Social Alignment Contagion in Online Social Networks

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***Abstract*— Researchers have already observed social contagion effects in both in-person and online interactions. However, such studies have primarily focused on users' beliefs, mental states, and interests. In this article, we expand the state of the art by exploring the impact of social contagion on social alignment, i.e., whether the decision to socially align oneself with the general opinion of the users on the social network is contagious to one's connections on the network or not. The novelty of our work in this article includes: 1) unlike earlier work, this article is among the first to explore the contagiousness of the concept of social alignment on social networks; 2) our work adopts an instrumental variable approach to determine reliable causal relations between observed social contagion effects on the social network; and 3) our work expands beyond the mere presence of contagion in social alignment and also explores the role of population heterogeneity on social alignment contagion. Based on the systematic collection and analysis of data from two large social network platforms, namely, Twitter and Foursquare, we find that a user's decision to socially align or distance from social topics and sentiments influences the social alignment decisions of their connections on the social network. We further find that such social alignment decisions are significantly impacted by population heterogeneity.**

***Index Terms*— Causal inference, social contagion theory, social network analysis.**

I. Introduction

PEOPLE can be, consciously or unconsciously, impacted by different thoughts and emotions expressed in online social content, even when exposed to such content for a short period of time [1], [2]. Studies have shown that social content can impact users' political views [3], health perceptions [4], purchasing behavior [5], and even more subtle aspect of behavior such as solidarity with migrants [6]. In addition to the content, online interactions that occur on social networks can have a significant impact on users, such as the impact on their mental and physical health [7], [8]. Moreover, there is evidence that online social influence can affect users' behaviors. For example, Aral and Nicolaides [9] and Althoff et al. [10] reported signs of social influence on physical activity, Schubert et al. [11] reported signs of social influence on sustainable food consumption choices, Corò et al. [12] reported signs of social influence on voting preferences, and Efferson et al. [13] reported signs of social influence on changing harmful traditional beliefs. Interestingly, researchers have reported that such online social influences exist despite the absence of nonverbal interaction typical of in-person experiences [8], [14].

There are works that attribute such social influence to a phenomenon known as homophily [15], [16], [17]. In other words, the notion of homophily, often referred to as "birds of a feather flock together," means that people with similar beliefs, emotions, and/or tendencies are more likely to be connected. Applied to the explanation of social influence, the concept of homophily suggests that since friends (and for that matter connections on social networks) tend to be similar to one another, they are likely to exhibit similar behavioral patterns, even if not directly influenced by each other. This can, for instance, be attributed to factors such as being exposed to similar external stimuli, known as environmental confounding effects [18], [19]. However, more recent studies are interested in exploring social networks as a medium for social contagion [20], [21]. Social contagion is often viewed as a form of effect or influence that leads to change in one or more members of the same network, whereby the recipient of the influence does not perceive an intentional attempt to be influenced by the influencer [22]. Therefore, when studying social influence based on exchanges in online social networks, it is important to distinguish between the potential effects of homophily and social contagion. To this end, observational techniques [16], [23] and randomized controlled trial (RCT) methods [24], [25] have been proposed in the literature.

Researchers have recognized the need to disentangle true contagion effects from other possible sources of influence such as homophily [15], [16], [17] when studying different behavioral and emotional phenomena ranging from work-related burnout in school teachers [26], to screen-based media consumption in adolescents [27], and to physical activities [28], just to name a few. These and other existing work on social contagion [29] have primarily focused on people's beliefs, mental states, and interests. In contrast, there is little work that has explored the impact of social contagion on users' decision-making, in the context of online social networks.

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The exploration of the effects of social contagion on the decision-making of social network users would require a study of whether decisions made by users on a social network will lead to similar decisions made by their network connections.

In this article, we expand the state of the art by exploring whether social contagion can have an impact on social alignment [30]. Social alignment refers to the decision-making process through which subjects decide to align with or distance themselves from popular social topics or sentiments. More specifically, we explore whether the decision to socially align oneself with the general opinion of the users on the social network is contagious to one's connections on the network or not. For example, we explore whether users who decide to comply (align) with a broadly adopted social topic and/or sentiment would cause their followers to adopt a higher degree of social alignment with the same topic and/or sentiment.

We would like to note that the concept of social alignment contagion is different from the well-studied notion of echo chambers and filter bubbles [31], [32]. In echo chambers and filter bubbles, similar people (in terms of their demographic, opinions, beliefs, among others) end up in the "same echo chambers" and thus are exposed to the same content, which perpetuates their opinions and beliefs and make them even more similar. However, in our work, we do not explore what particular beliefs or sentiments the users adopt, but rather explore whether the decision to socially align (or distance) oneself will lead to a similar decision by the associated network users, leading to a contagious effect. In other words, our work does not explore whether social alignment will be toward specific topics or sentiments of the user's network connections but rather explores whether users will make decisions to align themselves with social topics and sentiments depending on the decisions of their social network connections.

To study whether social alignment is contagious in the context of online social networks, we adopt the instrumental variable (IV) method [33]. It is a widely used method for identifying causal relations between two variables through a third variable that impacts the outcome variable only through the causal variable. We apply the IV method on data collected from two social network platforms, namely, Twitter and Foursquare. Data collected from Twitter are used to observe users' online social alignment, while data from Foursquare are used to depict users' offline activities that we use as the IV. We systematically show that users' offline activities, collected from Foursquare, are suitable to serve as the IV as they satisfy the required conditions of IVs, namely, the correlation condition and the exclusion restriction condition. We also explore how measures of population heterogeneity, such as users' level of activity, behavioral consistency, emotionality, and network position, can impact contagion effects. The results of our experiments provide insightful findings about the contagiousness of social alignment. We specifically find that:

1) A user's decision to socially align or distance from social topics and sentiments influences the social alignment decisions of their connections on the social network.
2) Activity level impacts the degree of social alignment contagion where users with higher levels of activity on the social network have a higher likelihood of influencing their followers' decision to socially align.
3) Users with higher degrees of behavioral consistency are more likely to lead to social alignment contagion on their social network connections.
4) The general sentiment of a user is a determining factor on how users impact others through social alignment contagion, where users with more negative sentiments are more likely to impact other users' decision to socially align.
5) Users with a higher number of network connections are both more likely to impact and be impacted by social alignment contagion on the social network.

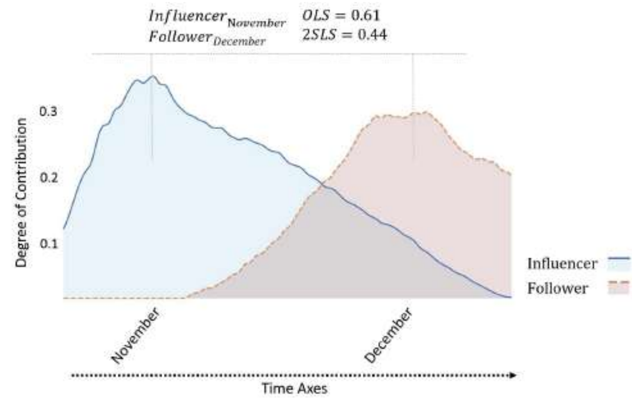

Fig. 1. Degree of contribution of influencer and follower groups in U.S. election topic in November and December.

The rest of this article is organized as follows. In Section II, we provide an overview of our research framework, including our research questions (RQs). Section III quantifies the variables that will be extracted and measured from social network content. Section IV provides the details of our methodology, including the causal model of social contagion. This is followed up by the description of the dataset and discussion on the suitability of the adopted IV. Section VI presents the study findings in relation to the RQs. Section VII provides a further discussion on our work, followed by its possible limitations in Section VIII. Finally, Section IX concludes this article.

II. Research Objectives

The main objective of our work is to study whether a systematic contagion effect can be observed between social network users as it relates to their social alignment decisions. Let us motivate the work in this article by showing the behavior of sample influencer and follower groups. For the sake of demonstration, we show the contributions of a group of users to the "U.S. elections" topic in Fig. 1. In this figure, the y-axis represents the users' contributions to this topic (whose method of computation will be presented later in this article), and the x-axis is time. The U.S. election became a trending topic in November. A group of leading users started talking and discussing this topic at the beginning of November and continued sharing their thoughts during this month. Subsequently, a subsequent group of users who followed the first group began engaging with this topic at the beginning of December.

TABLE I
OVERVIEW OF THE RQs

<table>
<tr><td colspan="4">RQ1. Impact of Contagion on Social Alignment</td></tr>
<tr><td colspan="2">RQ1.1. Social Topic Interest Alignment</td><td colspan="2">RQ1.2. Social Topic Sentiment Alignment</td></tr>
<tr><td colspan="4">RQ2. Impact of Population Heterogeneity on Social Alignment Contagion</td></tr>
<tr><td>RQ2.1 Activity Level</td><td>RQ2.2 Behavioral Consistency</td><td>RQ2.3 Emotionality</td><td>RQ2.4 Network Position</td></tr>
</table>

In Fig. 1, we depict the contributions of the two groups toward this topic. We find that not only is the second group (followers) influenced by the contributions of the first group to the U.S. elections topic, but also their alignment with the general public on this topic is also influenced by the degree of alignment of the first influencer group. We find that the social alignment of followers in December is significantly correlated with the social alignment of influencers in November, which shows that the followers' social alignment is affected by the influencer group. The objective of our work is to systematically study this observed pattern to see whether it can be generalized across a larger group of users with the ultimate goal of identifying causal relations between influencers' and followers' social alignment.

To this end, we adopt two central concepts: 1) social topic interest alignment (STIA), which addresses users' tendency to share the public's topical interests, and 2) social topic sentiment alignment, which addresses users' tendency to share the public's topical sentiments [30]. These form the basis for our RQs, outlined in Table I.

1) *First RQ (RQ1):* Are there any causal relationships between the degree of social alignment of a user and that of their social network connections?
2) *Second RQ (RQ2):* Do population heterogeneity measures, such as activity level, behavioral consistency, emotionality, and network position, play a role in the degree of on social alignment contagion?

We contextualize and explain each RQ in detail in the following.

A. Impact of Contagion on Social Alignment

The theoretical assumptions of our work are based on the existing research on social influence [34], [35]. Several researchers have argued that individuals could be influenced by behaviors, thoughts, and opinions of those they are surrounded by. For instance, Cialdini et al. [19] observed that college students who have just observed other students littering are more likely to litter themselves compared to those students who have just seen other students picking up litter from the ground. This is aligned with Bandura's theory of social learning, which posits that people tend to learn from one another, through observation, imitation, and modeling [36]. Social influence can happen for various reasons, including the need to avoid being rejected by others within a social context. Social influence that leads to social conformity is known as normative social influence. According to Deutsch and Gerard [37], individuals are often subject to normative social influence when they desire to feel a sense of belonging or would like to be accepted in a group.

Furthermore, research shows that social influence could impact emotions and cause others to have similar feelings [38], [39]. For instance, Parkinson [40] and Hatfield et al. [1] reported that when a person interacts with someone who is joyful, eager, or nervous, and they may feel similarly pleased, thrilled, or anxious. Also, van der Löwe and Parkinson [41] observed that not only can emotions be contagious between directly connected individuals, but the effect can also extend to and impact others on the social network who are not directly related. Similar research done by von Scheve and Ismer [42] shows that being surrounded by others who share a similar emotional outlook can help to improve each group member's sense of solidarity and social identity, resulting in communal emotions.

Taking inspiration from existing literature, we position our work within the framework of normative social influence and study the change in people's topical interests and sentiments as a result of a shift in the state of an influencing entity. We study such an influence in the context of online social networks and view social network users as both influencers and followers who can influence or be influenced by users they interact with. Previous research has shown that users' mental states, e.g., beliefs and sentiments, can be impacted by those with whom they engage [13], [43], [44]. This study extends beyond users' mental state and reaches into their decisions. Specifically, our work explores how under social influence (social contagion) people adapt their interests and sentiments to align with or distance from their social network.

Accordingly, in RQ1, we explore whether the degree of social alignment of a user's connections on the social network impacts the social alignment of the user themself. We refine RQ1 into two sub-RQs to explore this phenomenon from two perspectives: 1) topics of interest and 2) sentiments toward topics of interest. Thus, RQ1 is split into two sub-RQs, through which we study the impact of social influence on the social alignment of users with regard to their topics of interest (RQ1.1) and sentiments toward their topics of interest (RQ1.2). More succinctly, this research will examine the extent to which social alignment in online social networks can be explained by social contagion.

B. Role of Population Heterogeneity on Social Alignment Contagion

Earlier works on social contagion have shown that even in cases when social contagion effects can be observed between influencers and their followers, the degree of contagion may vary depending on the heterogeneity of the two populations. Therefore, in RQ2, we explore how heterogeneity level can impact social alignment contagion. Different measures can be used to assess the heterogeneity of a population; our focus in this study is on four measures: 1) level of activity; 2) behavioral consistency; 3) emotionality; and 4) network position.

1) Level of Activity: In the area of online social networks, several works have shown that users with higher daily activity have a higher social contagion effect. For example, Tutgun-Ünal [45] studied the effect of social media on students. They found that the effect of social media increased with the increase in the students' daily use of social media. In addition, Aral and Nicolaides [9] observed that users' physical activity on social networks exhibits social contagion. However, the positive influence of more active users was lesser than the negative influence of less active users on their peers. Similarly, we split the user population based on their Twitter activity into two groups—less active users and more active users—and in RQ2.1, we explore whether users' level of activity impacts the degree of social alignment contagion.

2) Behavioral Consistency: Past research has already [9], [46] considered an interaction model that investigates the role of behavioral consistency in social contagion. For instance, the work in [9] explored whether a friend who is a consistent runner is more influential on her followers compared to a sporadically active friend or the other way around. To explore that, they divided social network users into two groups: consistent runners who ran regularly without interruptions and inconsistent runners with interruptions in their running periods. In another research, Moscovici et al. [47] studied how the consistency of a minority group can influence the majority of people. They showed to a group of liberal arts, law, and social science students a series of slides and asked them to fill out a questionnaire about the color of the slides, while two confederates exerted influence by calling the color "green." In the first experiment, the confederates were consistent, that is, they gave the same response each time. The second experiment was identical to the first one, except that the consistency degree of the confederates was diversified. The results showed that in the second experiment, the number of "green" responses among the participants was significantly lower than in the first experiment. Thus, when the behavior of the minority was consistent, the number of "green" replies in the experimental group was significantly higher. On this basis, Moscovici et al. [47] asserted that the trait of possessing consistent and unchanging viewpoints was a key to influencing others. This motivated us to explore how behavioral consistency can impact social alignment contagion. To that end, we divide the users into two groups depending on the degree of consistency in their offline behavior. Specifically, we consider those influencers who have regularly checked in at the same venue category at least once a month to have consistent behavior, whereas those with interruptions in their offline activity to form the inconsistent group. This allows us to study, in RQ2.2, whether influencers with (in)consistent behavioral patterns have differing contagious influences on the follower population.

3) Emotionality: Besides the contrast between the degree and consistency of activities of the influencer and follower populations, there have been indications that the type and intensity of emotions (sentiments)—the construct we refer to as emotionality—may play an important role in social contagion. In this regard, Sun and Ng [48] showed that users who published posts with negative emotion could have a greater sentimental influence on their followers. In addition, Tiedens [49] showed that the expression of anger, when compared to the expression of sadness, had a higher likelihood of influencing the target population's perception of social status. We explore the role of emotionality on social alignment contagion in RQ2.3, by dividing our users into two groups, the "negative group" where negative emotions are dominant in their posts and the "positive group" whose posts express predominantly positive emotions.

4) Network Position: Finally, we consider the impact of network position on the degree of social alignment contagion since prior research has shown that social network position may impact social contagion [50], [51], [52]. For instance, Sung et al. [53] showed that users with a larger number of followers are often more influential than those with a lower number of followers. Centola and Macy [50] believed that contagion necessitates multiple reinforcing signals of adoption from diverse peers to elicit behavior change and that clustered social networks are thus more likely to transfer contagion from one population to another. Based on such studies, in RQ2.4, we explore the impact of network position on social alignment contagion. To that end, we divide the users into two groups: users with a low number of Twitter followers and users with a high number of followers in order to study the impact of network position on social alignment contagion.

III. Related Work

People live in different social contexts and learn from each other by interacting with others, seeing their behavior, and comparing it to their own. Much of people's decisions, beliefs, or opinions is directly or indirectly impacted by others through a phenomenon often referred to as social contagion. Manski [54] proposed three reasons why social contagion is observed and why people in a group tend to behave similarly. First, he postulated that the behavior of an individual in a group depends on the average behavior of its members. Second, the individual's behavior in the group changes with the average characteristics of the group members. Third, group members tend to behave similarly because they have exposure to similar environmental conditions.

A. Social Influence and Contagion

The underlying theoretical assumption of our work has been motivated by such existing work in the social contagion literature [34], [55]. Several researchers have already argued that it is possible for individuals to be influenced by the behavior, thoughts, and opinions of those they are surrounded by. For instance, Cialdini et al. [19] observed that college students who had just observed other students littering are more likely to litter themselves compared to those students who have just seen other students picking up litter from the ground and placing it in the trash can. This finding is fully aligned with Bandura's theory of social learning, which posits that people tend to learn from one another, through observation, imitation, and modeling [36]. Social influence can happen for various reasons, including the need to avoid being rejected by others within a social context. The type of social influence that leads to social conformity is often referred to as normative social influence. Deutsch and Gerard [37] argued that individuals are often subject to normative social influence when they desire to feel the sense of belonging or urge the need to become accepted as a part of a group.

With the emergence of online social networks, people are repeatedly exposed to a large amount of information, opinions, and beliefs, which can be overwhelming or can intensify the need for social conformity. Abraham et al. [56] conducted interviews with 30 college students to understand the influential factors, experiences, and reflections of young adults who participated in a viral social media challenge. They found that social influence factors, such as social pressure and attention seeking, were among the key factors that impacted college students when engaging with social networks. There is further research that shows not only do opinions and beliefs influence other users, but other users' emotions can also influence others [39], [57]. For instance, several studies [40], [58] have reported that when a person interacts with others who are joyful, eager, or nervous, they may feel similarly pleased, thrilled, or anxious. Also, van der Löwe and Parkinson [41] observed that not only emotion can be contagious, but when more than two people connect, the social implications of their emotions can extend through their social networks more widely. Similar research done by von Scheve and Ismer [42] shows that being surrounded by others who share a similar emotional outlook can help to improve each group member's sense of solidarity and social identity, resulting in communal emotions.

Social influence analysis has been extensively studied by previous researchers from different perspectives [3], [5], [6]. One aspect of social influence that has gained increasing attention in the recent years concerns informational social influence [59], and this is how behaviors of influential users at time t spread to other users at time $t + \tau$ [60], [61]. For example, Peng et al. [62] utilized a graph theory approach to quantify how influence spreads in a mobile social network, directly and indirectly, among users. Castellini et al. [63] studied the role of social influence in misinformation diffusion and how influential users impact public opinion about accepting fake news in regard to food using an online questionnaire. In other studies, informational social influence was investigated using online social media in the context of online shopping to learn how consumers make purchasing decisions while being influenced by others [64].

In addition to informational social influence, there is a rich body of work that explores social emotional influence. Understanding emotional influence plays an important role in studying society due to the variety of impacts that emotion can have on people [65]. In this regard, Sun and Ng [48] found that public topics with negative sentiment can have a greater sentimental influence than those with positive sentiment on their receptors. Also, the credibility of a post can be related to its emotion. Morozov and Sen [66] found that the least credible messages are associated with negative social events and contain strong negative sentiment words and opinions. In addition, emotion can affect status conferral. Tiedens [49] showed that people confer more status on targets who express anger than on targets who express sadness. When studying social influence in online social networks, in addition to the type and sentiment of content, researchers showed a positive correlation between the amount of users' online activity and their degree of influence [67], [68], [69].

Based on the literature, we find that depending on the context, some researchers use social influence and social contagion interchangeably. However, from a clear semantics perspective, social influence is a broader and more relaxed term, which refers to any form of observed social impact. However, in contrast, contagion is a process that can be clearly attributed to a known phenomenon. Our work in this article falls within the broad umbrella of social influence but is specifically studying how social contagion can happen between the social alignment of users within an online social network.

B. Factors Impacting Social Contagion

The other aspect of social contagion that has attracted attention relates to the factors that affect the strength of contagion. Prior research suggests that different types of emotions, depending on the context, can lead to differing degrees of contagion [70], [71]. For instance, Coviello et al. [72] used data from millions of Facebook users to examine the effect of positive and negative emotions of Facebook posts on users. They showed that positive and negative emotions had a significant effect on each other; specifically, positive content from Facebook users tended to decrease the number of negative posts of their friends, whereas a negative post would decrease friends' positive posts. Similarly, Sun and Ng [48] found that being exposed to valence-consistent posts on Facebook increased the likelihood of posting such content on the social network. In this article, we have studied the effect of emotionality on the degree of social contagion and found that users who were more likely to express negative emotions had the highest degree of influence on the social alignment of other users on the social network. Our findings align with earlier work such as the work by Joa and Yun [73], which examined the emotions of Twitter users during the 2016 elections. Their results suggested that both positive and negative contents were contagious, but negative content spreads faster and deeper on the social network. Also, Mahajan and Shaikh [74] studied the effect of emotion in information contagion. Their dataset included tweets about a protester who ran his car through a group of antiprotesters, sparking online and offline social movements. They found that it was more likely to observe information contagion when social content expressed negative sentiments such as sadness.

More recently, researchers have focused on how habits and behavioral patterns are passed from one user to another and what factors inhibit or facilitate this process [75], [76], [77]. For instance, Althoff et al. [78] studied the influence of online social networks on physical activity. Their dataset included 791 million online and offline actions of 6 million users over the course of five years. The results showed that 55% of the observed changes in user behavior were due to social influence. They used the difference-in-difference method [79], [80] to find the causal effect of joining an online social network on the users' physical activity (average daily steps count), but this method may not be able to remove counterfactual variables such as homophily. Aral and Nicolaides [9] used the IV method to examine the social contagion of social network users who used the network to share their exercise behaviors with their friends. In particular, Aral and Nicolaides [9] studied the running pattern of 1.1 M members of a global running social network over the period of five years, using the contents from an online social network combined with records of the daily temperature and precipitation patterns as IVs. Their results showed that the contagion effect on exercise (running), mediated by the online social network, was strong and additional runs by a user would have influenced friends to run more. Similar to Aral and Nicolaides [9], in our work, we used the IV method to estimate social alignment contagion, but instead of daily global weather information, we utilized the users' offline activities, captured as Foursquare check-ins, to serve as the IV.

IV. Proposed Study Framework

In this work, we consider that each actor (node) in a social network can have one or both of the following roles: influencee or follower, the characteristics of which we wish to model and explore, and influencer. To assume the influencer role, an actor has to be connected to at least one other actor in the network (follower). Any actor in the network, depending on the context, can have the follower and/or influencer role. On this basis, we define the causal effect as the influence of an influencer on a follower, whereas the contagion is defined as a causal effect on a follower's outcome at time t based on their influencer's outcome at time s, where $s < t$. For consistency, we will use the terms contagion, influencer, and follower as described in this section throughout this article.

A. Preliminaries

Given that the objective of our work is to study social contagion effects on users' social alignment, specifically, STIA and social topic sentiment alignment, we first formally define our representation of a topic and how a set of topics can be derived from social content.

Definition 1 (Topic): We let $\mathbb{Z} = \{z_1, z_2, \ldots, z_k\}$ be k active topics on Twitter, extracted from the content of a corpus of tweets using the TwitterLDA method, which is a well-known topic modeling method [latent Dirichlet allocation (LDA)] adapted to micro posts such as tweets [81].

Definition 2 (User Topical Interest Profile): The interest profile of user $u \in \mathbb{U}$ in time interval t, denoted as UTIP_u^t, is represented by a vector of weights over K topics, i.e., $(f_u^t(z_1), \ldots, f_u^t(z_k))$, where $f_u^t(z_i)$ denotes the degree of u's interest in topic $z_i \in \mathbb{Z}$ in time interval t. A user interest profile is normalized by the ℓ_1-norm. We define θ_m^z to be a binary variable that is 1 if tweet m belongs to topic z and 0 otherwise. On this basis, $f_u^t(z)$ is defined as

$$f_u^t(z) = \frac{\sum_{m\in\mathbb{M}_u^t} \theta_m^z}{|\mathbb{M}_u^t|} \tag{1}$$

where $\mathbb{M}_u^t$ is the set of tweets posted by user u in time interval t.

Given a user's topical interest profile, as defined above, it is also possible to define a user's sentiments toward these topics. We formalize the user topical sentiment profile based on the analysis offered by linguistic inquiry and word count (LIWC) [82]. LIWC is a text analysis suite that captures moods and sentiments by counting relevant words in psychologically meaningful categories. Empirical studies have shown that LIWC is able to adequately capture mood and sentiment in a variety of settings, including mood sharing, fake reviews, and social media content, among others [83], [84], [85]. Based on a user's topical interest profile and LIWC measurements, we define a sentiment profile for each user as follows.

Definition 3 (User Topical Sentiment Profile): The sentiment profile of user $u \in \mathbb{U}$ in time interval t, denoted as UTSP_u^t, is represented by a vector of weights over k topics, i.e., $(g_u^t(z_1), \ldots, g_u^t(z_k))$, where $g_u^t(z_i)$ denotes the average sentiment of user u with respect to topic $z_i \in \mathbb{Z}$ in time interval t and is normalized by the ℓ_1-norm.

We measure the topical sentiment for each user u in time interval t for topic z based on the sentiments of the tweets published by u in t on topic z. As such, $g_u^t(z_i)$ in Definition 3 is formalized as

$$g_u^t(z) = \frac{\sum_{m\in\mathbb{M}_u^t[z]} \mathrm{sentiment}(m)}{\sum_{m\in\mathbb{M}_u^t} \mathrm{sentiment}(m)}. \tag{2}$$

As suggested in [86], we have computed the sentiment of tweet m [sentiment(m)] as the difference between the positive sentiment and the negative sentiment associated with tweet m, as produced by LIWC. $\mathbb{M}_u^t[z]$ represents a subset of $\mathbb{M}_u^t$ that is related to topic z.

To calculate the social alignment of users to public interests and sentiments, we would need to also determine how the general community views active topics in terms of interest and sentiment. To this end, we extend Definitions 2 and 3 as follows.

Definition 4 (Community Topical Interest Profile): The community topical interest profile, denoted by CTIP^t, is represented by a vector of weights over K topics, i.e., $(h^t(z_1), \ldots, h^t(z_k))$ and is normalized by the ℓ_1-norm. Here, $h^t(z)$ is defined as

$$h^t(z) = \frac{\sum_{m\in\mathbb{M}^t} \theta_m^z}{|\mathbb{M}^t|} \tag{3}$$

where $\mathbb{M}^t$ is the set of tweets posted by all users U in time interval t. As such, CTIP^t represents the normalized topic distribution for all tweets published in time interval t. Based on the information captured in $h^t(z)$ over several time intervals t, it is possible to contrast it against the interest profile of each user u to measure how much the user is aligned with the interests of the general public.

We also define a community sentiment profile to represent the sentiments of the general community toward the set of active topics Z.

Definition 5 (Community Topical Sentiment Profile): The community topical sentiment profile in time interval t, denoted by CTSP^t, is represented by a vector of weights over K topics, i.e.,$(v^t(z_1), \ldots, v^t(z_k))$, where $v^t(z_k)$ is computed as the average sentiment of users with respect to topic $z_i \in \mathbb{Z}$

and is normalized by the ℓ_1-norm. $\upsilon^t(z)$ is defined as

$$\upsilon^t(z) = \frac{\sum_{m \in \mathbb{M}^t[z]} \text{sentiment}(m)}{\sum_{m \in \mathbb{M}^t} \text{sentiment}(m)} \tag{4}$$

where $\mathbb{M}^t[z]$ is a subset of $\mathbb{M}^t$ denoting tweets posted by all users in time interval t about topic z.

It is possible to contrast the trends observed in the community sentiment profile with the sentiment profile of each user to see whether the user's sentiments are aligned with those of the general community. For instance, does the user show similar positive sentiment toward a topic that is generally liked by the community and vice versa.

B. Quantifiable Outcomes

We build on the four preliminary definitions, two at the user level and two at the community level, to formally quantify the two outcomes of our study:

Definition 6 (Social Topic Interest Alignment): It is the degree of difference between a user topical interest profile and the community topical interest profile and is denoted by STIA

$$\text{STIA}_{u,t} = 1 - \left(\sum_{z \in \mathbb{Z}} h^t(z) - f_u^t(z)\right). \tag{5}$$

Definition 7 (Social Topic Sentiment Alignment): It is the difference between a user topical sentiment profile and the community topical sentiment profile and is denoted by STSA

$$\text{STSA}_{u,t} = 1 - \left(\sum_{z \in \mathbb{Z}} \upsilon^t(z) - g_u^t(z)\right). \tag{6}$$

These outcomes show how close the user and the community are in terms of the topics they are interested in and the sentiments they express toward those topics. If the topic and sentiment distributions for user u are the same as the community's distributions, i.e., there is a perfect alignment between the user's and community's topical interests and sentiment, the user profile and community profile will be the same, and hence, STIA and STSA will be equal to one; in the opposite case, their value will be zero.

As another illustrative case study, Fig. 2 shows users' emotions toward a topic related to the Star Wars movie. The y-axis is the users' emotions toward this topic, and the x-axis is time. The Star Wars movie became a trending topic in July. The first group of users began expressing their positive emotion toward this topic at the beginning of July and continued sharing positive thoughts on this topic going forward. A subsequent group of users who followed the first group of users began to share more positive sentiments about this topic starting from August. We found that similar to Fig. 1, in this case, not only does the first group of influencer users influence the positive sentiments of their followers, but the degree to which the followers are aligned with the overall community sentiments on this topic also increases. We find that the social sentiment alignment of influencers in July and the social sentiment alignment of followers in August are highly correlated in the term of ordinary least squares (OLS) and two-stage least squares (2SLS), which shows that the followers' social alignment is affected by the influencer group.

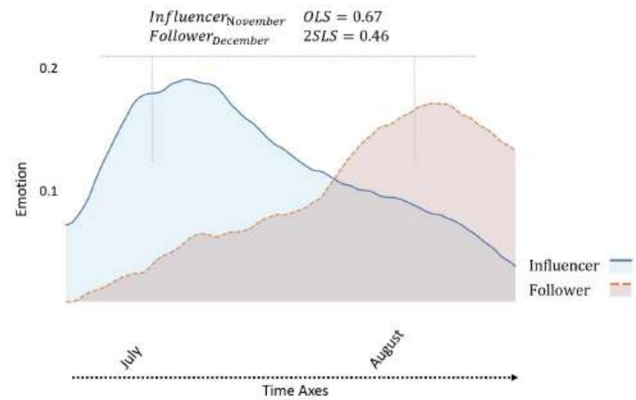

Fig. 2. Emotion of influencer and follower groups in Star Wars movie topic in July and August.

V. Methods

To study whether users' social alignment can be attributed to social contagion, we adopt the OLS method. OLS is a linear least squares method for estimating the coefficient in a linear regression model, which can be expressed as follows [87]:

$$y = g(x) + \varepsilon_1 \tag{7}$$

where y is the outcome variable, x is the treatment variable, $g(x)$ is the causal response function, and ε_1 is the error term that contains unmeasured confounders. In our work, the outcome variable is the followers' social alignment and the treatment variable is the influencers' alignment. Let $\text{STIA}_{i,t}$ be the STIA and $\text{STSA}_{i,t}$ be the social topic sentiment alignment of individual i on day t. We note that individual STIA and social topic sentiment alignment are measured on a daily basis. Based on this, we specify a linear model for the STIA and social topic sentiment alignment of individual i at time $t + \delta_t$ as follows:

$$\begin{aligned} \text{STIA}_{k,t+\delta t} &= \beta^{\text{STIA}}\text{STIA}_{i,t} \\ &\quad + \mu_1^{\text{STIA}}\text{STIA}_{k,t+1} + \cdots \\ &\quad + \mu_n^{\text{STIA}}\text{STIA}_{k,t+\delta t-1} \\ &\quad + d_{k,t+\delta t} + \varepsilon_{k,t+\delta t} \end{aligned} \tag{8}$$

$$\begin{aligned} \text{STSA}_{k,t+\delta t} &= \beta^{\text{STSA}}\text{STSA}_{i,t} \\ &\quad + \mu_1^{\text{STSA}}\text{STSA}_{k,t+1} + \cdots \\ &\quad + \mu_n^{\text{STSA}}\text{STSA}_{k,t+\delta t-1} \\ &\quad + d_{k,t+\delta t} + \varepsilon_{k,t+\delta t}. \end{aligned} \tag{9}$$

In (8) and (9), β^{STIA} and β^{STSA} are the social influence coefficients (causal effect) that we are interested in estimating. μ^{STIA} and μ^{STSA} are the coefficients representing the marginal effect of STIA or STSA of user's previous time periods and $\varepsilon_{k,t+\delta t}$ is an error term.

The above model is the OLS estimation and assumes that $\text{STIA}_{i,t+\delta t}$ and $\text{STSA}_{i,t+\delta t}$ of follower i at time $t + \delta_t$ ($\delta_t = 0, 1, 2, \ldots$) is an additive linear function of other factors

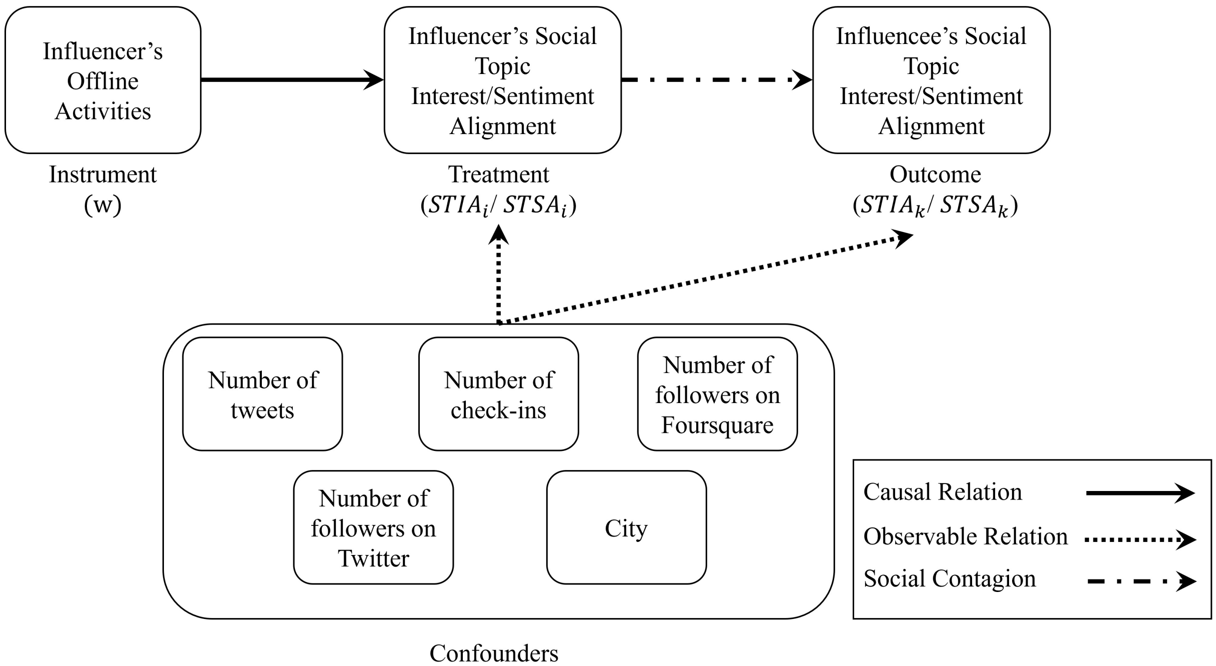

Fig. 3. Schematic of the contagion model studied in this article.

measured at the same time $t + \delta_t$ or previous time periods $t + \delta_t - 1, \ldots, t$.

The usual assumption is that the error term $\epsilon_{k,t}$ is independent and identically distributed (i.i.d.). In the OLS estimation, β can be an unbiased coefficient if $\mathbb{E}[\epsilon_{k,t}|\text{STIA}_{k,t+\delta t}] = 0$ and $\mathbb{E}[\epsilon_{k,t}|\text{STSA}_{k,t+\delta t}] = 0$. However, this is clearly violated here since our estimation takes place in a population of individuals connected in a network and affected by confounding variables such as homophily. Thus, it is infeasible to estimate the causal relationship between influencers' social alignment and followers' social alignment via directly estimating $\mathbb{E}[\text{STIA}_{k,t+\delta t}|\text{STIA}_{i,t+\delta t}]$ and $\mathbb{E}[\text{STSA}_{k,t+\delta t}|\text{STSA}_{i,t+\delta t}]$ because of the confounding effect caused by the unobserved error $\epsilon_{k,t}$.

If $\mathbb{E}[x|\epsilon_1] \neq 0$ in (7), then OLS gives a coefficient that does not reflect the underlying causal effect of interest. The IV method [88], [89], [90] helps fix this problem by identifying a new coefficient β not based on whether x is uncorrelated with ϵ_1, but based on whether another variable z is uncorrelated with ϵ_1. If the theory suggests that z is related to x but uncorrelated with ϵ_1, then the IV method may identify the causal parameter of interest in cases when OLS fails.

A reliable implementation of the IV (denoted by z) should satisfy the following conditions.

1) *Correlation Condition:* This condition ensures that the IV is correlated with the independent variable x, i.e., $\mathbb{P}(x|z) \neq \mathbb{P}(x)$.
2) *Exclusion Restriction Condition:* This condition requires that any effect of the proposed instrument on the dependent variable y is exclusively through its potential effect on the independent variables x, i.e., $\mathbb{P}(y|x, z, \varepsilon) = \mathbb{P}(y|x, \varepsilon)$

The goal of the IV method is to obtain an estimation function $\hat{g}$ that is close to the true response function g, $\mathbb{E}[y|z] = \mathbb{E}[g(\hat{x})|z]$. The IV method allows for measuring the causal effect of a treatment on the outcome by introducing a random variable that affects the treatment but has no direct effect on the outcome. When the treatment–outcome relation suffers from unmeasured confounding variable(s) and an IV can be found that is not confounded with the outcome, the IV method can be used to recover valid estimates of the causal effect of the treatment on the outcome.

The IV method relies on the 2SLS approach as follows:

$$\text{1st Stage: } \hat{x} = \hat{\alpha_0} + \hat{\alpha_1} z + \varepsilon_2 \tag{10}$$

$$\text{2nd Stage: } y = \beta_0 + \beta_1[\hat{\alpha_0} + \hat{\alpha_1} z + \varepsilon_2] + d + \varepsilon_1. \tag{11}$$

In the first stage, (10), 2SLS, estimates the independent (x) variable. This stage involves estimating an OLS regression on the set of instrument variables with error term ε_2. The second stage, (11), is a regression of the original, (7), which now uses the fit values from the first-stage regressions with error term ε_1. β_0 is the intercept of the regression and β_1 is the social influence coefficient that we are interested in estimating.

Fig. 3 shows a schematic of the contagion model that is studied in this article based on the IV method. In this context, we define the IV to be the number of check-ins at venues in each specific venue category by each user, extracted from the Foursquare social network; we denote the IV as $w_{i,t}$ for individual i during time period t.

To select the cofounders, we were inspired by the selection of confounding variables in similar prior work. Specifically, Aral and Nicolaides [9] considered the city a user lives in as one of the confounders. Similarly, we have selected *city* as a confounding variable that can have an effect on the users' topical interests and sentiment. Like Aral and Nicolaides, we believe that city is a relevant confounding variable as people living in the same have a higher likelihood to share similar topical interests given the events that are happening around them. For instance, major events that happen in a city can shape how the citizens of that city engage with online social topics related to that event.

Furthermore, De Choudhury et al. [91] used the number of posts on social media and the number of comments and upvotes received on posts as confounding variables when performing their observational study over social network data. Other studies, such as [92], have used topics and length of content that users shared on their social network, the number of feedback messages they received, and the number of friends the users' had on the social network as confounding variables. Similarly, we use users' social network activity such as the number of tweets, number of check-ins, and number of connections as confounders.

In summary, we specified the following confounding variables.

1) The degree of engagement of a user with the online platform (Twitter) that measures as the number of tweets posted in each time period by each user.
2) The count of offline activities reported by the user across all venue categories. We capture each user's total number of offline activities across all venue categories in each time period through the check-ins they make on the Foursquare platform.
3) User's offline social connections represent the number of followers that the user has on the Foursquare platform.
4) User's online social connections stand for the number of followers that the user has on Twitter.
5) Finally, the city where the user is active, which is derived from check-ins made by the user on Foursquare.

In order to identify the hidden (unobserved) correlation between the influencers' and followers' STIA and STSA, we use an IV. Equations (12) and (13) show the estimated value of STIA and STSA of influencers using the number of check-ins at venues in each specific venue category as IV (w)

$$\text{1st Stage: } \overline{\text{STIA}}_{i,t} = \alpha_0^{\text{STIA}} + \alpha_1^{\text{STIA}} w_{i,t} + d_{i,t} + \varepsilon_{it} \tag{12}$$

$$\text{1st Stage: } \overline{\text{STSA}}_{i,t} = \alpha_0^{\text{STSA}} + \alpha_1^{\text{STSA}} w_{i,t} + d_{i,t} + \varepsilon_{it}. \tag{13}$$

The above model assumes that $\overline{\text{STIA}}_{i,t}$ and $\overline{\text{STSA}}_{i,t}$ of influencer i at time t are additive linear functions of other factors measured at the same time t. α_0 is the intercept and α_1 is the slope of the linear regression model.

In the second stage, (14) and (15), the STIA and STSA outcomes of the follower group are estimated after replacing the independent variables with the predicted values from the first stage. Thus, the second stage estimation can be specified as follows:

$$\begin{aligned}\text{2nd Stage: } \text{STIA}_{k,t+\delta t} = {} & \beta^{\text{STIA}} \overline{\text{STIA}}_{i,t} \\ & + \mu_1^{\text{STIA}} \text{STIA}_{k,t+1} + \cdots \\ & + \mu_n^{\text{STIA}} \text{STIA}_{k,t+\delta t-1} \\ & + d_{k,t+\delta t} + \varepsilon_{k,t+\delta t}\end{aligned} \tag{14}$$

TABLE II

FOURSQUARE VENUE CATEGORIES AND SUBCATEGORIES PRESENT IN OUR FOURSQUARE DATASET

Category	Number of Subcategories	Sample Subcategories
Food	190	Cafe, Food Courts, BBQ Joints
Gym	12	Pool, Martial Arts, Yoga Studio
Shops	146	Jewelry Stores, Malls, Arts Crafts Stores
Travel	58	Plane / In-flight, General Travel, Boat / Ferry

$$\begin{aligned}\text{2nd Stage: } \text{STSA}_{k,t+\delta t} = {} & \beta^{\text{STSA}} \overline{\text{STSA}}_{i,t} \\ & + \mu_1^{\text{STSA}} \text{STSA}_{k,t+1} + \cdots \\ & + \mu_n^{\text{STSA}} \text{STSA}_{k,t+\delta t-1} \\ & + d_{k,t+\delta t} + \varepsilon_{k,t+\delta t}\end{aligned} \tag{15}$$

where in the second stage, $\overline{\text{STIA}}_{i,t}$ and $\overline{\text{STSA}}_{i,t}$ are the predicted values from the first stage.

VI. EXPERIMENTAL SETUP

A. Dataset

Considering the objective of our study, we collected data from Twitter to represent users' online behavior. To curate our dataset, we gathered a Twitter dataset, which consists of 5 075 088 tweets from 15 800 unique users in the range of one year between January and December 2010. Furthermore, given the IV is defined as the offline activities of each user, we additionally collected relevant Foursquare social network check-in data. We use Foursquare data to extract users' check-ins, which provide data about their offline activities. Our dataset from Foursquare includes 6564 263 check-ins, posted in the range of one year between January and December 2010 (the same time period as the one during which tweets were collected). Each check-in record in the dataset includes a user ID, a location ID, and a timestamp, where each location has latitude, longitude, and venue category information [93]. The check-ins venue categories include four main categories, namely gym, food, shop, and travel, as described in Table II. The other venue categories were excluded due to the low level of presence in our dataset (less than 8% of the total check-ins).

We additionally used the swarm application[1] to identify those users who had posted both on Foursquare and Twitter. In this way, we were able to identify the users who were simultaneously active on both platforms. Given that offline activities of each user were considered to be the IV in our work, we ensured that the users in our Foursquare dataset did not share their check-ins on Twitter in order to satisfy the exclusion restriction condition. We would like to note that we had to resort to Twitter and Foursquare data from earlier years since these social networks have now placed substantial limitations on the data that can be accessed from their platforms; which would impose limitations on performing similar studies to the one in this article.

Furthermore, given that the study of social contagion requires information about influencers, we collected follower relations using Twitter API for all users in our dataset. In this

[1] https://www.swarmapp.com/

process, for each Twitter user in our dataset, we made sure that the user and their collected followers are not friends on the Foursquare network so that they are unaware of each other's offline activities, i.e., their offline activities do not have any indirect influence on any observed contagion effect.

We note that in all of our experiments, statistical significance was measured based on a paired t-test with $\alpha = 0.001$.

B. Ensuring the IV Conditions

In order to satisfy the correlation condition of the IV, we need to show that there is a strong relationship between the number of offline check-ins at each venue category by each user (as the IV) and STIA and STSA of influencers.

We use an interrupted time series design with treated and control groups. Given that the goal is to discover the effect of offline activities on users' online behavior, the treatment in our experiment is users' offline activity and its outcome is users' STIA and STSA. The treatment, in our study, is defined as participation in or abandoning of an offline activity, which impacts the exposure of the users to or their retrieval from social situations. The treated group is the group of users who are impacted by the treatment. More precisely, we define the treated group as those users who can be identified as impacted by the treatment based on their Foursquare check-ins. We study two treatments, namely, embarking on and abandoning an offline activity. Each of these two treatments is studied in the context of four venue categories, which include gym, shop, food, and travel.

We perform our observations on each user over a four-month time period, which consists of two months prior to treatment and two months posttreatment. In order to form the treated group for each venue category, for the treatment of embarking on an offline activity (e.g., starting to go to bars), we identify and select those users who did not have any check-ins in the related venue category for a period of two months and subsequently made at least 16 evenly distributed check-ins in the subsequent two months. A similar approach was adopted for abandoning treatments. In these treatments, we ensured that the subjects selected for the treated group had consistently checked in at venues of the given venue category at least 16 times and at least once every week over a two-month period after which the subject would abandon venues in that venue category and would not make any check-ins in such venues for a two-month period.

We performed stratified propensity score matching (PSM) [94] in order to rule out the impact of the confounding variables that, if not handled, could potentially yield unreliable causal relations. Following the PSM method, users in the treated and control groups were matched based on their propensity scores. Propensity scores are used for balancing the treated and control groups such that the distributions of the measured confounding variables are similar in the treated and the control subpopulations.

For measuring the effect of treatment, we have adopted the relative treatment effect (RTE), as a suitable measure in the context of our study [95]. An alternative measure, such as absolute treatment effect (ATE), would not be applicable since the emotions and moods considered in the study tend to differ in the frequency of online expression (e.g., expressions of positive emotions tend to be more present in tweets than, for example, expressions indicative of sleepy or calm moods). We first determine the RTE in each stratum per outcome, as a ratio of an outcome measure in the treated group to that in the control group [96]. After that, we acquire the mean RTE per outcome measure by using a weighted average across the strata. RTE greater than 1.0 indicates that a particular type of offline activity had a positive effect and that the outcome has effectively increased in the experimental group, while RTEs lower than 1.0 indicates the opposite.

1) Causal Relation Between Offline Activities and STIA: We separate the involvement of users with offline activities in embarking and abandoning treatments and present our findings individually for each of the four venue categories listed in Table II. For measuring the treatment effect, we have adopted the RTE, as a suitable measure in the context of our study. Based on [95], RTE greater than 1.0 indicates that a particular type of treatment has a positive effect and that the outcome has effectively increased in the treated group, whereas RTE below 1.0 indicates the opposite. The results (RTE) for STIA based on the treated group and the control group are reported in Fig. 4. As shown in Fig. 4, when users embark on an offline activity that increases their exposure to social situations, the alignment of their topical interests with the interests of the community increases. The reverse happens when users abandon such an offline activity, namely, their alignment to the community with respect to topical interests, decreases. In all four venue categories and for both treatments, the change in the STIA of the treated group is statistically speaking larger compared to the control group.

We find that offline activities that impact the users' exposure to social situations influence how users' topical interests align with the community. Embarking on an offline activity that exposes a user to social situations has a positive impact on terms of aligning users' interests with the topics of interest of the general community whereas abandoning such offline activities has a negative impact on STIA.

2) Causal Relation Between Offline Activities and STSA: Similar to STIA, we find that embarking and abandoning treatments have an inverse impact on STSA, as shown in Fig. 5. Specifically, the findings suggest that embarking on an offline activity increases STSA with respect to the topics of interest. In other words, when a user embarks on such an offline activity, it becomes more likely for that user to share sentiments of the general community regarding topics of interest. On the other hand, when a user abandons an offline activity, a significant reduction happens in the alignment to the community with respect to the sentiment toward topics of interest.

To sum up, we find that offline activities that alter users' exposure to social situations tend to have a significant measurable influence (p-value < 0.001) on the alignment of users' topic sentiments with sentiments of the community.

The above presented results show that offline activities causally impact both STIA and STSA. Therefore, offline activities satisfy the correlation condition of the IV approach.

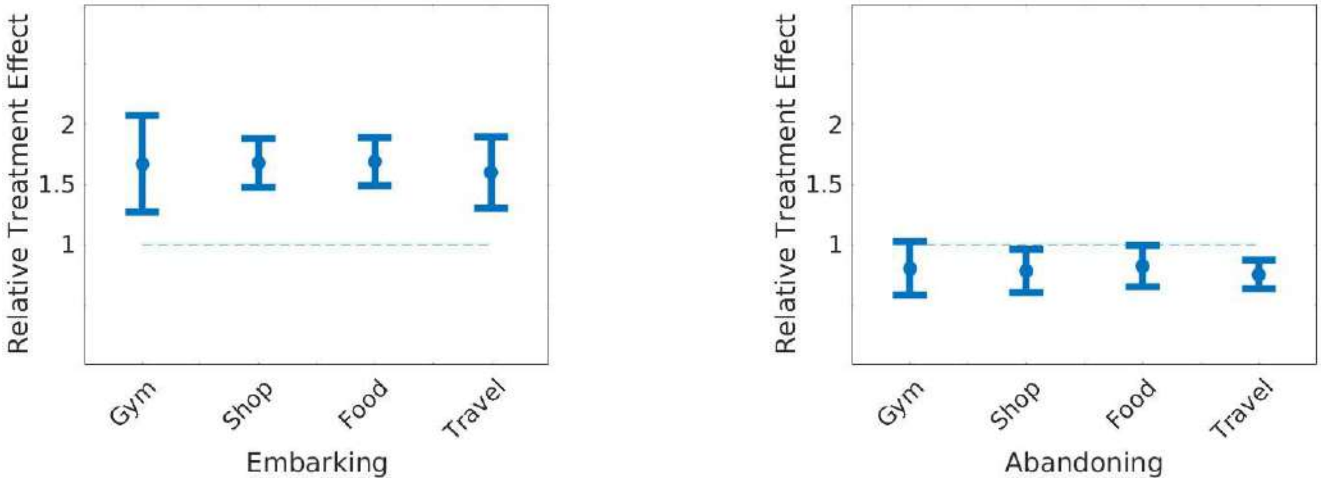

Fig. 4. Distribution of RTE for STIA as the outcome. All the results have a p-value < 0.001.

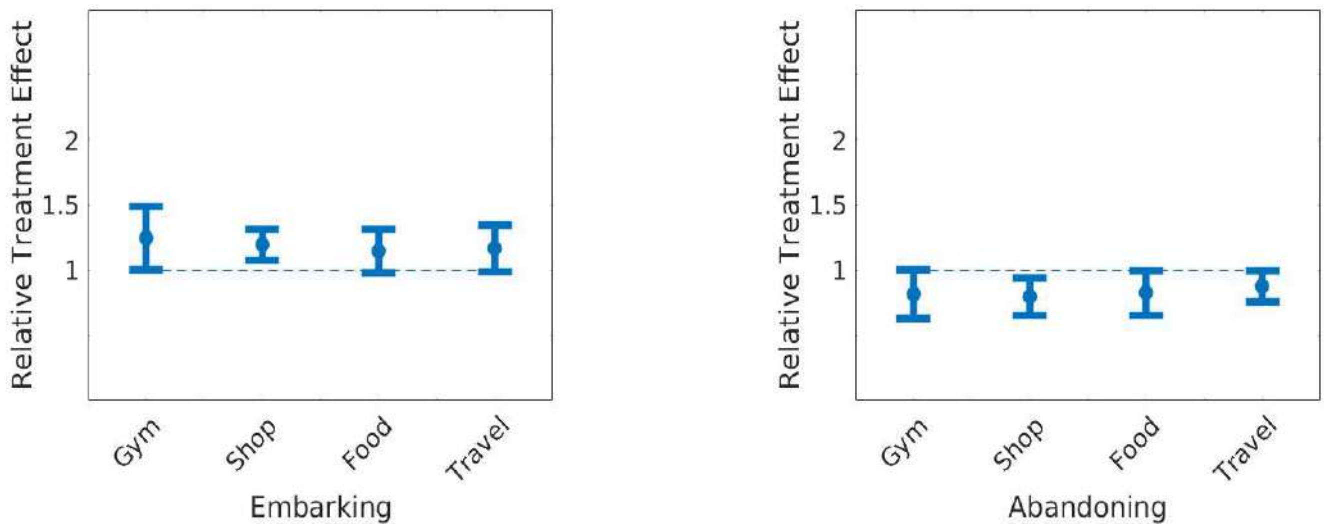

Fig. 5. Distribution of RTE for social topic sentiment alignment as the outcome. All the results have a p-value < 0.001.

Furthermore and as outlined earlier, when collecting our dataset, we ensured that the users in our Twitter dataset did not share their location information nor Foursquare check-ins on Twitter; hence respecting the exclusion restriction condition of the IV approach. This allows us to conclude that users' offline activities, as reported on Foursquare, qualify to serve as the IV in our experiments.

VII. Findings

Here, we report the findings of our social contagion study based on the two groups of measured outcomes, namely, STIA and STSA. The objective is to study whether these two outcomes are socially contagious on social platforms.

A. RQ1. The Contagiousness of Social Topic Interest and Sentiment Alignment

Our RQ1 explores whether STIA and STSA are socially contagious or not. We first study the effect of influencers' STIA on followers' STIA. To that end, we explore whether changes in influencers' STIA will lead to changes in followers' STIA. As such, we identify the group of users who have shown at least 20% variation in their STIA and consider them to be influencers. Based on the IV setup introduced in Section III-C, we study the effect of influencers' STIA on followers' STIA at time intervals $t + 1$, $t + 2$, and $t + 3$, where t is the time period when the influencer showed a change in their STIA and $t + 1$, $t + 2$, and $t + 3$ are subsequent months after t.

The results of our analysis reveal strong contagion effects for STIA. Fig. 6 presents β, which is the social influence coefficient (causal effect) expressed in (7) for OLS and (11) for 2SLS, which represents the degree of social contagion that we are interested in estimating. We report the contagion effects for when the users were engaged with different offline activities. Our observations can be summarized as follows.

1) There are strong observable social contagion effects between influencer and follower groups regardless of which offline activities they were engaged with;
2) The social contagion effect is stronger in the first time interval after the influencer's change in STIA and gradually decreases in subsequent time intervals;

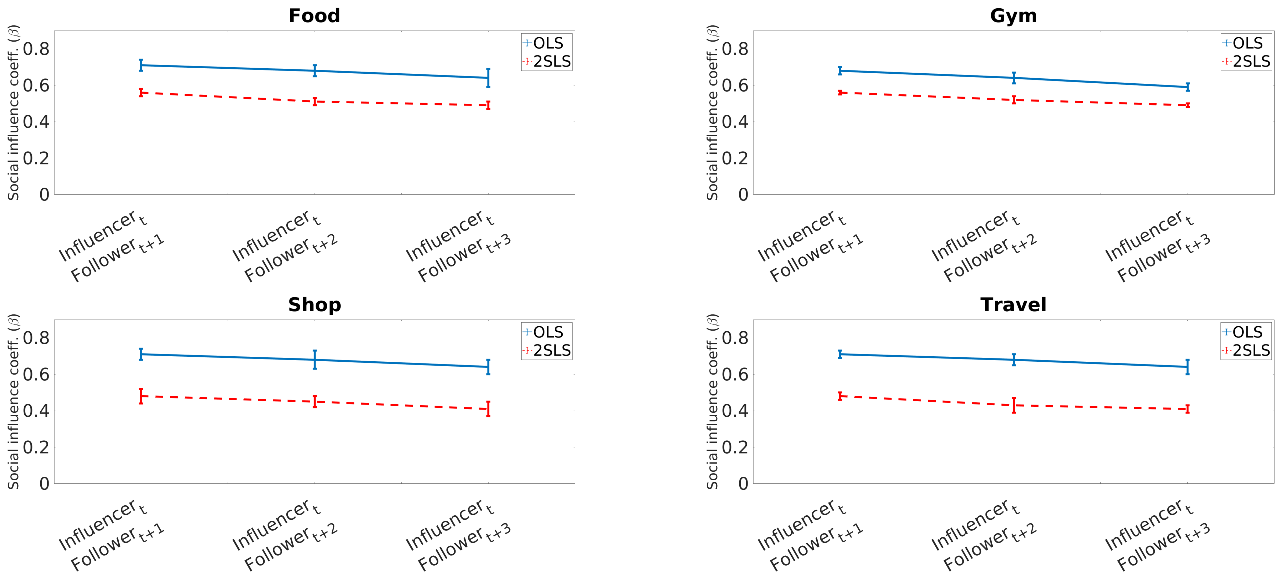

Fig. 6. Social influence coefficients from 2SLS and OLS for STIA at time intervals t, $t+1$, and $t+2$ for four different venue categories. All the results have a p-value < 0.001.

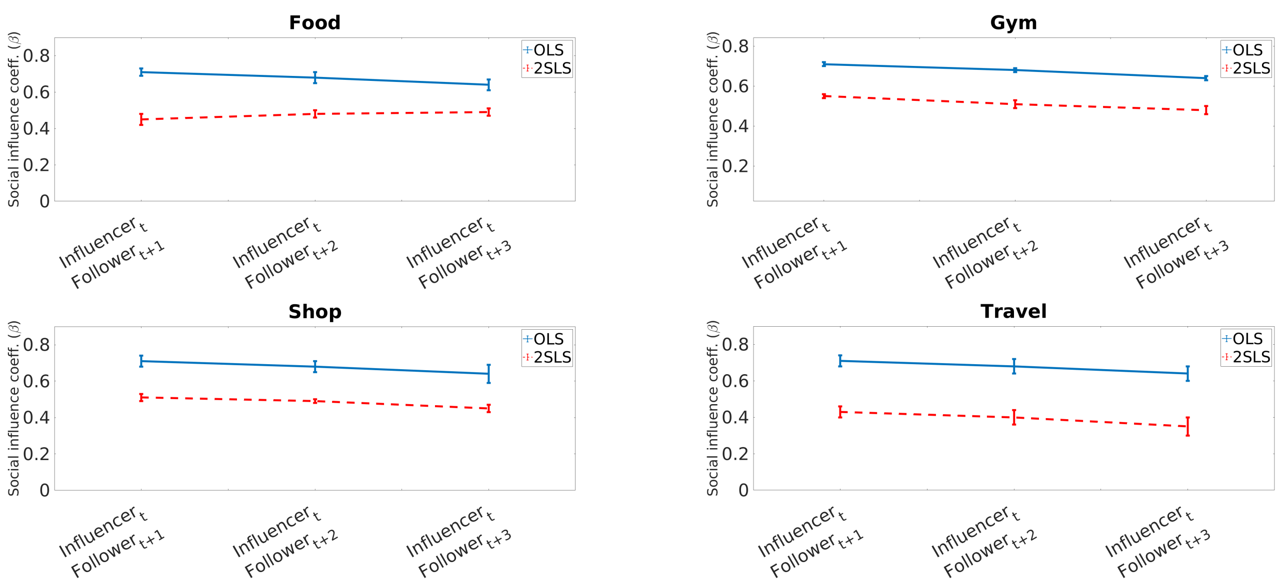

Fig. 7. Social influence coefficients from 2SLS and OLS for STSA at time intervals $t+1$, $t+2$, and $t+3$ for four different venue categories. All the results have a p-value < 0.001.

3) Models such as OLS that do not account for endogeneity biases created by homophily and other confounding effects, can overestimate social contagion. As shown in Fig. 6, the OLS model overestimates the degree of social influence. The difference between the degree of social influence reported by OLS and 2SLS can be the degree of relationship attributable to other factors such as homophily [9], [97], [98].

In the second set of experiments, we examine the contagion of influencers' STSA on their followers' STSA. We adopt a similar strategy to the one used for examining the contagiousness of STIA, to study whether a shift in the influencer's STSA will lead to notable changes in the STSA of their followers. Analogous to STIA, we consider users whose STSA has changed by at least 20% to form the influencer group. We report the effect of influencers' STSA on their followers' STSA at time intervals $t+1$, $t+2$, and $t+3$, where time interval t indicates when changes in influencer's STSA were observed.

Fig. 7 shows STSA social contagion coefficients after the users in the influencer group change their STSA outcomes. We find a consistent pattern in social influence coefficients for STSA as the one observed for STIA. More specifically, there is a strong contagion effect between the influencer and follower groups on STSA, showing that when users in the influencer group align or distance themselves from the social topic sentiment, the followers will exhibit a similar behavioral pattern in the next time interval. The effect of this

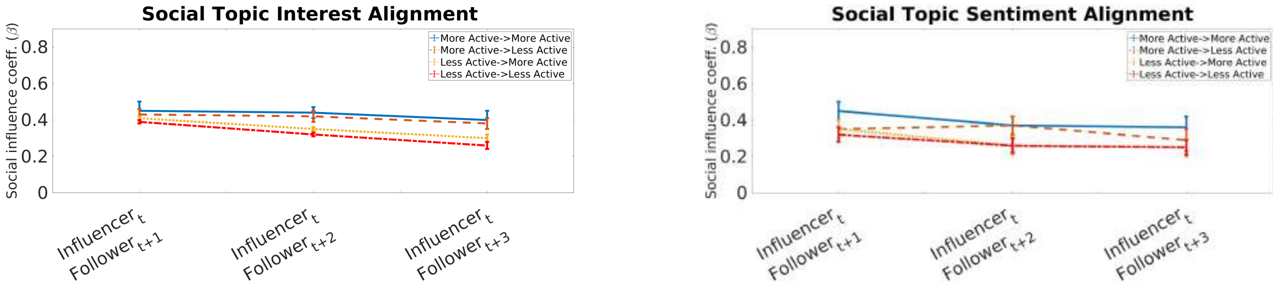

Fig. 8. Social influence coefficients from 2SLS at time t, $t+1$, and $t+2$ for more active and less active user groups based on their Twitter activity. All the results have a p-value < 0.001.

TABLE III
RMSE FOR THE FIRST-STAGE ESTIMATION

	STIA	STSA
Food	0.22	0.27
Gym	0.31	0.28
Shops	0.25	0.26
Travel	0.28	0.24

contagious behavior has gradually decreased in the subsequent time intervals. There is also a notable difference between OLS and 2SLS, which may be attributable to the control of 2SLS over homophily and other confounding effects [9], [97], [98].

In summary and in response to RQ1, we find that strong observable contagion effects exist over the social alignment. We find that a strict strategy for studying social contagion, namely, 2SLS through IVs, shows notable contagion effects. This means that in addition to what the literature has shown concerning the contagiousness of psychological characteristics [21], [34], [99], [100], our findings demonstrate that users' decisions such as deciding to align with or distance from social topics or sentiments are also impacted by social contagion effects.

Table III shows the root-mean-square error (RMSE) of the first-stage estimation using (16). RMSE is the standard deviation of the residuals (prediction errors). Residuals are a measure of how far from the regression line data points are, and hence, RMSE is a measure of how spread out these residuals are

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{n} |x_i - \hat{x}_i|}{n}\right]^{\frac{1}{2}}. \tag{16}$$

B. RQ2. Impact of Population Heterogeneity on Social Alignment Contagion

In RQ2, we study the impact of activity level, behavioral consistency, emotionality, and network position on the degree of observed social contagion on both STIA and STSA. We divide the users into two groups to find the effect of population heterogeneity on social alignment contagion. To find the impact of activity level, we divide the users in influencer and follower groups into less active and more active users based on their activity level on Twitter. Then, we explore the effect of influencers' STIA and STSA on followers' STIA and STSA of each group separately by following the same approach as RQ1. We repeat the same approach for behavioral consistency by dividing the influencer group into consistent and inconsistent groups, for emotionality by dividing users in influencer and follower groups into negative and positive groups, and for network position by dividing the influencer and follower groups into high and low position groups as explained in the following.

1) Activity Level: To study the impact of activity level on social contagion, we split the user population into two groups: less active users and more active users based on their Twitter activity. To categorize the users into these two groups, we compute the average number of tweets per user over all of the dataset. Users with the number of tweets higher than or lower than this average value are placed into more active and less active groups, respectively. The results are reported in Fig. 8, which shows the impact of activity level on STIA and STSA. We make two important observations based on this figure.

1) Those influencers who are placed in the more active category can show tend to exert a higher degree of influence on both the more active and less active followers. As such, the degree of activity of the influencer is a determinant of the degree of social contagion on both STIA and STSA outcomes. We further observe that the highest amount of influence is present between more active influencers and their more active followers. (2)
2) Less active influencers show comparable degrees of influence on their followers in the immediate time interval after a change in their social alignment compared to more active influencers. However, they are not able to maintain similar degrees of influence compared to more active influencers in subsequent time intervals. We observe that the lowest degree of influence is seen between less active influencers and less active followers.

In summary, we find that activity level is a factor in determining social contagion for both of the social alignment outcomes where more active influencers are more likely to impact their followers to a greater extent.

2) Behavioral Consistency: We further investigate whether the behavioral consistency of the influencers impacts the degree of contagion. We divide the influencers into two groups depending on the degree of consistency in their offline behavior. Specifically, we consider influencers who have regularly checked in at the same venue category at least once a month

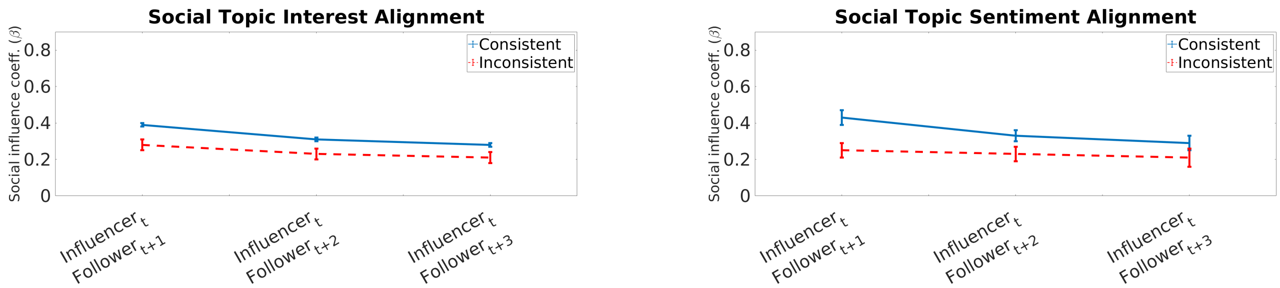

Fig. 9. Social influence coefficients from 2SLS at time intervals t, $t+1$, and $t+2$ for consistent and inconsistent user groups based on their check-ins activity. All the results have a p-value < 0.001.

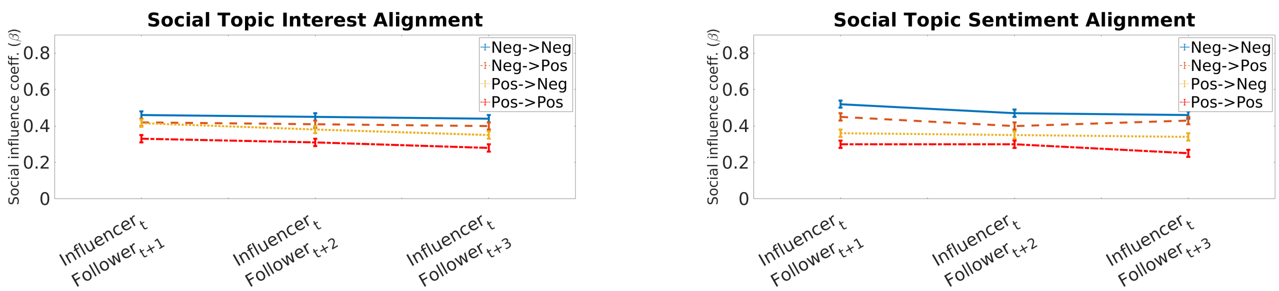

Fig. 10. Social influence coefficients from 2SLS at time t, $t+1$, and $t+2$ for users divided into negative and positive groups based on the overall emotion of their tweets. All the results have a p-value < 0.001.

for the whole 12-month period to have consistent behavior (e.g., a user who has checked in at a gym at least once a month). Based on the results of our experiments, we find that the influencers with consistent behavior have a higher likelihood of affecting their followers. This applies to both outcomes, namely, STIA and STSA. Based on Fig. 9, we further notice that the contagion effect of inconsistent influencers is quite weak (the social influence coefficient (β) is around 0.2). Therefore, we conclude that behavioral consistency is an important factor that can shape how contagious users' social alignment is.

3) Emotionality: To examine whether sentiments expressed by influencers impact the degree of social contagion, we categorize our users into two groups, namely, users who predominantly express negative sentiments and those whose online expressions are predominantly positive. To determine such users, similar to activity level, we compute the average positive and negative sentiments of users. The individuals with positivity higher than average are considered positive users and those who are less positive than average are considered negative users.

Fig. 10 shows the degree of social contagion associated with positive and negative user groups. We make three important observations that apply to both STSA and STIA outcomes.

1) Influencers who are classified as negative users have the highest degree of influence on others on the social network. This is true for both positive and negative followers although their degree of impact on negative followers is higher. This means that those influencers who predominantly express negative sentiments have a higher degree of changing decisions of their followers in relation to social alignment;
2) When comparing across sentiment categories of followers, those with predominantly negative sentiments are more likely to be impacted by influencers regardless of the sentiments of their influencers, while positive followers are less "susceptible" to the impact from their influences.
3) Overall, users with positive sentiments, whether influencers or followers, have a lower likelihood of impacting or being impacted by social alignment contagion.

In summary, we find that emotionality is a consequential factor in determining the contagiousness of social alignment. We show that negative users have a higher likelihood of causing impact or being affected by social contagion.

4) Network Position: To investigate the impact of network position [53] on social alignment contagion, we identified two groups of users depending on their position in the social network they are engaged with. As suggested in [101] and [102], we define the network position of a user as the number of direct social connections the user has in the network. We calculate the average number of social connections on Twitter for users in our dataset based on which we divide the users into two groups. In this way, we are able to identify influencers and followers with high and low network positions. We note that high and low network positions can also be interpreted as users having more or less advantageous network positions. Fig. 11 shows the degree of social influence across groups with different network positions. Based on these results, we are able to make the following observations for both outcomes (STIA and STSA).

1) Influencers with a high network position have a higher degree of impact on their followers, and at the same time, followers with a high network position receive

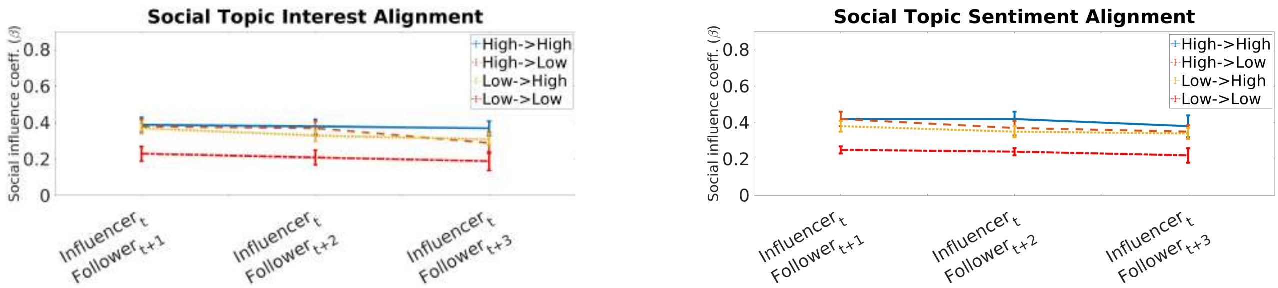

Fig. 11. Social influence coefficients from 2SLS at time t, $t+1$, and $t+2$ for users in high and low network position groups. All the results have a p-value < 0.001.

a higher degree of impact from the behavior of their influencers;

2) The lowest degrees of social influence are observed between influencers and followers with low network positions.
3) When comparing the network position of an influencer with that of the followers, we find that the network position of an influencer has a higher degree of impact on social contagion. Specifically, an influencer with a high network position is able to significantly influence followers with high and low network positions.

In summary, we find that the network position of users is a significant factor impacting social alignment contagion in social networks where users with high network positions have a high likelihood of impacting their followers.

Finally, we are interested in understanding the degree of impact of different population heterogeneity measures. In order to do so, we measure the impact of each population heterogeneity measure as the average differences of social influence coefficients of users in every population heterogeneity group and all users according to the following equation:

$$\text{Impact} = \frac{\sum_{i=1}^{n} |q_i - q_{\text{all}}|}{n}. \tag{17}$$

The degree of impact of the different population heterogeneity measures allows us to understand which measure has the highest impact on STIA and STSA. Table IV reports the impact of different population heterogeneity measures. The impact of activity level for STIA is 0.14 and for STSA is 0.18. Activity level has the most effect on STSA among other measures. Existing work in the literature has shown that as the activity of a user in social networks increases, it will also lead to an increased impact on the users' emotional expressions [67]. Other researchers have also found that users who use social media more frequently are more likely to express higher degrees of emotional expressions such as stress, anxiety, and depression [45].

We also report that the impact of behavioral consistency is 0.31 for STIA and 0.09 for STSA. Behavioral consistency has the most effect on users' STIA. This result is aligned with findings from other researchers about behavioral consistency who report that the effect of users' with consistent behavioral patterns have the most impact on their friends [9]. Moscovici et al. [47] also reported that minority groups have

TABLE IV
IMPACT OF POPULATION HETEROGENEITY

population heterogeneity	STIA	STSA
Activity Level	0.14	**0.18**
Behavioral Consistency	**0.31**	0.09
Emotionality	0.10	0.04
Network Position	0.20	0.11

a higher likelihood of impacting the majority group when their behavior is consistent.

VIII. Potential Applications

Conformity is the act of matching attitudes, beliefs, and behaviors to group norms or being like-minded. Norms are specific rules that guide their interaction with others. One of the potential impactful use cases of social alignment is in recommender systems to show items to those users who will be truly interested in them [103], [104]. A recommender system is more likely to be successful if it recommends items to users who are influenced by another group of users who have already approved or shown interest in that item. In other words, instead of making recommendations based on a pure collaborative filtering strategy, a recommender system that considers influential users and their contagion effects have a higher likelihood of making effective suggestions. This is inline with the work by Guo et al. [105], which suggests using a trust network of users to solve the cold start problem of new products. They propose a trust-based matrix factorization technique and show that not only the explicit but also the implicit influence of both ratings and trust should be considered in a recommendation model. Our work on the impact of social contagion on social alignment can be seen as causal relation that can be broadly captured through notions of: 1) trust by Guo et al. [105]; 2) online word of mouth by Lin et al. [106]; and 3) implicit social relationships by Wei et al. [107]. The strategy to adopt social contagion for recommendation has already been adopted by high-tech companies such as Apple to change social norms by influencing people's perception of product value [108].

Another potentially highly relevant and impact area where the findings from our work could be applied is the area of information diffusion and belief adoption [109]. With increasing concerns with misinformation [110], researchers have been looking into ways to identify how misinformation disseminate and how they potentially impact different subpopulations [111], [112]. Phenomena, such as filter bubbles, confirmation bias, echo chambers, and selective exposure, among others, have been extensively explored [113]. We believe that the findings from our work can help understand how some people are impacted by misinformation by explaining this through the concept of social alignment and the contagiousness of social alignment. Aligning one's social stance to align with the general population or to align with one's influencing group could be among the reasons that users decided to adopt certain information or beliefs. As shown in this article, aligning one's belief and sentiments can be contagious from the influencer population to their followers, which can lead to high social conformity and, as a result, a higher likelihood of adopting information that is not necessarily accurate.

Finally, it would be noteworthy to mention that our work not only can help with understanding the contagiousness of social alignment but can also provide the basis for understanding the contagiousness of nonconfirming (or nonaligning) behavior. Researchers, such as Bellezza et al. [114], have already explored the so-called "red sneakers effect" where nonconforming behaviors in certain contexts can be perceived as signs of status or competence and are hence used to this end. The famous case of Zuckerburg and Jobs' nonconforming outfits for a person in an executive role is an example of such nonconforming behavior that then has a contagious impact on others within the industry. Another example of using a nonconforming advertisement strategy is the LittleMissMatched socks. First, it may seem unusual and strange to sell three pairs of unmatched socks, but based on a nonconformist idea, the idea was able to create a contagious advertising strategy and convince a large number of users to purchase and wear unmatched socks [115]. This can be interpreted in the context of our work where nonconforming behavior (lack of social alignment) can be contagious from influencers to their followers.

IX. Limitations

It is important to acknowledge that our work could have been impacted by limitations. One possible limitation of our work might be a confounding effect, which refers to cases where changes in the dependent variable can be attributed to an observed or unobserved confounding variable. In our work, based on the data, we have gathered from the two social networks, we tried to find the variables that might have affected the outcome and controlled them as confounding variables. It is, however, possible that some external unobserved confounding variable, such as real-world events, may have confounded the findings.

Furthermore, given that our work requires the users to have been active both on Twitter and Foursquare, the findings can only be generalized to the population of users who have joined both platforms. In other words, user characteristics, such as social topic and sentiment alignment, may be different between users who are only active on Twitter or Foursquare and those who are active on both. Another potential limitation relates to the way we capture sentiment (emotions), which is primarily based on the counts of emotion bearing words in the text based on LIWC. As acknowledged in Section IV, even though LIWC has been widely used for the detection of different kinds of psychological characteristics, including emotions, it is a dictionary-based tool and thus has the limitation of being context agnostic. In particular, given that emotion-bearing words are sometimes systematically used for purposes other than emotional expression (e.g., "happy birthday," "I would be happy to help"), it is realistic to expect that emotion-related words might not necessarily reflect a person's true emotions in all contexts of their use.

In addition, we have limited our experiments to the behavior of users based on four Foursquare venue categories, while this social network has ten main categories. We explored the possibility of including other Foursquare category venues such as arts and entertainment, or education. However, we were not successful in identifying a sufficient number of users and check-ins in these venue categories to warrant a reliable analysis of the data.

X. Conclusion

Our work in this article explores possible contagion effects between social network users with regard to the social alignment of their topical interests and sentiments. This work ventures to understand whether social network users are impacted by how their social connections align themselves with the opinions and sentiments of the general public. Our work distinguishes itself from the literature in two main ways. First, it is among the few to propose a systematic way for using two separate social networks (Twitter and Foursquare) to collect users' online and offline activities and to utilize information from one social network to develop an IV to learn contagion effects on the data from the other social network. We have shown that users' offline activity can serve as an appropriate IV as it respects both the correlation condition and the exclusion restriction condition in the context of our work. Second, while existing work in the literature focuses on social influence of users' mental states such as beliefs and sentiments, our work in this article moves beyond mental states and into users' decisions and examines whether other users' decisions are contagious and impact how social network users make decisions to align or distance themselves from the opinions or sentiments of their influencers. We have additionally studied the effect of population heterogeneity measures such as activity level, network position, emotionality, and behavioral consistency on social alignment contagion, which has not been explored in the related literature on social alignment contagion. We find that social alignment decisions are contagious on social networks and are also influenced by population heterogeneity measures, which impact the extent of social contagion on users' social alignment. This is an important finding as it will allow researchers to expand beyond earlier findings in the literature that discuss the contagiousness of emotions and interests into the realm of users' decisions on social networks.

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