Recruitment Promotion via Twitter: A Network-centric Approach of Analyzing Community Engagement Using Social Identity

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With the proliferation of online technologies, social media recruitment has become an essential part of any company's outreach campaign. A social media platform can provide marketing posts with access to a large pool of candidates and at a low cost. It also provides the opportunity to quickly customize and refine messages in response to the reception. With online marketing, the key question is: which communities are attracted by recruitment tweets on social media?

In this work, we profile the Twitter accounts that interact with a set of recruitment tweets by the U.S. Army's Recruitment Command through a network-centric perspective. By harnessing how users signal their affiliations through user information, we extract and analyze communities of social identities. From Social Identity Theory, these social identities can be critical drivers of behavior, like the decision to enlist in the military. With this framework, we evaluate the effectiveness of the U.S. Army's recruitment campaign on Twitter, observing that these campaigns typically attract communities with military exposure like veterans or those that identify with professional careers and fitness (e.g., student, professionals, athletes). The campaign also attracts, but at a much lower level, interaction from those in the digital industries—data scientists, cybersecurity professionals, and so forth. When analyzing the accounts in terms of their degree of automation, we find a set of intent-unknown bot accounts interacting with the tweets, and that many of the recruitment accounts are perceived as automated accounts. These observations can aid in campaign refinement: targeting the digital community and getting a broader reach for online recruitment publicity campaigns.

CCS Concepts: • **Human-centered computing** → **Empirical studies in collaborative and social computing;**

Additional Key Words and Phrases: Twitter, bot detection, network analysis, social signaling, social identity

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1 INTRODUCTION

Many companies and government organizations have integrated social media into their recruitment strategies. Shifting some of the recruitment publicity efforts from traditional in-person forms of recruiting to the online space provides the advantages of reducing recruiting costs and extending the reach of the publicity messages [27]. Social media-based recruitment is an attractive alternative for target sampling and can potentially provide a higher return on investment [5]. Thus, any successful recruitment campaign needs to consider the use of social media as part of its strategy.

While social media can be effectively harnessed as part of a recruitment strategy, its drawbacks involve being blind to the user profiles of the potential applicants who take notice of the recruitment efforts [31]. Further, the nature of social media means that sharing of information occurs through social links and platform promotion, which can obfuscate who and how recruitment efforts reach potential candidates [58]. This problem is further confounded by the presence of automated accounts, which can dilute the message and the measurement of the reach of the recruitment messages.

One way to identify the nature of users who interact with these publicity posts is to analyze the user profile information. Social media users typically signal their social identity within their user profile information, which includes their user name, screen name, location, and description [39, 40, 58, 60]. By capturing these cues of social signaling, we analyze the social interactions with recruiting publicity messages. Through a network-centric perspective, we extract and analyze communities of social identities, categorizing groups of people who interact with the recruitment posts that are put out by U.S. Army recruitment accounts on social media, specifically Twitter.

We formulate three research questions to guide our analysis of communities that interact with the U.S. Army's recruitment tweets:

(1) Which groups of people are interacting with the recruitment tweets? We construct network diagrams of communications (i.e., use the @mention, retweet, or reply mechanism) between the users who interact with the recruitment accounts, then identify themes of user clusters using a substring-matching algorithm.
(2) What are the social identities that interacting accounts associate with? We do this by extracting self-expressed identities from the users' Twitter biographic fields, then construct a network graph that represents the interacting identities. We also analyze the words that commonly co-occur with the top-occurring identity terms.
(3) Are there automated accounts within the set of users? If so, what are the groups of user profiles of automated accounts? We analyze the presence of automated accounts using social media bot detection techniques. We observe that several of the U.S. Army's recruitment accounts are identified as bot accounts, which may cause human users to ignore their tweets. Further, we identify and characterize groups of automated accounts that interacted with the recruitment accounts' tweets.

With these research questions, we make two key contributions. First, we demonstrate a methodology for analyzing the communities of people who interact with publicity tweets by their social identities. This methodology combines data analysis and natural language processing to extract groups of identities from self-identifying features of social media accounts, and network science to analyze and visualize interactions between different identities. It encapsulates how users express themselves in the user profile information on Twitter as well as how those communities of identities surrounding recruiting publicity interact with each other.

Second, we employ our proposed methodology to analyze the U.S. Army recruitment efforts on Twitter. The U.S. military currently faces significant, and not fully understood, challenges in recruitment [2]. Alongside the strong industry job market, especially in the technology sector, the job opportunities or free education that comes with joining the military is no longer as attractive as it used to be [54, 55]. In Fiscal Year 2022, all the services of the military experienced recruitment challenges, with the Marine Corps and the Navy being the only military services to barely meet their recruitment goals [9, 43]. By analyzing the nature of recruitment activities on Twitter, we are able to infer the effectiveness of the social media outreach strategy for recruiting efforts in the U.S. Army and identify gaps between the recruiting efforts and the readership, which aids in refining the social media strategy.

2 BACKGROUND

The U.S. military, in particular the U.S. Army, has struggled to meet its recruitment goals in recent years [9]. While there is no agreed-upon reason as to why fewer people are considering the U.S. Army as a potential job or career, there are many speculated reasons for this drastic change in the propensity to serve in the Army. First, it has generally been accepted that poor economic conditions favor military recruitment; lack of opportunities in the civilian job sector can lead to more people considering jobs in the military [9, 23, 32, 52]. Since the onset of the COVID-19 pandemic recovery, there have been historically low unemployment rates, which some see as the reason for low recruitment numbers. Other analysts cite the recent politicization of the military as the reason for reduced recruitment [29, 35]. Finally, a number of analysts have also pointed to the growing lack of exposure of young people to servicemembers and veterans as a reason for declining recruit numbers [2, 32, 52]. It has long been established that having a close social connection with a servicemember or veteran, often in the form of a family member who had served in the military, leads to higher rates of propensity to serve in the military [2, 47]. Therefore, with less exposure to the military for the recruitable population—combined with fewer veterans recommending service [35, 52]—the recruiting numbers are declining. While it is still not clear what is causing the relatively sudden drop in military recruitment numbers, it is clear that there is a social aspect to producing the propensity to serve in the military among the populace.

The U.S. Army has been using social media platforms like Twitter for their recruitment efforts in recent years. Social media recruitment allows for the publicity team to focus on specific subgroups or diversify the targeted population through publicly observable activity and the platform's accessible search features rather than associating with the general online population. This strategy also enables the publicity team to reach physically difficult-to-reach demographics, such as people who reside far away from recruiter teams [8, 14]. Several survey experiments have used social media platforms as an advertising medium to directly recruit users to complete their survey questionnaires, selecting for the desired respondent characteristics through the online users' digital traces such as the accounts they follow and the pages they like [33].

Within the military, use of social media for recruitment purposes has produced mixed results. While some recent studies find that social media, especially Twitter, is good at promoting awareness of the military, that awareness does not correlate with improved recruitment results [40, 58]. Furthermore, the same studies also demonstrate that content focused around vocations or financial benefits of military service tend to do less well than content that appeals to values or history [58]. Thus, while the U.S. Army has used social media to enhance its recruiting efforts, and that social media can improve recruiting outcomes, its not clear that current U.S. Army use of social media is actually improving recruiting outcomes.

When it comes to creating and disseminating social media messages, there are software tools for social media automation that assist in crafting messages and posting on social media platforms. These software tools also return a series of engagement metrics for each post, such as the number of likes and retweets of each post. These engagement metrics can also be plotted across time for the social media managers to analyze the change in their brand's outreach. Examples of these platforms are Sprinklr,[1] Digimind,[2] and SparkSocial.[3] With the information drawn from a user's profile information, these platforms can provide measurements of reach such as a summary of the geographic location of interacting profiles or a summary of the device type used to view the posts. However, the metrics shown on these automation software suites are typically metrics that are directly

[1]https://www.sprinklr.com/
[2]https://www.digimind.com/
[3]https://spark.us/about/social-media/

extracted from the user's profile; they do not feature inferred metrics such as affiliations revealed in a profile's user name. Additionally, these software suites focus on the managed social media account, i.e., the interactions to and from the managed account; they do not present the larger perspective where interacting users also interact among themselves. This work bridges this gap by analyzing the interactions of communities of users derived from inferred information.

A particular theoretical lens for understanding human behavior is Social Identity Theory. "Social identity" is a word or phrase that people use to signal their association with a particular social group [39]. Social identity is shaped by one's group memberships, where people affiliate themselves with an identity, be it an occupation, a political leaning, an interest, or a social movement, in order to find like-minded friends [50] and have a sense of belonging to the social world [49]. Examples of such phrases can be job related (e.g., doctor, lawyer, engineer), family related (e.g., mom, husband, son), or interest related (e.g., hiking, K-pop). People gain positive feelings from the group membership, as they place value on the group's communication and behavior [15]. Thus, these social identities are important drivers of human behavior.

People can present their social identity in four ways: expressing preference ("i love chocolate"), personal descriptors ("i am intelligent"), affiliation to social groups ("swiftie"), or actions ("hiker") [39]. Another classification of social identities is via relations ("father of"), occupation ("nurse"), political affiliation ("democrat", "republican"), religion or ethnicity ("christian"), and social or cultural norms ("nerd") [41]. Social affiliations with a group can even be stratified into even finer distinctions. A survey by [28] on the social identity of Korean pop music fans show that the fans believe their membership in K-pop fandom can be summarized as characteristics of the fandom members, i.e., how often they stream music and videos and check for updates.

Social identity theory has also been used to explain crowd behavior, especially in the context of protests and riots. [53] put forth that crowds gather for a specific purpose and the members of the crowd have a clear set of shared norms, and violent attacks are often specific to symbolic intergroup targets. Additionally, during and after riots, participants often feel a strong sense of social identity. Most recently, this has been observed within the context of the 2021 U.S. Capitol Riots, where a group of people "stormed the Capitol Building" in Washington D.C. to protest the U.S. presidential election results. This group identified with the mantra "Stop the Steal" and "Make America Great Again" [12]. On social media, groups of users affiliated with identities such as "patriot" and "QAnon" while organizing the protests and disseminating real-time information about the ongoing situation [37]. Some users use the same screen names and affiliation across multiple social media platforms, growing their influence across platforms and dispersing messages to other users who resonate with the same social identity [34].

On social media platforms, identity presentation is related to content propagation. For example, Tumblr users are more likely to reblog content by other users who present similar identities [60]. A study on Facebook users shows that the manner and strategy of online self-presentation influences the liking and respect received from other users, measured by the interactions and the response of their posts [4].

Recent work using Social Identity Theory has also been used to elucidate military recruitment. A recent study of those who chose to enlist in the military found that those individuals who had social identities more in line with a military organization were more likely to complete the recruitment process [13]. Furthermore, another study found that concepts like "patriotism" or being a "patriotic" person, as well as being surrounded by a family context that valued patriotism, were important identities for people's decisions to serve in the U.S. military [23, 58]. Similar studies have also found that particular social identities around political beliefs (e.g., being a conservative in the U.S. political spectrum) or regional affiliations (e.g., being from the southeastern United States) were also important drivers for military service [2, 58]. In summary, social identities play a critical role in the decision to serve in the military.

Finally, the categorization process of social identity lends itself as a casual driver of power and stereotypes. Embodying the prototypical characteristic of the group maximizes influence, which is the basis of power. Having power also provides the influential group member with increased control over resources and information [18].

Furthermore, the use of certain identities, like those surrounding women or minorities, can shape stereotypes, which can affect recruitment [19]. Thus, social identity can be important in shaping the recruitment process by its interactions with societal constructs like stereotypes.

When it comes to identifying social identities, social psychological work on social identity reveals that it is possible to compile a possible list of social identity words that people use to describe themselves. Additionally, the accompanying words and phrases that elaborate on the social identity are typically related to the identity itself [20]. For example, a user who adopts the identity of a writer is likely to elaborate on his or her identity using the words "author," "reader," or "notebook," while one who adopts the identity of a soldier will likely use words like "veteran," "soldier," or "army." Users can also take on multiple identities at the same time, including using different conversational techniques to target separate audience groups while maintaining authenticity [30].

The structure of Twitter bios—also known as user descriptions—can be harnessed to analyze the self-presentation of identities by Twitter users. Words and phrases within the description can be seen as a marker of shared identity between users, reflecting their chosen social identities and providing meaning to online interactions [39]. Twitter descriptions or bios have been used to evaluate changes in a person's political self-identity, where a 4-year study of millions of Twitter profiles shows an increasing integration of politics into one's social identity [42]. Twitter users have also been observed to change their description on their user profile in tandem with new trends (i.e., "Pokemon Go"), seasons (i.e., "Halloween"), or events (i.e., "Black Lives Matter") [45], reflecting their association with the currently trending activity.

We build on past work on social identity theory to analyze the social media accounts that are interacting with the U.S. Army's recruitment accounts, categorizing the online users that could potentially be interested in a military career, by use of their observed interactions on Twitter (i.e., retweet, @mention, reply). The structure of interactions and ways users can represent their social identities on Twitter provide a way to analyze interest in a set of posts that a particular group of accounts puts forth on social media space.

Finally, whenever one analyzes social media interactions, one must also consider the possibility of automated accounts. Most recruitment accounts are automated to some degree, given the use of third-party software assistance to draft posts and post them at specific times. While automation provides the ability to disseminate the same post to a large number of accounts at once, it causes the recruitment accounts to lose the "human touch" and appear robotic [5]. Social media bots on Facebook and Twitter are also used by Islamic terrorist groups to recruit new members by encouraging family ties within their following [22]. Within this study, we analyze the degree of automation of the recruitment accounts to gain an idea of the potential perception of the accounts, which will by extension affect the reception of the publicity messages.

Another type of automation is social media bot accounts, which can make malicious or digressive comments through their interactions, diluting publicity efforts. A survey to recruit participants for a health care project through social media resulted in 100% bot responses, which resulted in the derailing of the project and extensions of the project's timeline and budget [25]. The presence of interacting bot accounts can also provide untrustworthy responses and metrics toward the recruitment engagement statistics and measurements [8]. Malicious bots have also been known to distort other users from the original message. Bots on the social media platform Twitter have been observed to distort the online discussion surrounding the U.S. presidential elections in 2016 and 2020 [7, 11]. In 2016, two groups of bots were discovered to be centrally embedded within the social network, spreading false information about both the Clinton and Trump factions. In 2020, bots performed narrative distortion manipulation by spreading conspiracy-related narratives related to the coronavirus, flat earth movements, and the "-gate" conspiracies (e.g., Obamagate, Pizzagate) [11]. These distorted messages of social bots enhance the spread of misinformation, potentially providing unverified or false information to real human users [7]. Other times, these bot accounts reframe and distract online users from the main message, diluting the message and potentially influencing human users to an alternate point of view [48]. Therefore, within this study, we analyze the degree of automation among the interactions of the respondents to the recruitment tweets to better understand the effectiveness of the recruitment efforts.

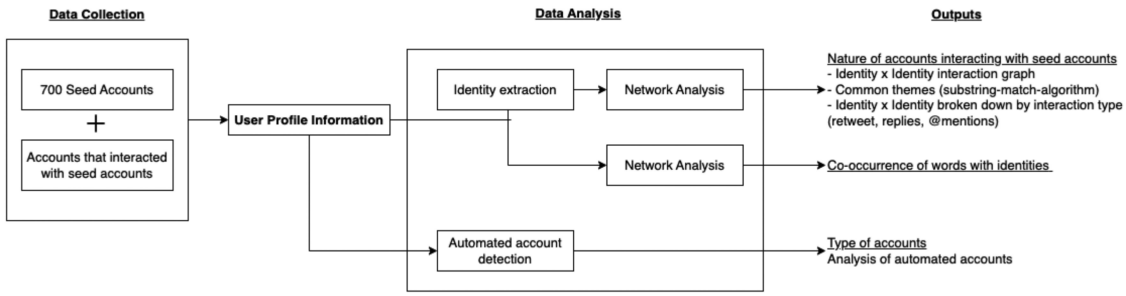


Fig. 1. Pipeline for analyzing interactions with recruitment publicity tweets.

Fig. 2. Combining user profile information into a single string for extraction of identities.

3 METHODOLOGY

3.1 Data Collection

We first obtained a list of 700 seed Twitter accounts originating from the U.S. Army Recruiting Command (USAREC). Then, we extracted a snowball sample of Twitter accounts that interacted with the recruitment tweets of these seed accounts. The three interactions we used to snowball sample were retweeting, replying to the tweets put out by the seed accounts, and @-mentioning them in a tweet. For both the seed accounts and the interacting accounts, we collected the tweets they posted and their user profile information (containing the user name, screen name, and user description). This Twitter data collection was performed using the Twitter V1 API using a Python script. The data collection was performed over the course of 2022. In total, we collected over 77,000 Twitter accounts and 6.8 million Tweets. These Tweets and users form the data for the social environment around USAREC's social media activities, including its recruiting publicity efforts.

3.2 Data Processing and Analysis

We apply a pipeline for analyzing the interactions of recruitment publicity tweets using network analysis, identity extraction, and bot detection. Figure 1 illustrates the pipeline of this study, from data collection to data analysis to the intended outcomes of the final results.

Identity Extraction. Previous works have extracted social identities that users have self-presented on social media platforms such as Tumblr [60] and Twitter [39] by means of the user's profile description or biography field. These fields are filled up by the users and thus represent a conscious effort by the user to associate with a particular social identity(ies). We adopt similar methods by extracting social identities through the user bios and descriptions in our Twitter dataset.

To classify users into their social groups, we extract personal identifiers that signal social affiliation from the user profile information of the Twitter accounts. A Twitter account has multiple fields by which a user can express his or her social affiliation. Therefore, we first combine a user's profile information into a single string, consisting of user name, screen name, and description, as illustrated in Figure 2. Then we remove non-ASCII characters and emojis, leaving alphabetical characters. We convert these characters into lowercase characters for consistency.

We then extract identities from the combined user profile information by comparing the string to an existing list of identities. The identities associated with an account are thus the list of identities found within the combined string, whether as standalone words or as substrings. For example, an account with a description like "a fun-loving cybersecurity professional and dad" would have the identities of "father" and "cybersecurity professional."

The identities list we used is derived from a 2015 population survey of U.S. residents that consolidates their representations of occupation and self-presentation [46]. This list is enhanced with military-specific identity terms (e.g., corporal, general) and other identity terms that have been observed to occur frequently (e.g., data scientist, cybersecurity professional) to suit the context of the data. Past studies on over half a million Twitter profile descriptions find that users heavily identify themselves with their job occupations [44], and we leverage the same concept where our list consolidates job occupations as identities.

We assume that the identity extracted from this methodology is in tandem with the affiliation that the Twitter user holds and intends to present on social media. All seed accounts have the name "army" as an identity.

Network Analysis. We use network analysis techniques to analyze the interactions between social media accounts. Network analysis is based on the importance of the relationships among the interacting units [56], which in this study are the users in Twitter and the corresponding social identities that they present on the Twitter platform. The attribute of homophily suggests that users who share attributes such as interests, gender, or occupation are more likely to be connected within social networks [60]. In this work, we plot three types of network graphs to investigate the user interactions via Twitter mechanics with the USAREC's recruitment accounts and the co-occurrence of words alongside social identities.

The first network graph reflects a bird's-eye view of the nature accounts that are interacting with the recruitment tweets. Each node represents an identity such as "army officer" or "hero." A link between two identity nodes **A** and **B** represents that an account affiliated with identity **A** has interacted with an account affiliated with identity **B**. This interaction can be in the form of retweets, replies, or @-mentions. We removed isolated nodes from the graph before segregating it into clusters using the Louvain clustering algorithm. The Louvain algorithm extracts communities from network graphs through an unsupervised hierarchical clustering algorithm. We later analyze the Louvain communities to understand the themes of the communities through a substring-matching algorithm, which is described in the next section.

The second network graph zooms in on the interactions between identity nodes by separating the graph into three graphs: one for @-mentions, one for replies, and one for retweets. That is, in the retweet graph, a link between two identity nodes is drawn when either one of them has retweeted the other. We have chosen to leave this as an undirected graph for ease of analysis. This further detailed network graph allows us to better analyze how account types use different interactions.

The last network graph is a representation of the co-occurrence of words with identity terms in user profile descriptions. To form this graph, we extract nouns from user profile descriptions. We then represent nouns and identities as nodes in a graph and draw a link between a noun and an identity node if they co-occur in the same user profile description. The graph is then pruned to retain only the core structure to remove noise and focus on the salient content.

These three graphs allow us to understand the interconnectivity between social identities, and the social communities and individual identities that interact with USAREC's tweets. We present all three types of network graphs as part of the Results section.

Extracting Common Themes from User Profile Information. After grouping users together via network ties, we seek to analyze the common themes from the user profile information. Having previously matched and constructed the network diagram using identity lists, we extract common themes from accounts grouped together by network forces using a substring-matching algorithm. We first form a combined user profile information string for each account (Figure 2) and preprocess the string by removing non-alphabet characters and converting the string into lowercase characters.

The algorithm then forms sequences of at least three consecutive characters through each string, then keeping the strings of the longest matches. Therefore, the strings "USArmyesports," "testesports," and "MoveUnitedSports" will return the substring "esport" and "esports" as consecutive strings of characters that are common within the names. We do not require all strings to contain the same substring. We consider a word a theme if at least 70% of the strings contain the substring and it is a legitimate word of at least three characters. Hence, "este" is not considered a substring, but "ode" is.

Identifying themes by substring matches across the social media accounts considers social groups of movements that the accounts identify with, apart from purely occupational identities as per the list. This technique enables us to capture the prevailing trends and is invariant to compiled lists.

Automated Account Detection. Publicity efforts on online spaces are an important means of broadcasting a message. Many social media publicity teams use third-party software like TweetDeck[4] or HootSuite[5] to facilitate drafting and publishing their content at specified timings to maximize viewership. As such, we seek to differentiate if the accounts that are interacting with the recruitment tweets are automated accounts—or bots—or humans. Ideally, the tweets should be making an impression on human users, who would therefore interact with them and hopefully translate into in-person recruitment inquiries.

To detect automated accounts, several bot detection techniques have been developed. These techniques typically construct supervised machine learning models on a set of manually annotated accounts. These models range from random forests [59] to support vector machines [1] to neural network models [57] to a combination of deep learning models [24, 36]. The constructed models differentiate whether an account is a bot or not by finding patterns in features extracted from the set of accounts such as post texts, the account metadata (i.e., number of followers, number of favorites, if account is verified) [59], or the account's social network [6, 10].

In this study, we make use of a bot detection algorithm, BotHunter. BotHunter is a random forest bot classifier that makes use of a Twitter account's name, posts, and other details to return a probability of whether an account is a bot or not. The probability is between 0 and 1, whereby we set a threshold of 0.7: a probability of equal to or above 0.7 means the account is classified as a bot; a probability below 0.7 means the account is classified as a human account [38]. After this, we manually glance through the user accounts that are labeled as automated accounts and segregate them into clusters of accounts.

4 RESULTS

4.1 Which Groups of People Are Interacting with the Recruitment Tweets?

Our first research question aims to find out which communities are interacting with the tweets put out by the recruitment command and its representatives. We analyze this through constructing a network graph of users that interact with the seed accounts. In the graph, each node is a user, while a link between users indicates that they have interacted with each other, through one of the @mention, retweet, or reply mechanisms.

Figure 3 shows the construction of the network diagram of communication, separated by Louvain clusters. This diagram encompasses communication of retweets, replies, and @mentions with the seed accounts. We observe that there are four clear clusters of user accounts. These user accounts are described through the substring-matching algorithm, which extracts common themes from the user profile information of the accounts in each community. These themes are then manually interpreted by the authors.

The largest group contains profiles related to the military, bearing names with themes related to the Army, Navy, and Guard. This shows that the recruitment tweets get interaction from those who wish to identify primarily as a military person, like a servicemember or a veteran. Another community that appears presents an affiliation with more extreme, often flying-based sports like skydiving, parachuting, and even airshows.

[4] https://tweetdeck.twitter.com
[5] https://www.hootsuite.com

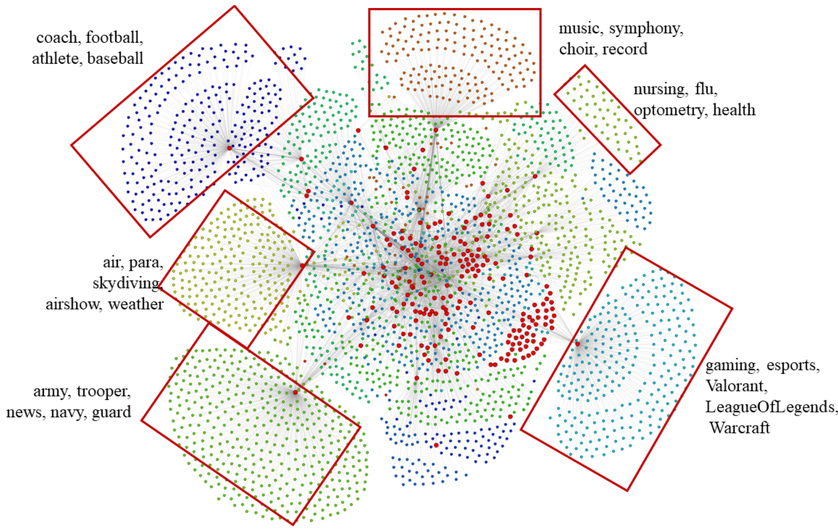


Fig. 3. Louvain clusters of communication (via retweets, replies, or @mentions) with seed accounts. The network graph is pruned to remove components that are less than 10 nodes. The clusters are manually inspected and described by their profiles. The larger red nodes represent the original seed accounts.

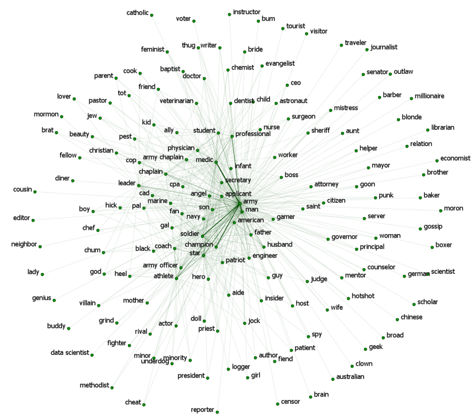
Much like the community that identifies with traditional sports-related terms (e.g., coach, football athlete), these two topics show a distinct link between physical activity, and sports in particular, and a willingness to engage with military recruiting messages. Other communities include athletic groups, music groups, and health care groups, which are key facets of the military: fitness, music, and health care job opportunities. The members of the last group affiliate themselves with video games and e-sports, which is likely a result of recent efforts by the U.S. Army to advertise more in the e-sports community (i.e., the Army began its own e-sports team in 2018). In sum total, we find only a few clusters of communities that interact with USAREC's Twitter recruiting presence, and these identities center around occupations typically associated with the military and sports.

4.2 What Are the Social Identities That the Interacting Accounts Associate With?

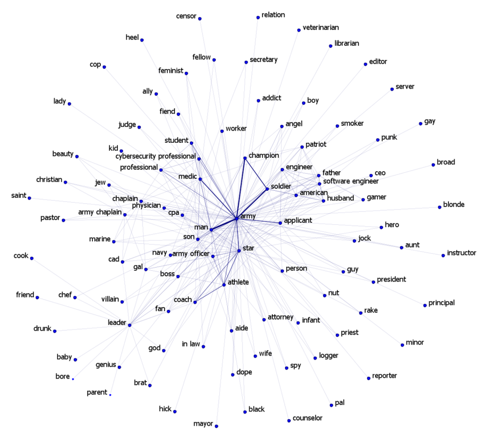
Identities extracted from interacting accounts are plotted as a network graph. Nodes represent an identity. Links between two nodes represent the number of times accounts with the two identities interact with each other.

Figure 4 shows the identities that accounts in the dataset interact with through a network graph visualization. This is broken down into the three main social media interactions: @mentions, reply, and retweet. These graphs show the extent of interactions between identity pairs. We observe that there are the most diverse identities with the @mention interaction and the least with the retweet interactions. Key examples of identity pairs within these interactions are:

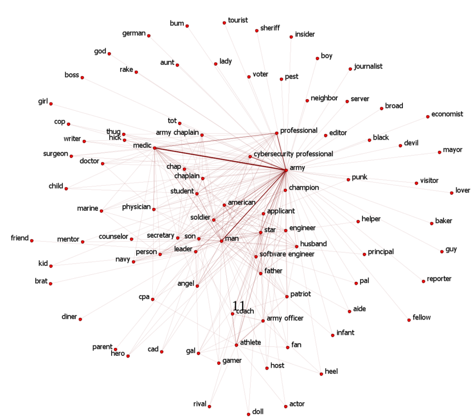
(1) @mention: (army, man), (army, medic). (army, soldier), (army, cybersecurity professional), (army, leader), (army, champion), (army, software engineer), (army, son)
(2) replies: (army, man), (army, medic), (army, champion), (army, soldier), (army, star), (army, athlete), (army, software engineer)
(3) retweet: (army, medic), (army, man), (army, soldier), (army, champion), (army, coach), (army, navy), (army, marine), (army, cybersecurity professional)



(a) Mentions



(b) Replies



(c) Retweets

Fig. 4. Network graphs of co-occurring identities through communication links. The nodes are identities extracted from user information. The links represent that users of two identity nodes interacted with each other. The width of the links represents the count of interaction. Graphs are manually pruned to retain the core network structure for visibility.

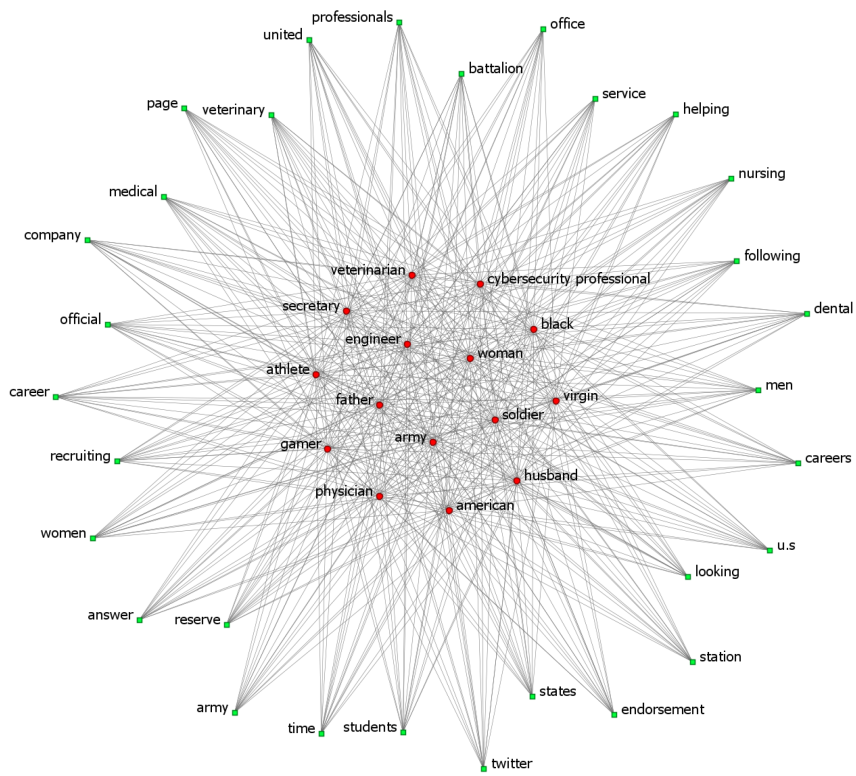


Fig. 5. Word associations of identities. Green nodes are the top-occurring identities, while blue nodes are words that co-occur with the identities within the user's profile information.

Figure 5 is a network diagram that depicts the words that commonly co-occur with the top-occurring identity terms. We observe that the words associated with each identity overlap across identities, resulting in the star-shaped network diagram. There are, however, terms that occur frequently and thus strongly associate with some of the identities. These terms are:

(1) Army: medical, career, professionals, student, women
(2) American: time, medical, veterinary, dental, nursing, service
(3) Athlete: career, reserve, battalion, endorsement
(4) Father: student, career, service, veterinary
(5) Soldier: officer, men, reserve, dental, service, station
(6) Marine: reserve, professionals

4.3 What Are the Groups of User Profiles of Automated Accounts?

Through automated account analysis, 7.56% of the accounts are identified as bot accounts. We manually separate these accounts into two distinct clusters: intent-unknown bot accounts and automated Army recruitment accounts.

Figure 6 shows the four main classes of intent-unknown bot accounts that interacted with the seed accounts. These classes are manually annotated by the authors. The four classes are:

(1) Accounts that showcase weapons or arms in their profile or banner pictures

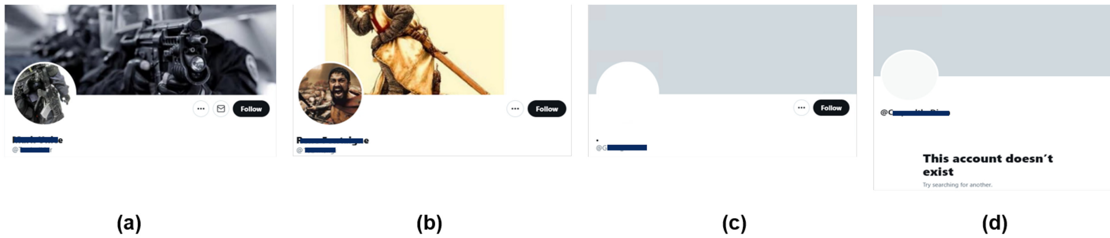


Fig. 6. Samples of intent-unknown bot accounts detected in the dataset.

(2) Accounts that have profile pictures drawn from the movie *300*, a fictional retelling of the Battle of Thermopylae in the Greco-Persian War
(3) Accounts that do not have a profile picture or a banner picture and typically have rather short screen names
(4) Accounts that have been suspended upon visiting them 3 months later

The other set of accounts that are identified as bot accounts are the U.S. Army's recruitment accounts (i.e., @ArmyMedLasVegas, @ArmyDenver, @ArmyRecruiterPA); 52.37% of the seed recruitment accounts are identified as bot accounts. At first, this is a surprising result, as we know these accounts to be the actual, professional accounts of USAREC. However, when one considers that a good portion of social media publicity efforts are usually semi-automated through third-party platforms, this result is perhaps expected. These third-party platforms allow publicity managers to control multiple accounts at once by providing them the functionality to make concurrent posts on multiple accounts, schedule posts, and view posts' statistics (i.e., number of likes, retweets, etc.), and could make an account that is managed through the platform have behaviors that resemble a bot.

Apart from these two categories of automated accounts, the rest of the accounts are classified as human accounts. At approximately 93% human accounts, these interactions feature a relatively higher proportion of humans than many other conversations on Twitter, which usually contain around 10% to 20% of bots [51].

5 DISCUSSION

Social identity theory describes the inter-group relationships and categorization of people into groups. This social classification provides a means to define the environment by cognitively segmenting them, providing order to the digital social environment [21]. In this study, we categorized the Twitter users to derive meaning from the group of users that interacted with the USAREC tweets ("interacting users"). We first observe that users who primarily identify with traditional, Army-relevant professions (e.g., soldier, nurse, band) and users who identify with sports (e.g., coach, athlete) make up most of the identities that interact with recruitment accounts. We also found that a prominent group of accounts that identify with e-sports also interact with these accounts. In the frame of past studies [39, 41, 58], the self-presentation of the users in our dataset are mainly occupational identities (e.g., soldier, guard, athlete) and interest-based group identities (e.g., football, music). The social groups surrounding the discourse of military recruitment are primarily those with occupational or activity-related identities and those with a service affiliation.

Additionally, by using identity extraction and substring-matching methods, we observe the clustering of users into several social groups, relating to the military, e-sports, sports, and medicine. This is similar to past studies where there are representations of groups of users that can be derived from their blog or user descriptions, and these categories correspond with the texts they write [60]. This result also matches previous studies on the content of online recruitment material, which often appeals to readers because of financial enticements or occupational concerns [58].

These results suggest that recruiter accounts are reaching, and generally appealing to, social identities that already have some exposure to the military in some form or another. Furthermore, from previous work and from an investigation of the recruiter Tweets in our dataset, recruiters frequently target their appeals toward occupational desires or special interest groups, like e-sports [58]. While this type of exposure suggests that recruiting messaging on Twitter is getting to a population that is more likely to have a propensity to serve in the military (i.e., previous studies by USAREC indicate that young Americans with a close—often familial—connection to someone who is serving or is a veteran are more likely to consider military service for themselves [2]), it also means USAREC's Twitter campaigns are not receiving interaction from the wider populace; their recruiting messaging—based on occupational and special interest appeals—are only reaching those with corresponding social identities and the veteran populace. This could be a problem for recruitment, as there are increasingly fewer individuals with exposure to the military in the United States, which means this messaging may not be geared toward the reality of the changing demographics of the United States.

Previous studies on social identities on social media platforms found that different identities use different groups of words. We found similar findings in our study, where different identities co-occur with different groups of words, suggesting how groups of social identities associate themselves with different aspirations and occupations. In the USAREC data, we observed certain associations like the term "army" associating with a professional career, student, and medicine, which reflects the aspiration of people joining the Army as a vocation and also seeking an education. The term "soldier" is associated with terms that are more masculine oriented and with traditional military terms, such as "men" and "officer." We can thus categorize the interacting users in terms of the aspirations they identify with: professional career aspirations and financial incentives for academic pursuits and military aspirations. The results suggest a strong link between traditional Army professions and USARECs recruiting efforts. These observations provide leads to the recruitment team on improving their publicity strategy. Individual differences between the groups can be targeted for special attention: to focus on tailored messages and programs for this group or to diversify the messaging to attract a more varied group of interested applicants.

While the majority of accounts interacting with the seed accounts (92% of accounts) are identified as human accounts, many U.S. Army recruitment accounts themselves are identified as bot accounts. This is likely because the composition of the tweets and behaviors of USAREC accounts have a consistent style and have indicators of automation. Its likely that some of these USAREC seed accounts may be controlled by third-party automation tools like HootSuite in order to facilitate the job of social media managers in crafting and broadcasting tweets across several accounts. Unfortunately, the resemblance of the official accounts to bot accounts often signals to other Twitter users that these are automated accounts that can be ignored. The structure of some of these recruitment messages can sometimes resemble spam messages and therefore be ignored by human users. An example of such a tweet is: "Our soldiers have access to competitive benefits during and after their time in the Army. [...] Find out how you can get an additional $2k signing bonus. [...]" This can cause a decrease in the reach of the tweets stemming from official accounts. To curb this issue, the use of automated tools by USAREC recruiters should be further investigated in terms of the reach of messages when automated tools are used in comparison to manual postings.

Additionally, recruiters could adopt more personalized behavior, like sharing of personal anecdotes or engaging with other users. Personal anecdotes serve to bridge the gap between the author and the reader through the recollection of experiences [3], which can help in boosting recruitment interest. This concept of having more personal interactions and establishing online personalities similar to techniques used by social media brand ambassadors has also been recommended by other commentators as a means to combat lackluster recruiting performance by the U.S. Army [17]. This includes providing relevant information and engaging with other users, providing a sense of aspiration and belonging [16], and highlighting identities around military values (e.g., service, commitment, doing something of importance beyond oneself). This latter group of value-driven identities has been shown in previous work to be an important driver for serving in the military [13, 58]. Finally, as part of changing recruiter behavior on social media, it is worth mentioning that some of the tweets stemming from the recruitment accounts aim to provide updates about military personnel but might be difficult for the layman to relate to. For example, in the tweet "The soldiers with the U.S. Army Marksmanship Unit like to occasionally throw in some fun in their challenging drills. These #TrickShotTuesday drills not only help maintain motivation, but they also double as some good target acquisition," it can be difficult for someone who has not had prior military experience to understand what drills and target acquisition are and therefore cause them to be uninterested. In summary, our results show that official recruiting accounts resemble run-of-the-mill automated accounts, which means they are likely failing to reach their targeted audiences in an effective way.

The dataset also revealed a group of intent-unknown bot accounts, which can be further subdivided into four main classes. Of these groups of bot accounts, the accounts that are of note are the group of accounts that showcase weapons and the group of accounts using images from the movie *300*.[6] While it is not clear why these accounts were created or why they interact with USAREC Twitter accounts, these accounts, both by their messaging and by their social identities, attempt to identify themselves as gun enthusiasts and have a sanguine view of war—and possibly even an anti-Eastern and anti-Iranian sentiment [26]. While these social identities would seem to naturally associate with the military, they can also represent politically charged beliefs. For example, the topic of gun control, of which gun enthusiasm represents the antithesis of gun control, is a highly politicized and contentious topic in the United States. Thus, the presence of automated accounts with these particular social identities may also damage recruitment efforts both by their automated nature and by the social identities they present by potentially politicizing and damaging engagement in conversations around social media campaigns. Again, it is not clear what the purpose or impact of these bot accounts is on USARECs' Twitter recruiting effort, but they can represent potential obstacles to achieving better reach and engagement and should be investigated further.

Given that many of the interacting profiles are affiliated with military professions, we believe that the Army's job recruitment campaign on Twitter is fairly successful at attracting the traditional profile of people who are interested in a military career: interested in the military (e.g., Army, Air Force), fitness-oriented and athletic individuals, and professionals. However, our methodology further revealed that there were some, but generally few, profiles of users from emerging occupations of interest to the Army, like cybersecurity professionals and data scientists. Since these types of identities are typically in high demand for both the Army and for industry, it's vital that recruitment messages see interactions with these types of people. However, our results suggest that recruiting messaging on Twitter still most reaches those with a military affiliation already or those from more traditionally propensed populations. Thus, the Army may need to consider its publicity campaigns if it wants to appeal beyond the already military-affiliated community to more high-tech-affiliated communities if it wants to have a force populated by more experts in fields like cybersecurity and data science.

Limitations and Future Work. Understanding the reach of recruitment publicity efforts on Twitter does have a few limitations. First, the reach of publicity efforts inferred from Twitter is only but a small slice of the recruitment reach; it does not necessarily generalize to the success of all publicity efforts, which are conducted across multiple social media platforms, and even in person. Second, the analysis relies on the self-presentation of identities of Twitter users in their user profile information. Not all users present themselves with their associated identity on social media, and these users are thus not accounted for in the analysis. Third, our list of identities consists mostly of job occupations and is non-exhaustive [46]. As more jobs are created, and in consequence jobs are lost, we have to constantly update our list to keep up with the changing times. Downstream work calls for expansion of the list beyond job occupations as identities, and social groups and trends (e.g., "kpop," "yoga") as social identities.

For future work, further investigations can be done with a more comprehensive and updated list of identities that can include affiliations toward cultural groups, or in refining the list of identities to include modern identities

[6]https://en.wikipedia.org/wiki/300_(film)

such as gender-related identities and digital-related identities such as emerging jobs. Furthermore, there is also room for future work on characterizing online users' social identities. This includes making use of profile images to categorize identities that online users present as part of their identities or by using other, more flexible means than substring matching for classifying a user's social identities. It also includes combining social media signals with offline signals obtained through surveys to provide a more well-rounded view of the reach of the publicity efforts. Future work could also consider new versions of the proposed method that could generate identities in an unsupervised way based on the profiles of users. Lastly, our analysis pipeline stems from non-response bias, whereby there may be Twitter users who read the recruitment tweets but do not respond to them online. While some of these responses can be captured through offline metrics such as surveying the people who applied to the jobs, we are unable to fully capture the reach of the tweets.

In terms of ethical considerations, we only collected Twitter data from public profiles and do not attempt to collect information from protected profiles. Most analyses were conducted on aggregated data, for we are interested in collective themes rather than individual profiles.

6 CONCLUSION

Social media is a useful platform for recruitment promotion. It provides visibility to the job openings at a company and attracts potential candidates. Compared to traditional surveys, career fairs, or individual recruitment, social media has the ability to disseminate a piece of information to many communities of users at a single time and at low cost. The next step in recruitment promotion is the analysis of community engagement to identify the communities of people that engage with the social media recruitment posts, which serves as an indication of their interest. To investigate this, we rely on the self-expression of identities, where users signal their affiliation through their user profiles.

In this article, we adopt a methodology comprising identity extraction and linguistic and network analysis to identify themes of groups of people that interact with recruitment tweets put out by the U.S. Army Recruiting Command. We rely on social identity theory to categorize users into key communities of users that interact with the tweets. This relies on observing the user's self-categorization through their Twitter bio and description. With this information combined into network graphs to analyze the relationships between identities, we derive four groups of users: users who are interested in the military, music, fitness, and e-sports. We also put forth ideas on how observations drawn from this technique can be used to refine recruiting strategies, such as developing approaches that can appeal to those without exposure to the military already.

This methodology can be extended to analyze other types of publicity campaigns and profile the interacting user groups as a proxy for offline interest in the campaign. This work serves as a preliminary insight into the communities that are interested in a military career, and we hope that the methodology will be harnessed to develop recruiting strategies on social media.

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