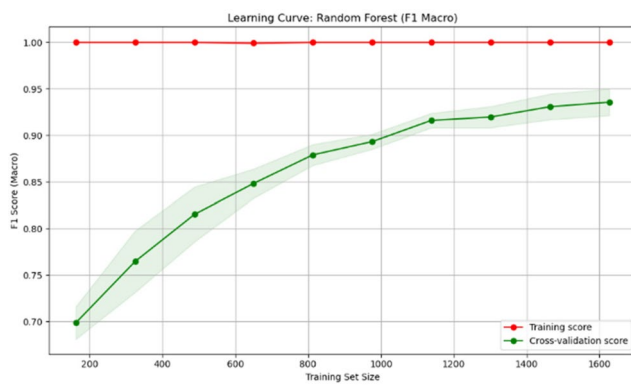
Left-lean African American donors



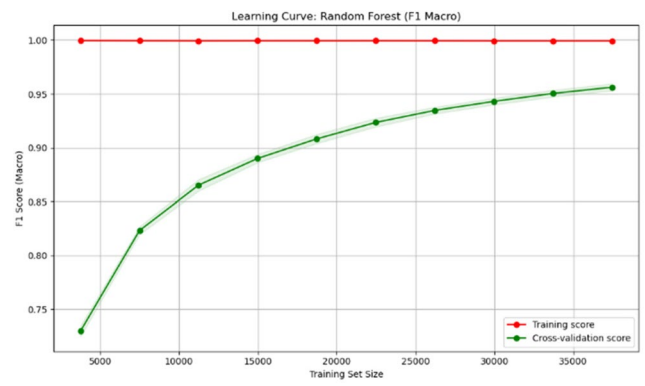
Left-lean Asian donors



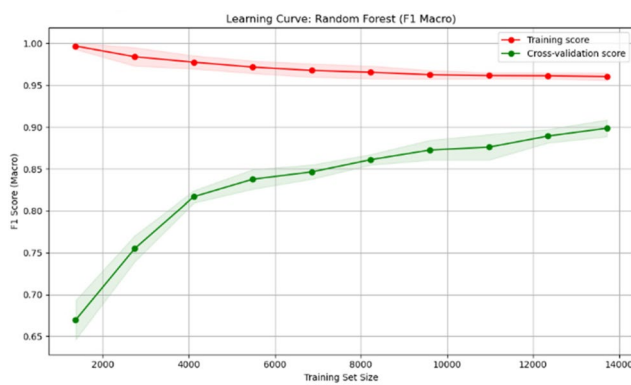
Left-lean Hispanic donors



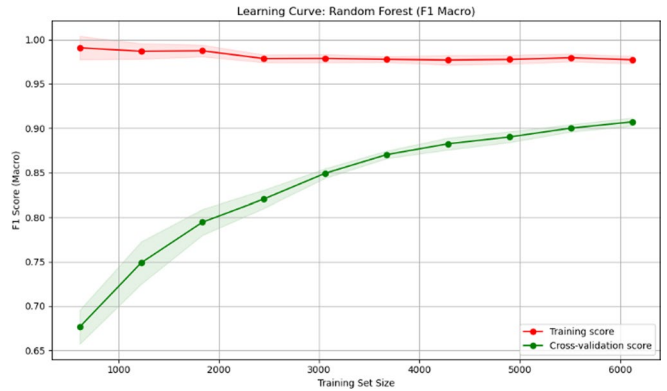
Left-lean White donors



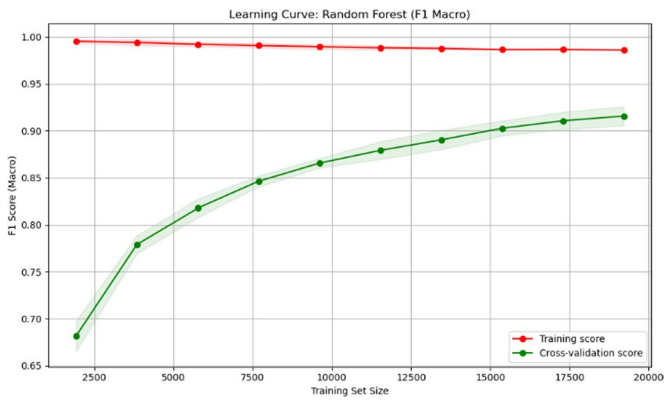
Right-lean African American donors



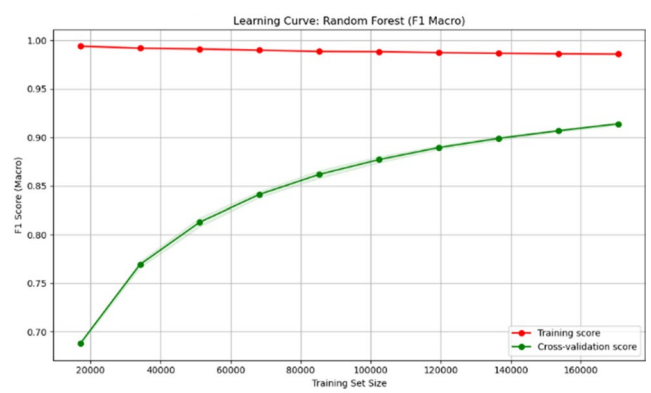
Right-lean Asian donors



Right-lean Hispanic donors



Right-lean White donors

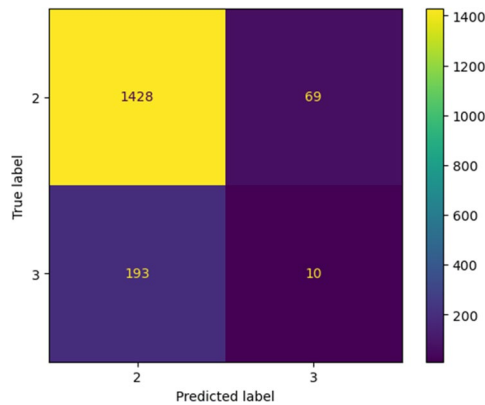


Appendix D

Model Performance of Network Measure Models

Left-lean donors

African American

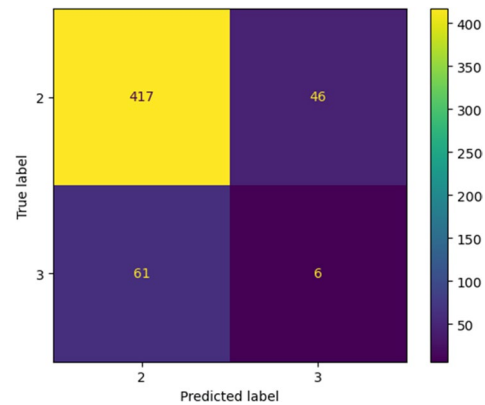


Confusion matrix

Model performance

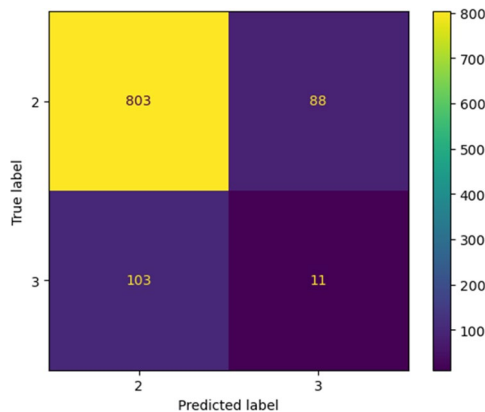
Precision for non-influenceable = 0.88  
 Precision for influenceable = 0.13  
 Recall for non-influenceable = 0.95  
 Recall for influenceable = 0.05  
 F1-score for non-influenceable = 0.92  
 F1-score for influenceable = 0.07  
 Train accuracy = 0.99  
 Test accuracy = 0.85

Asian



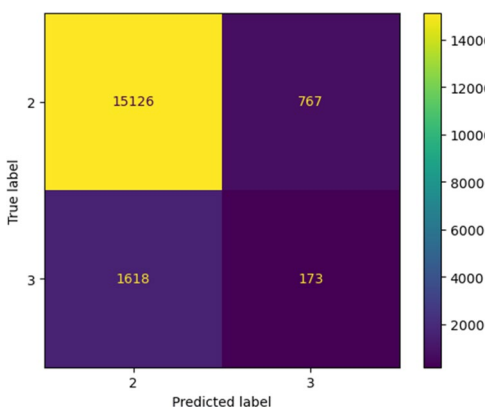
Precision for non-influenceable = 0.87  
 Precision for influenceable = 0.12  
 Recall for non-influenceable = 0.90  
 Recall for influenceable = 0.09  
 F1-score for non-influenceable = 0.89  
 F1-score for influenceable = 0.10  
 Train accuracy = 0.99  
 Test accuracy = 0.79

Hispanic



Confusion matrix

White



**Left-lean donors**

Model performance

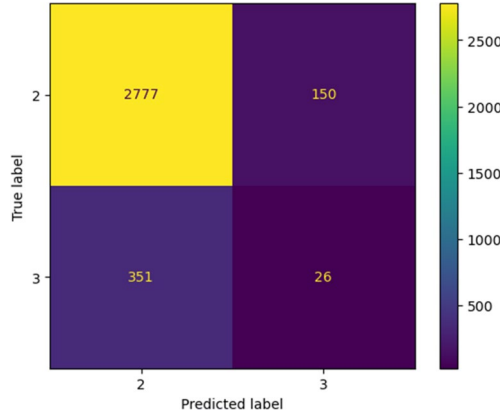
Precision for non-influenceable = 0.89  
 Precision for influenceable = 0.11  
 Recall for non-influenceable = 0.90  
 Recall for influenceable = 0.10  
 F1-score for non-influenceable = 0.89  
 F1-score for influenceable = 0.10  
 Train accuracy = 0.99  
 Test accuracy = 0.81

Precision for non-influenceable = 0.90  
 Precision for influenceable = 0.18  
 Recall for non-influenceable = 0.95  
 Recall for influenceable = 0.10  
 F1-score for non-influenceable = 0.93  
 F1-score for influenceable = 0.13  
 Train accuracy = 0.98  
 Test accuracy = 0.87

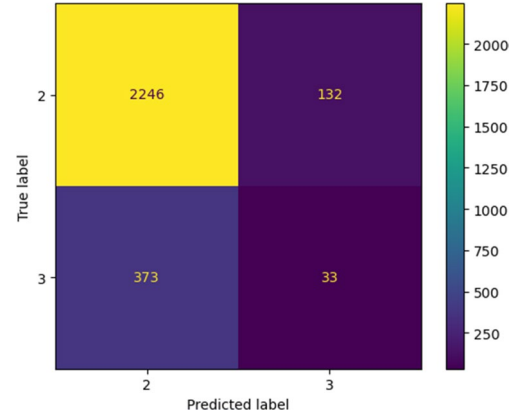
**Right-lean donors**

Confusion matrix

African American



Asian



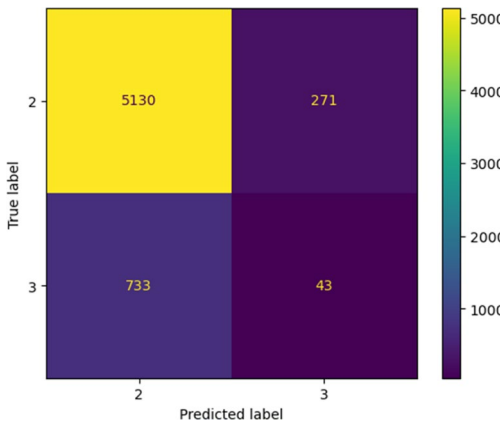
Model performance

Precision for non-influenceable = 0.89  
 Precision for influenceable = 0.15  
 Recall for non-influenceable = 0.95  
 Recall for influenceable = 0.07  
 F1-score for non-influenceable = 0.92  
 F1-score for influenceable = 0.09  
 Train accuracy = 0.99  
 Test accuracy = 0.85

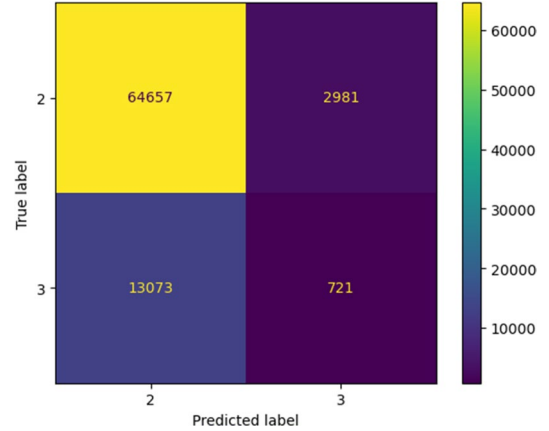
Precision for non-influenceable = 0.86  
 Precision for influenceable = 0.20  
 Recall for non-influenceable = 0.94  
 Recall for influenceable = 0.08  
 F1-score for non-influenceable = 0.90  
 F1-score for influenceable = 0.12  
 Train accuracy = 0.98  
 Test accuracy = 0.82

Confusion matrix

Hispanic



White



Model performance

Precision for non-influenceable = 0.87  
 Precision for influenceable = 0.14  
 Recall for non-influenceable = 0.95  
 Recall for influenceable = 0.06  
 F1-score for non-influenceable = 0.91  
 F1-score for influenceable = 0.08  
 Train accuracy = 0.98  
 Test accuracy = 0.84

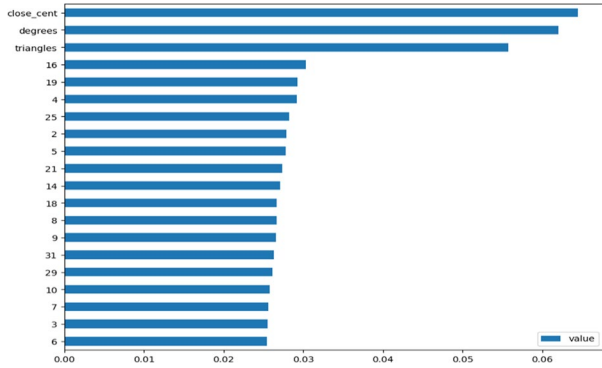
Precision for non-influenceable = 0.83  
 Precision for influenceable = 0.19  
 Recall for non-influenceable = 0.96  
 Recall for influenceable = 0.05  
 F1-score for non-influenceable = 0.89  
 F1-score for influenceable = 0.08  
 Train accuracy = 0.99  
 Test accuracy = 0.81

**Appendix E**

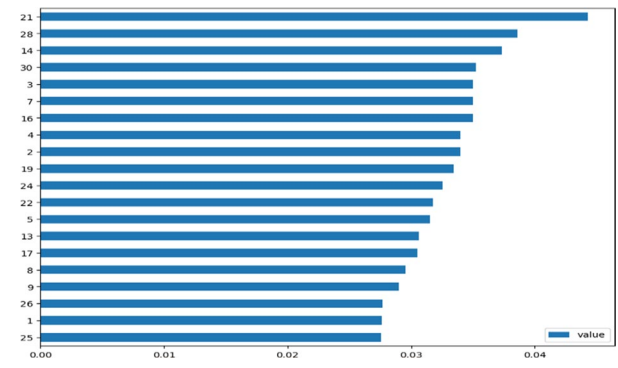
**Feature Importance of Network Measure Models**

**Left-lean donors**

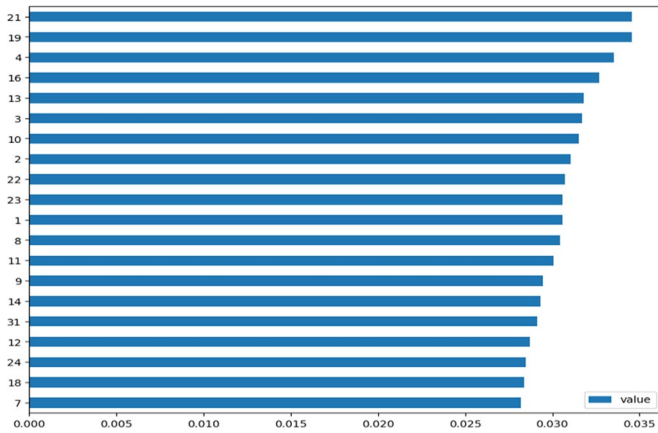
**African American**



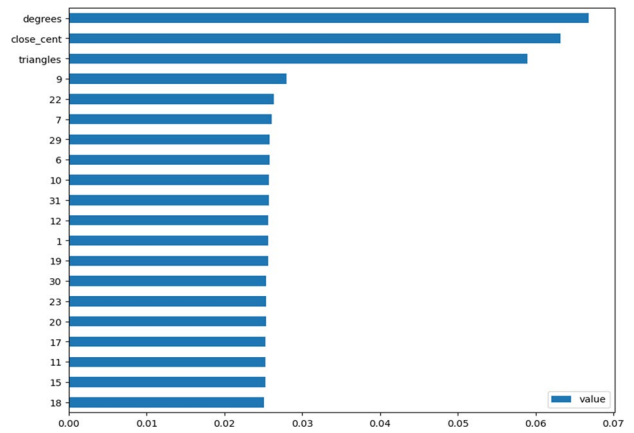
**Asian**



**Hispanic**

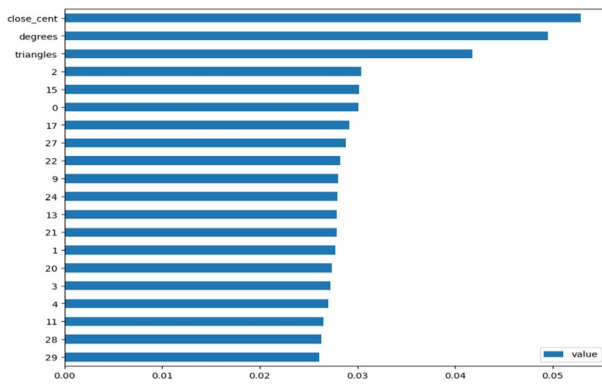


**White**

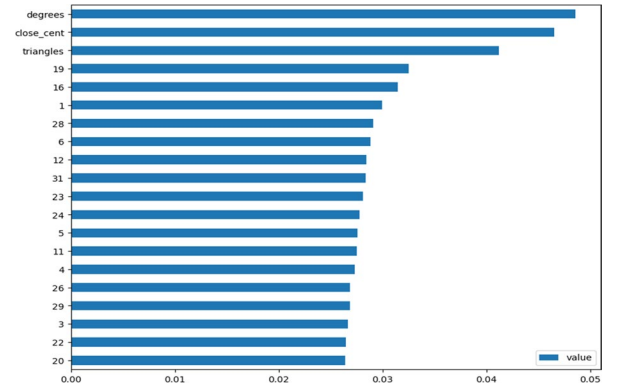


**Right-lean donors**

**African American**



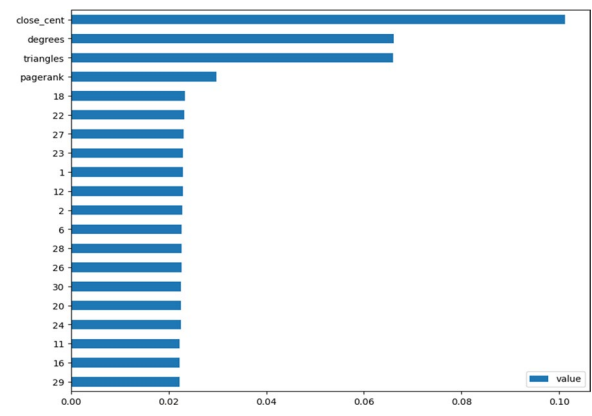
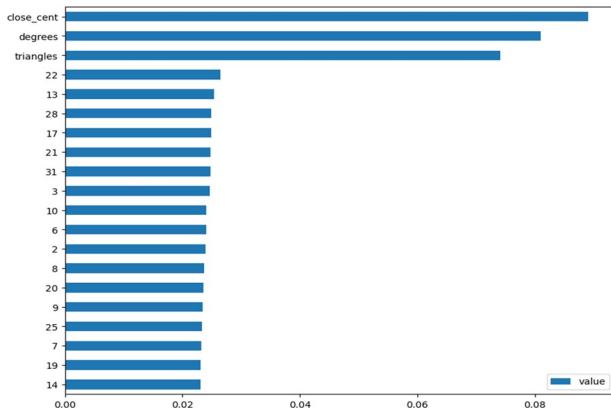
**Asian**



**Hispanic**

**White**

### Right-lean donors



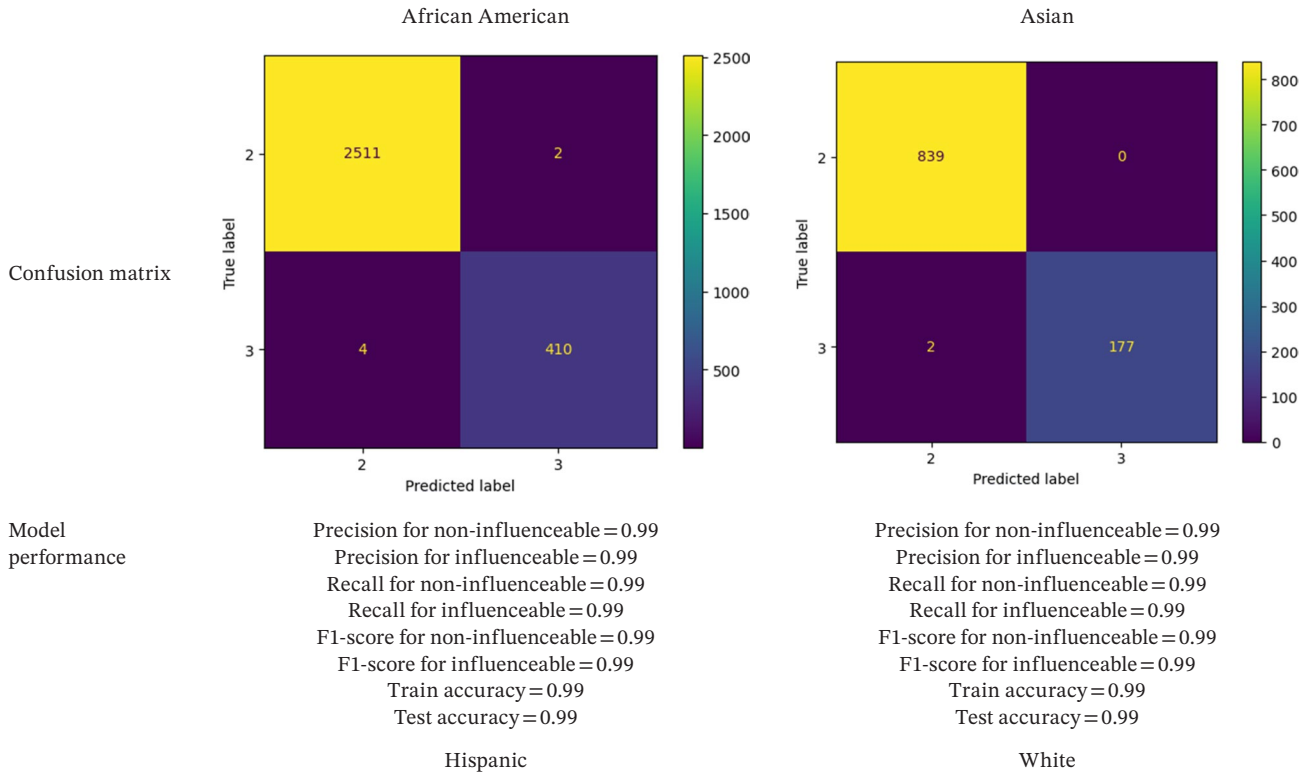
Note: Each bar represents a feature, and its length indicates how much that

feature influences the model's output.

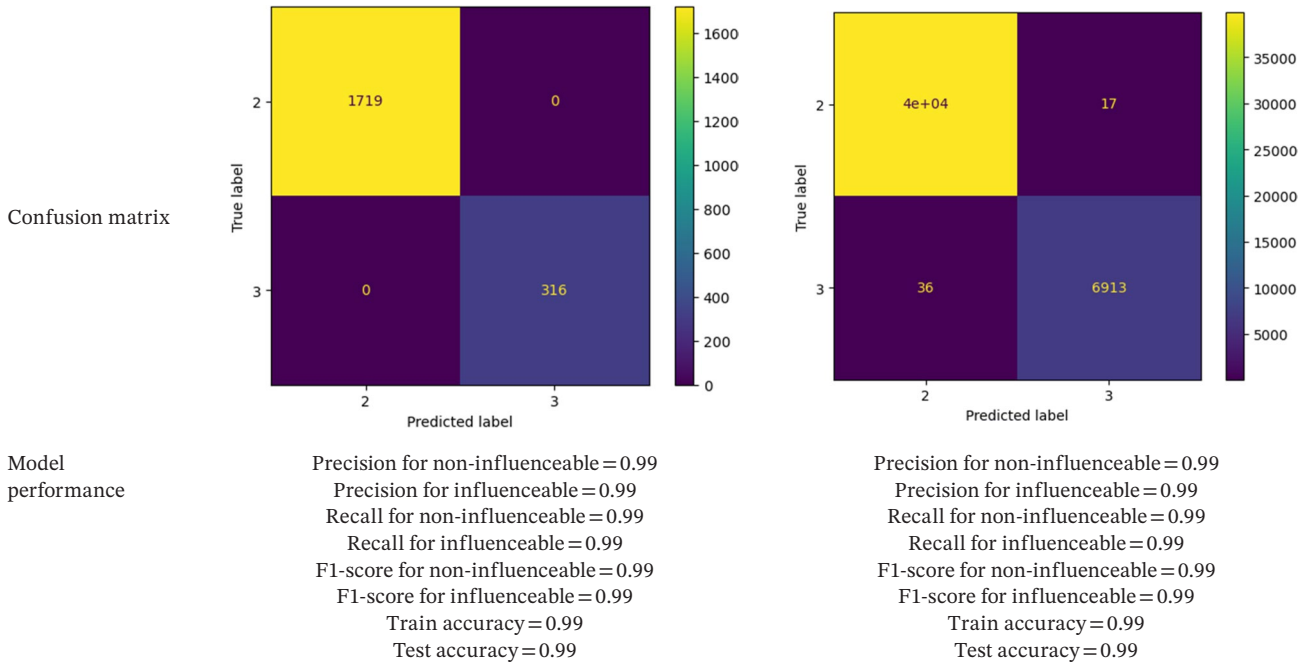
### Appendix F

#### Model Performance of Capability and Motivation Measure Models

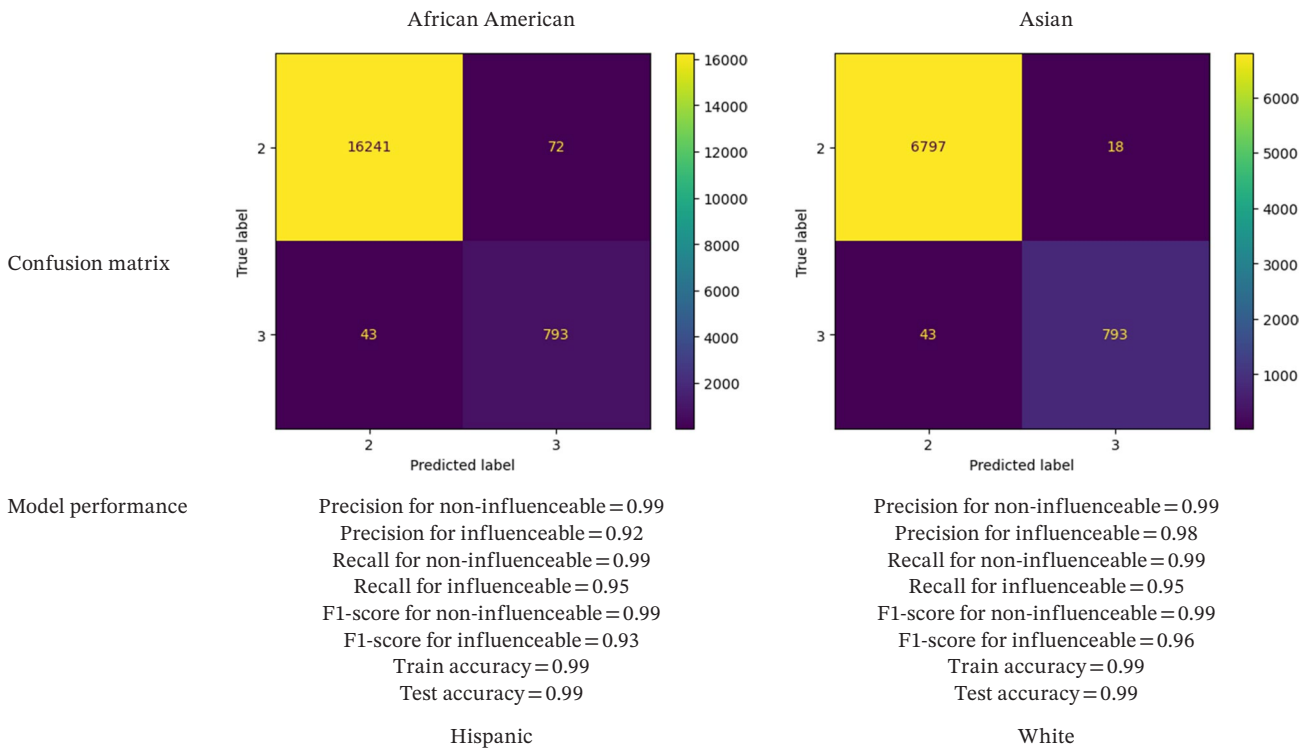
#### Left-lean donors



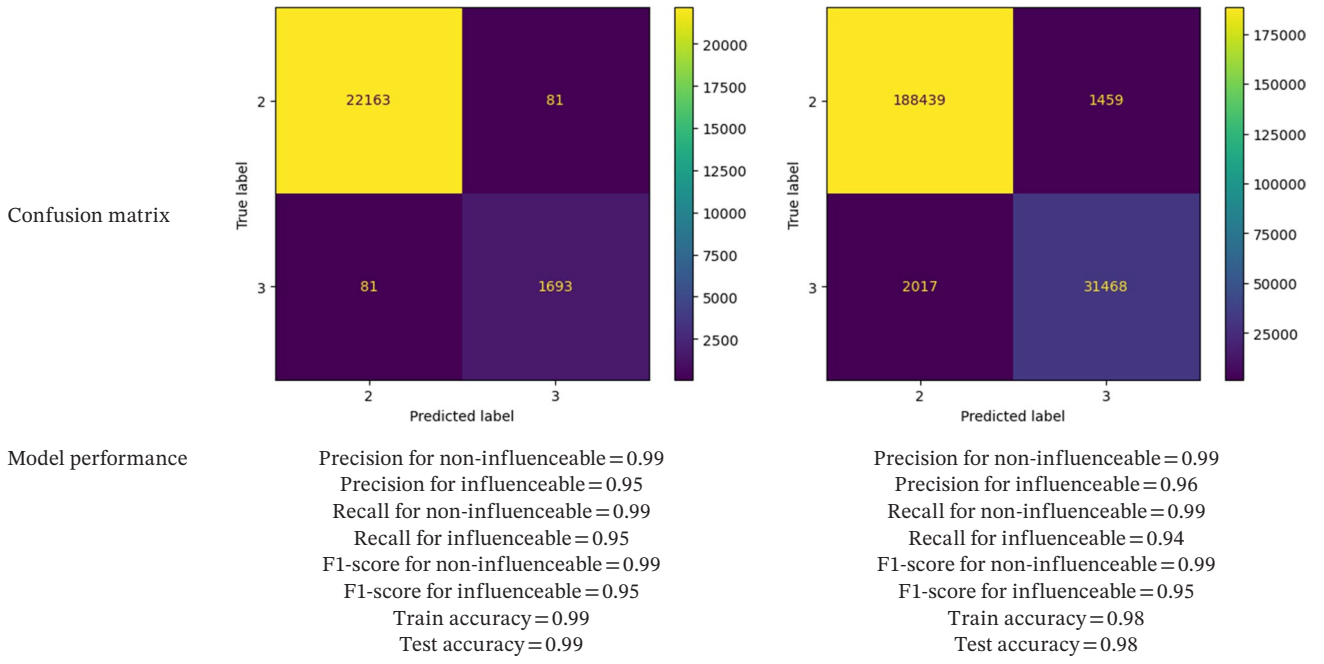
**Left-lean donors**



**Right-lean donors**



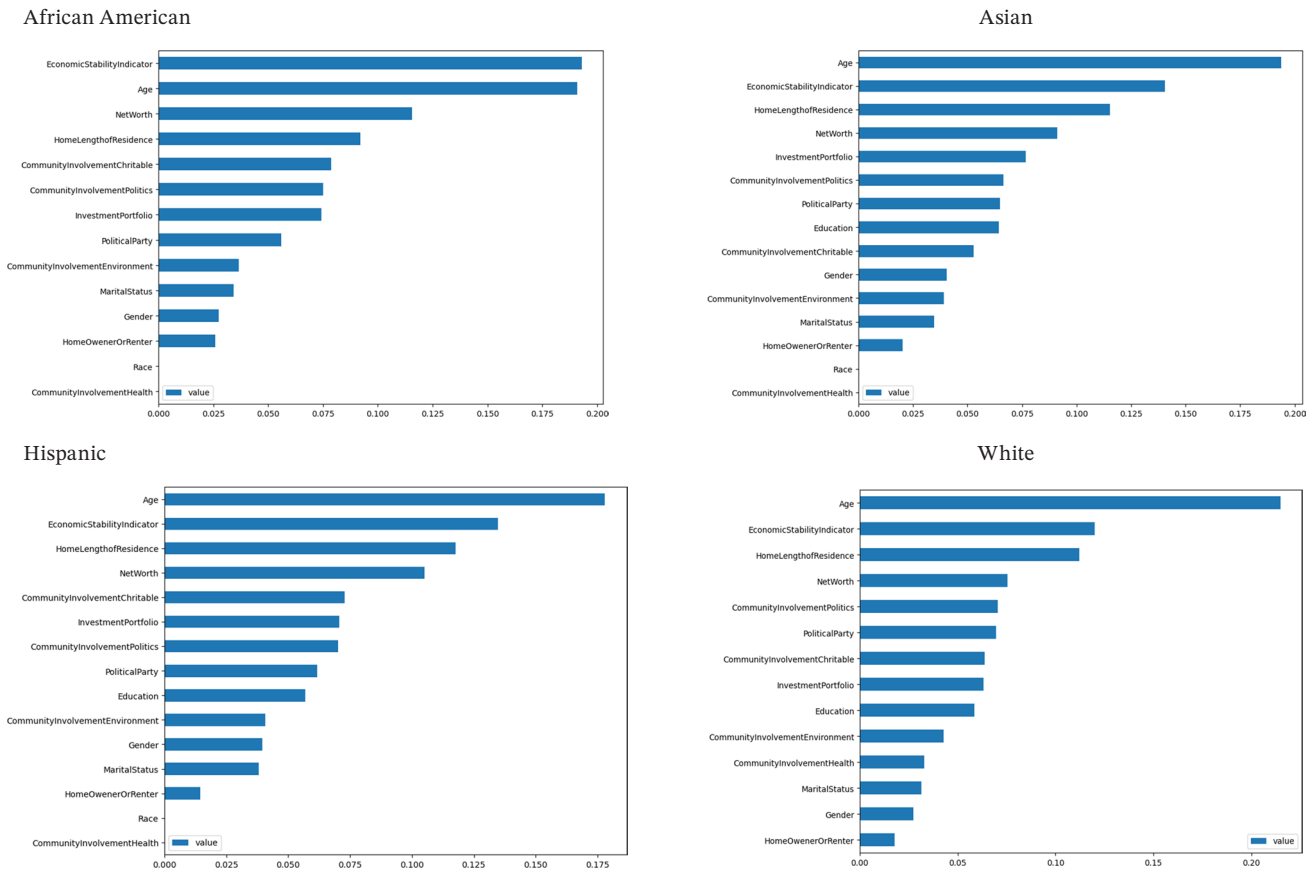
**Right-lean donors**



**Appendix G**

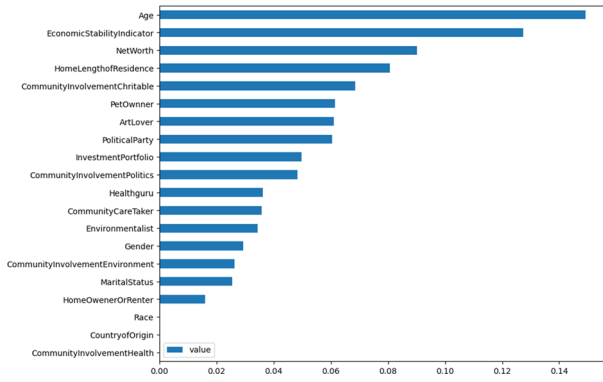
**Feature Importance of Capability and Motivation Measure Models**

**Left-lean donors**

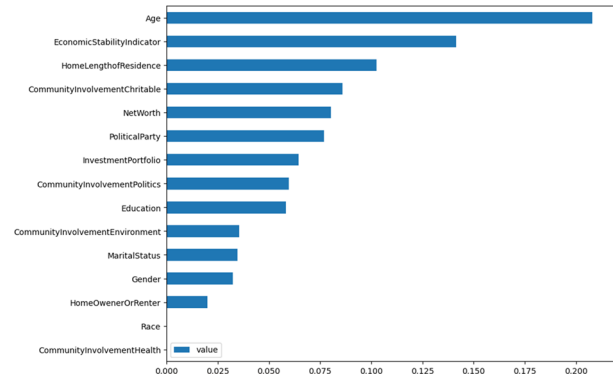


## Right-lean donors

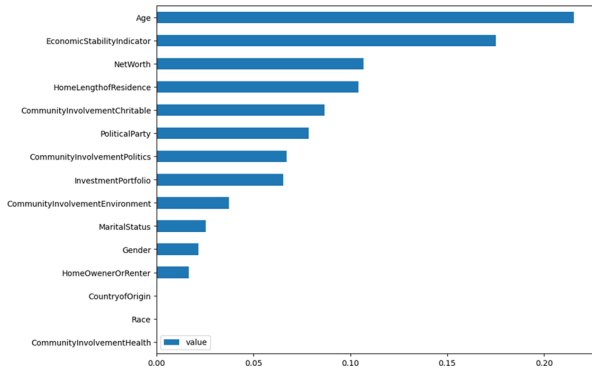
### African American



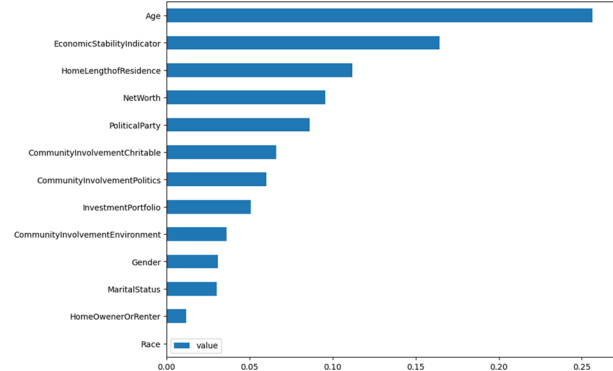
### Asian



### Hispanic



### White



Note: Each bar represents a feature, and its length indicates how much that

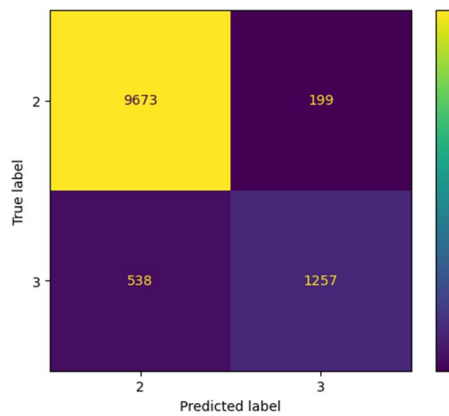
feature influences the model's output.

## Appendix H

### Model Performance of Full COM-B Measure Models

#### Left-lean donors

##### African American

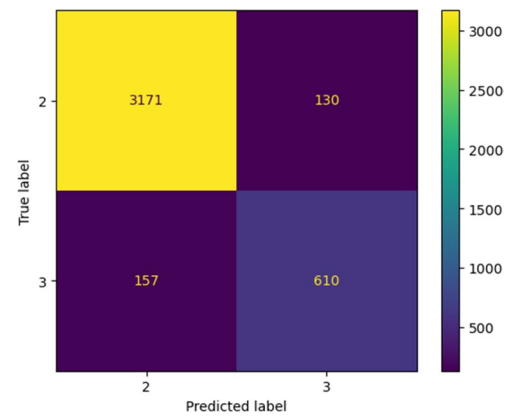


Confusion Matrim

Model performance

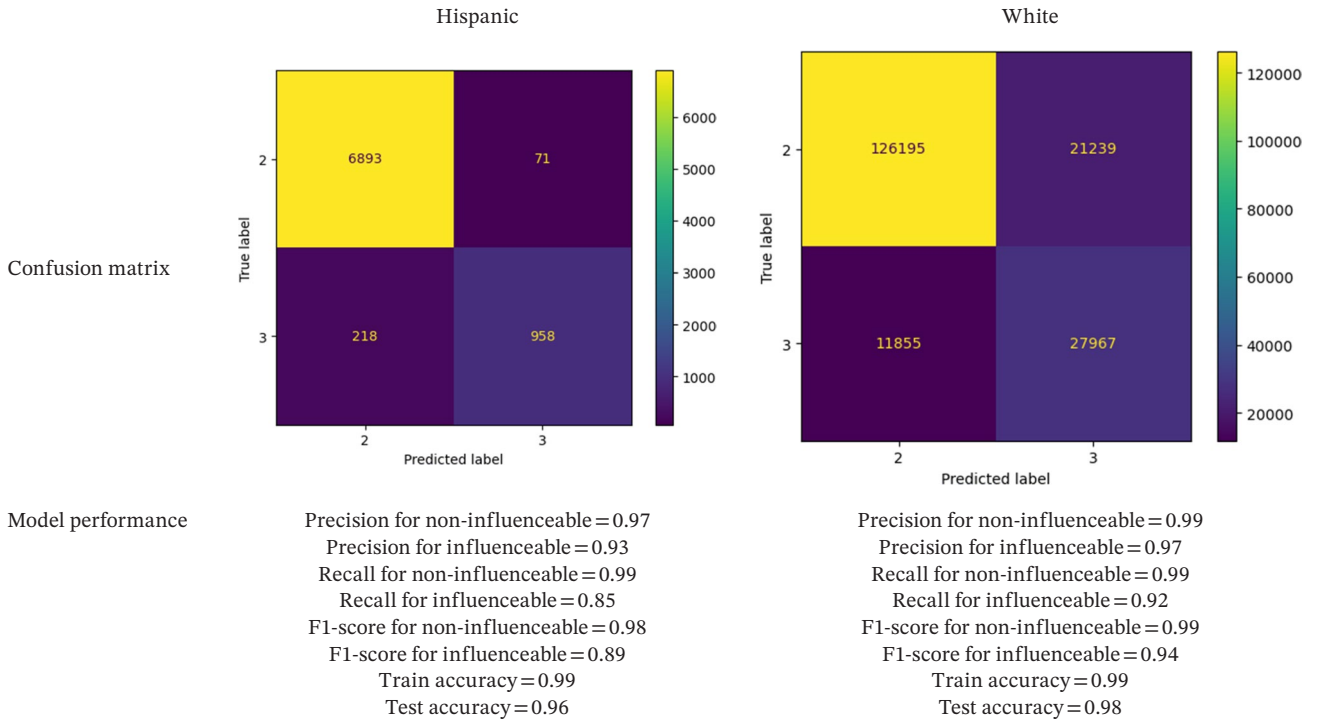
Precision for non-influenceable = 0.98  
 Precision for influenceable = 0.92  
 Recall for non-influenceable = 0.99  
 Recall for influenceable = 0.86  
 F1-score for non-influenceable = 0.98  
 F1-score for influenceable = 0.89  
 Train accuracy = 0.99  
 Test accuracy = 0.96

##### Asian

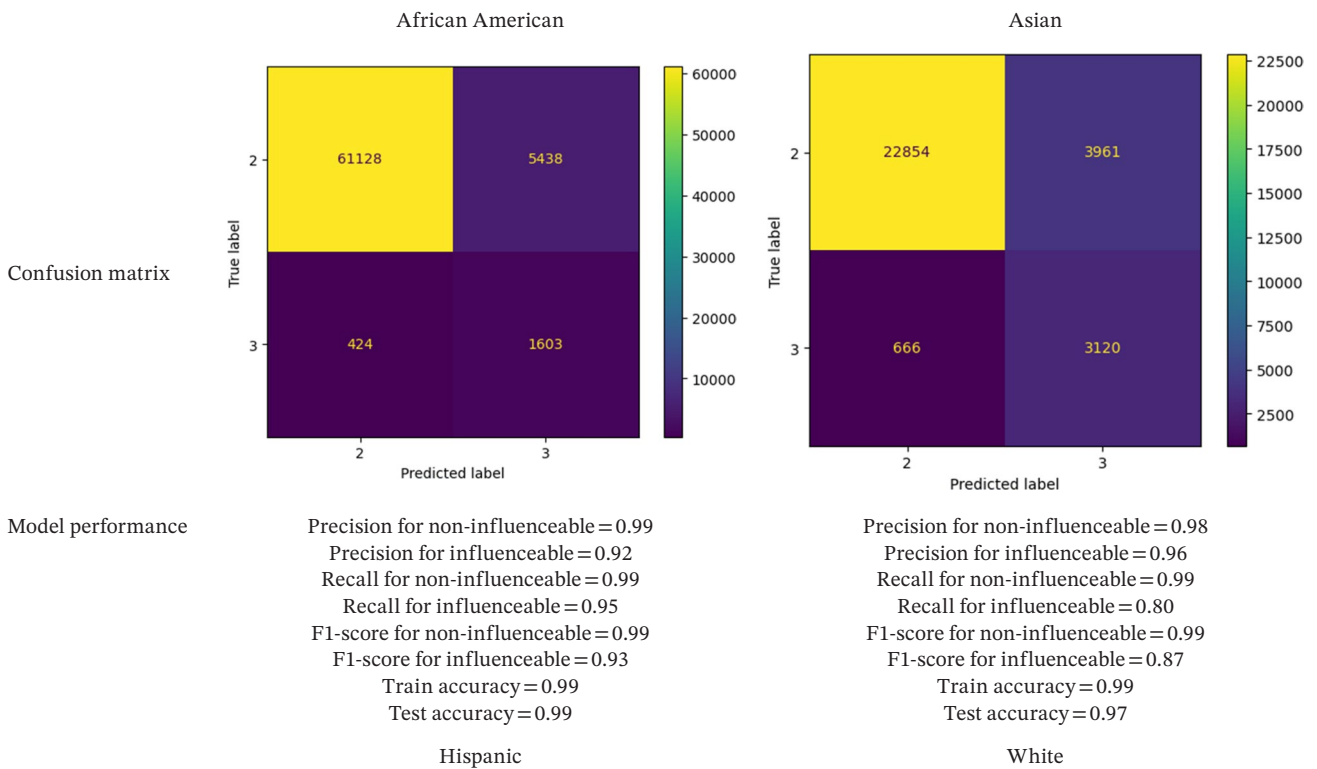


Precision for non-influenceable = 0.98  
 Precision for influenceable = 0.94  
 Recall for non-influenceable = 0.90  
 Recall for influenceable = 0.90  
 F1-score for non-influenceable = 0.98  
 F1-score for influenceable = 0.92  
 Train accuracy = 0.99  
 Test accuracy = 0.97

**Left-lean donors**

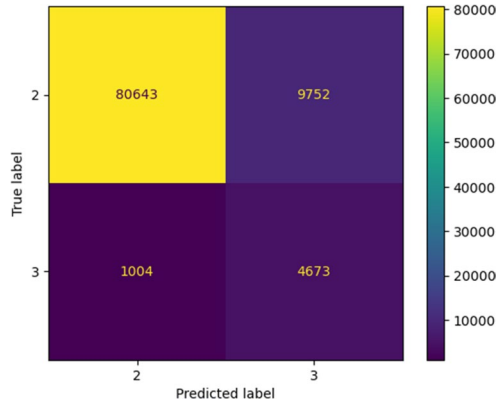


**Right-lean donors**



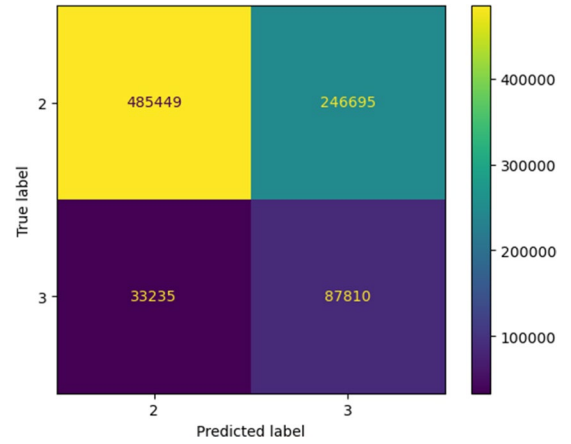
### Right-lean donors

Confusion matrix



Model performance

Precision for non-influenceable = 0.99  
 Precision for influenceable = 0.98  
 Recall for non-influenceable = 0.99  
 Recall for influenceable = 0.82  
 F1-score for non-influenceable = 0.99  
 F1-score for influenceable = 0.89  
 Train accuracy = 0.99  
 Test accuracy = 0.99



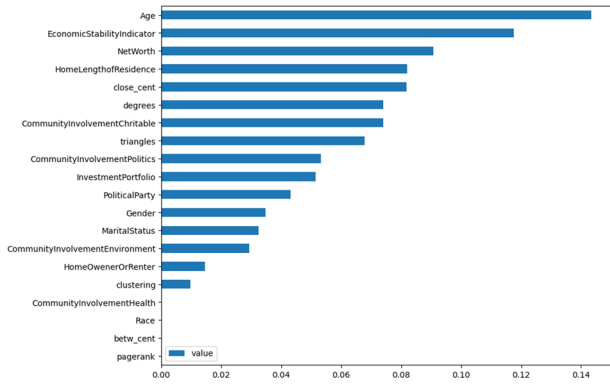
Precision for non-influenceable = 0.97  
 Precision for influenceable = 0.98  
 Recall for non-influenceable = 0.99  
 Recall for influenceable = 0.83  
 F1-score for non-influenceable = 0.99  
 F1-score for influenceable = 0.90  
 Train accuracy = 0.98  
 Test accuracy = 0.97

### Appendix I

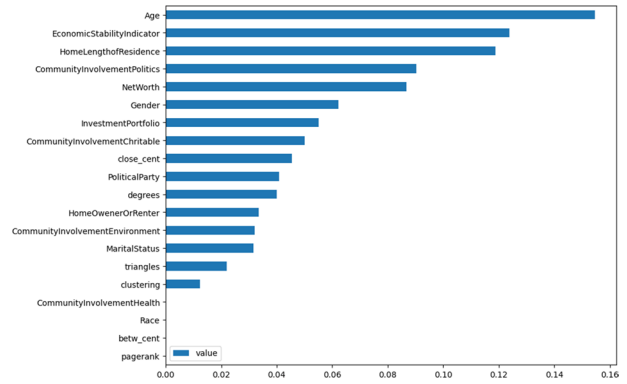
#### Feature Importance of Full COM-B Measure Models

#### Left-lean donors

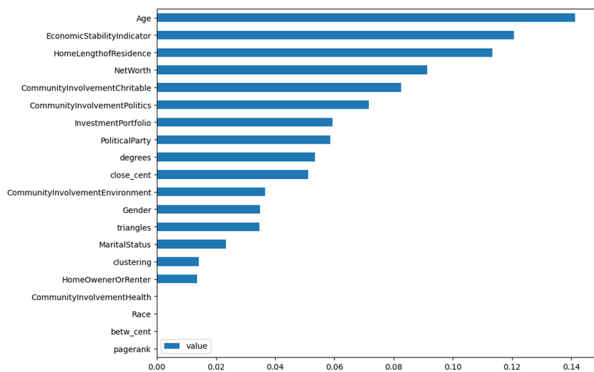
##### African American



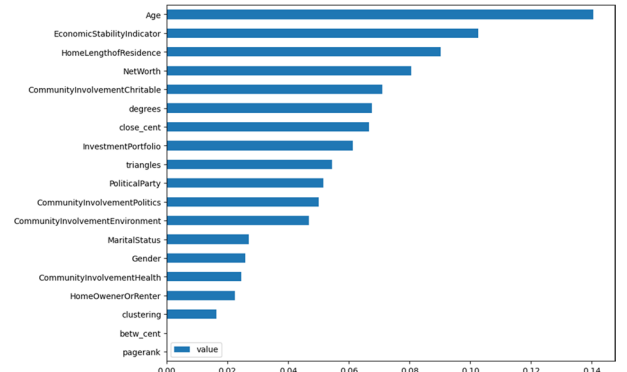
##### Asian



##### Hispanic

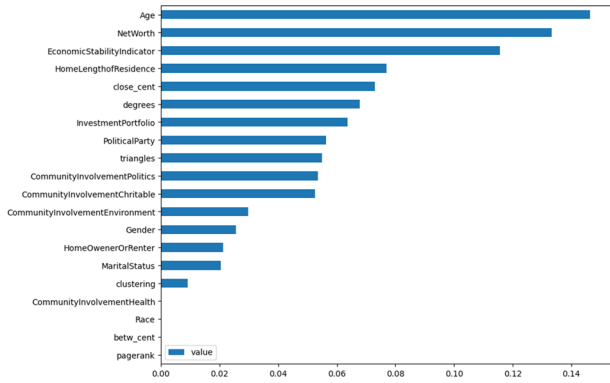


##### White

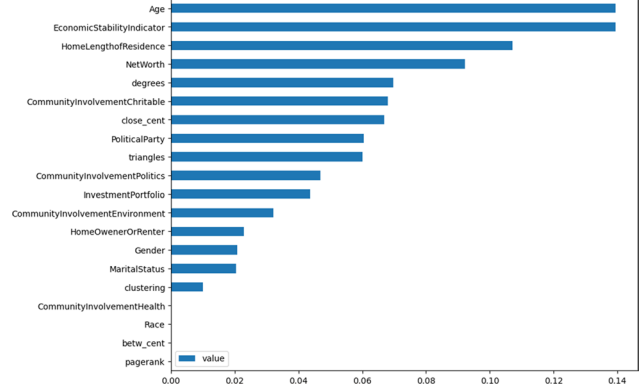


## Right-lean donors

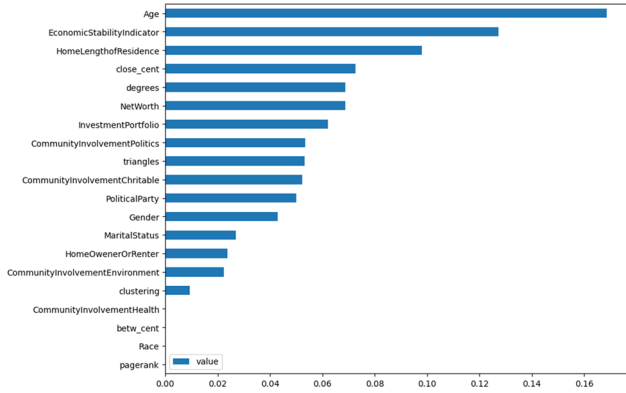
### African American



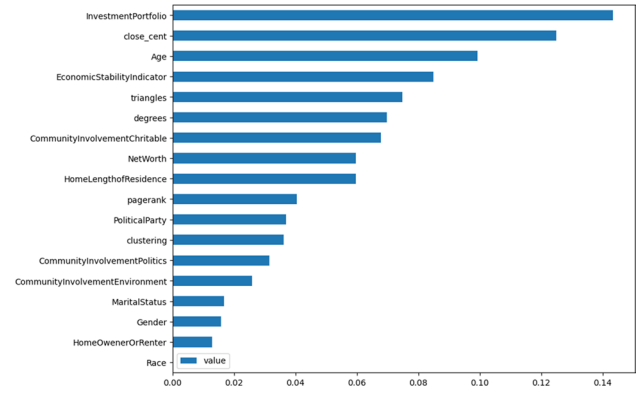
### Asian



### Hispanic



### White



Note: Each bar represents a feature, and its length indicates how much that feature influences the model's output.