INVITED PAPER

Social Persuasion in Online and Physical Networks

This paper proposes that social persuasion will seamlessly span and use computationally and empirically rigorous methods to understand both the cyber and physical worlds.

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ABSTRACT | Social persuasion to influence the actions, beliefs, and behaviors of individuals, embedded in a social network, has been widely studied. It has been applied to marketing, healthcare, sustainability, political campaigns, and public policy. Traditionally, there has been a separation between physical (offline) and cyber (online) worlds. While persuasion methods in the physical world focused on strong interpersonal trust and design principles, persuasion methods in the online world were rich on data-driven analysis and algorithms. Recent trends including Internet of Things, "big data," and smartphone adoption point to the blurring divide between the cyber world and the physical world in the following ways. Fine grained data about each individual's location, situation, social ties, and actions are collected and merged from different sources. The messages for persuasion can be transmitted through both worlds at suitable times and places. The impact of persuasion on each individual is measurable. Hence, we posit that the social persuasion will soon be able to span seamlessly across these worlds and will be able to employ computationally and empirically rigorous methods to understand and intervene in both cyber and physical worlds. Several early examples indicate that this will impact the fundamental facets of persuasion including who, how, where, and when, and pave way for multiple opportunities as well as research challenges.

KEYWORDS | Cyber–physical social networks; networked intervention; persuasive computing; social persuasion

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I. INTRODUCTION

Imagine Alice, a 20-year-old senior in college, trying to quit smoking. She has not smoked in a month. On a Saturday afternoon, she goes alone to the terrace of her dorm with a cigarette and a lighter. Just as she is about to light her cigarette, her friend, Jane, from the adjacent room comes and says, "Stop! I will come with you to watch *The Hobbit* if you do not light that cigarette." Alice does not light the cigarette, and the two friends enjoy a wonderful movie together.

This was not a coincidence. Multiple events took place in the background that allowed Jane to persuade Alice to stop smoking. Alice had signed up for a program to quit smoking. The program collects information about Alice and her friends. Several pieces of information such as location, intent, friendship patterns, and recent actions were monitored. The program recognized that Alice was lonely, because her boyfriend was out of town, and she could not find someone to go watch *The Hobbit* with her. She had reported on her online social network that she is looking for company to go watch the movie. Alice did not get along with her roommate, so when her roommate came to the room, she found an excuse to go to the terrace and smoke. The risk for Alice slipping was very high, so the program recognized that it was the right moment to persuade her to not smoke. Given Alice's location and the availability of her friend, Jane, next door, Jane was the perfect candidate to persuade her. Alice's risk of smoking at the terrace and her intent to watch the movie was communicated to Jane by a mobile app message and that suggested Jane the ideal way to persuade Alice.

Stories of social persuasion like this are going to be very common in future. The persuasion here was optimized for the aspects of *who*, *how*, *when*, and *where*. With the emergence of fine-grained data about users and their social context in the physical (offline) and cyber (online) worlds, always-on sensing, and widespread accessibility of

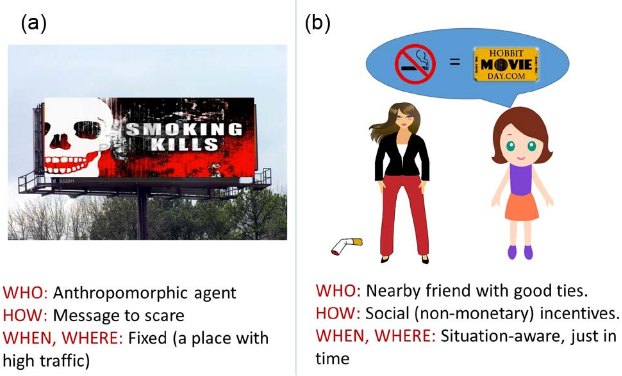

Fig. 1. ***Comparison between (a) traditional and (b) emerging persuasion strategies. Emerging strategies will frequently leverage a user's social ties and positive nonmonetary incentives, and be situation aware.***

enabling technologies, we are stepping into an era of *ex-post* optimization of social persuasion. As shown in Fig. 1, not too long ago, the mechanisms of persuasion for quitting smoking involved banners on highway that said, "Smoking kills." The message and the location were *ex-ante* optimized to persuade the largest population of smokers to not smoke. Today, due to the availability of rich personal, social, and contextual data, similar persuasion attempts can leverage social ties, employ nonmonetary incentives, and be responsive to user situations.

This is possible in large part due to the technological trends including the Internet of Things, mobile phone usage, and mediated human interaction. These trends are paving way for an era where computational systems will break the conventional silos of the physical and cyber web. People's real world movements, habits, and social connections will be accessible via the ubiquitous web, and multiple layers of "cyber" data including information hidden in webpages, databases, and online social networks will be available to apps running on each user's mobile phone. Such apps will be able to integrate heterogeneous data to understand both the spatio–temporal and social contexts, and be able to respond to human needs at the right time, right place, and in the right social context.

These trends will impact the persuasion frameworks being employed. Traditionally, the persuasion framework involving user actions, generated data, and interventions (see Fig. 2) have been siloed, i.e., focused within one realm. For example, in the cyber realm, a user's online search history was used to recommend products and the click through (if undertaken) was tracked. Soon, the computational mechanisms will be able to select the right approach for persuasion which could also be based on combination of the cyber and physical webs. For example, a user's online patterns indicating emotional needs could be intervened by real-world actions by friends and family. Taken together, these methods will allow humans to persuade each other and impact multiple facets of human lives including health, traffic, water, disaster mitigation, epidemic control, financial mechanisms, security, and politics.

In this position paper, we illustrate the emerging technological changes and discuss how they will impact social persuasion in the emerging cyber–physical social networks. We expect the technology to impact the persuasion landscape in multiple important ways: 1) merging of the silos of data; 2) persuasion mechanisms that work in an always-on and just-in-time manner; 3) scale and resolution of the data available to persuasion systems; and 4) the emergence of closed-loop persuasion systems. While such technologies and corresponding methods will impact societies in multiple ways, we scope the discussion here on persuading users individually (rather than *en mass*) via intervention mechanisms that optimize for the essential aspects of who (social), when, where (situational), and how (channel).

The focus of this paper is different from automated intervention mechanisms (alerts, automated reminders) that do not have any other human in the loop. This is because, first, human actors are known to be much more persuasive than anthromorphized agents. Even more importantly, humans can act as a "sounding board" for the advice generated by automated means. Multiple aspects of intervention (ethical, social, and also verificational) are best judged by a fellow human than an entirely automated process. For example, in the smoking scenario, Jane could act as a social filter who could first do a "sanity check" to ensure that Alice might indeed be at risk, and second, consider that watching a movie together is an appropriate and ethically sound method for intervention. Hence, while automated systems will increasingly provide better recommendations, a human in the loop would still be crucial to their impact in real-world social settings. Similarly, a human-in-the-loop intervention is different from changes made by system designers, who are aware of the global network structure, and can manipulate the network structure or the information content without the users realizing it. Such scenarios raise ethical questions, as was seen in the recent response to [18]. This paper instead focuses on scenarios in which there is an explicit action by a human in the loop to persuade his or her peers.

II. CURRENT APPROACHES

There are multiple tools and approaches that are already being applied at large scales in both cyber and physical social networks.

In physical social networks, the importance of social proof and trust has been well documented. For example, Golembiewski and McConkie [12] have argued the case for the importance of trust in mediating social processes. Similarly, Brown and Reingen [5] have reported quantitative

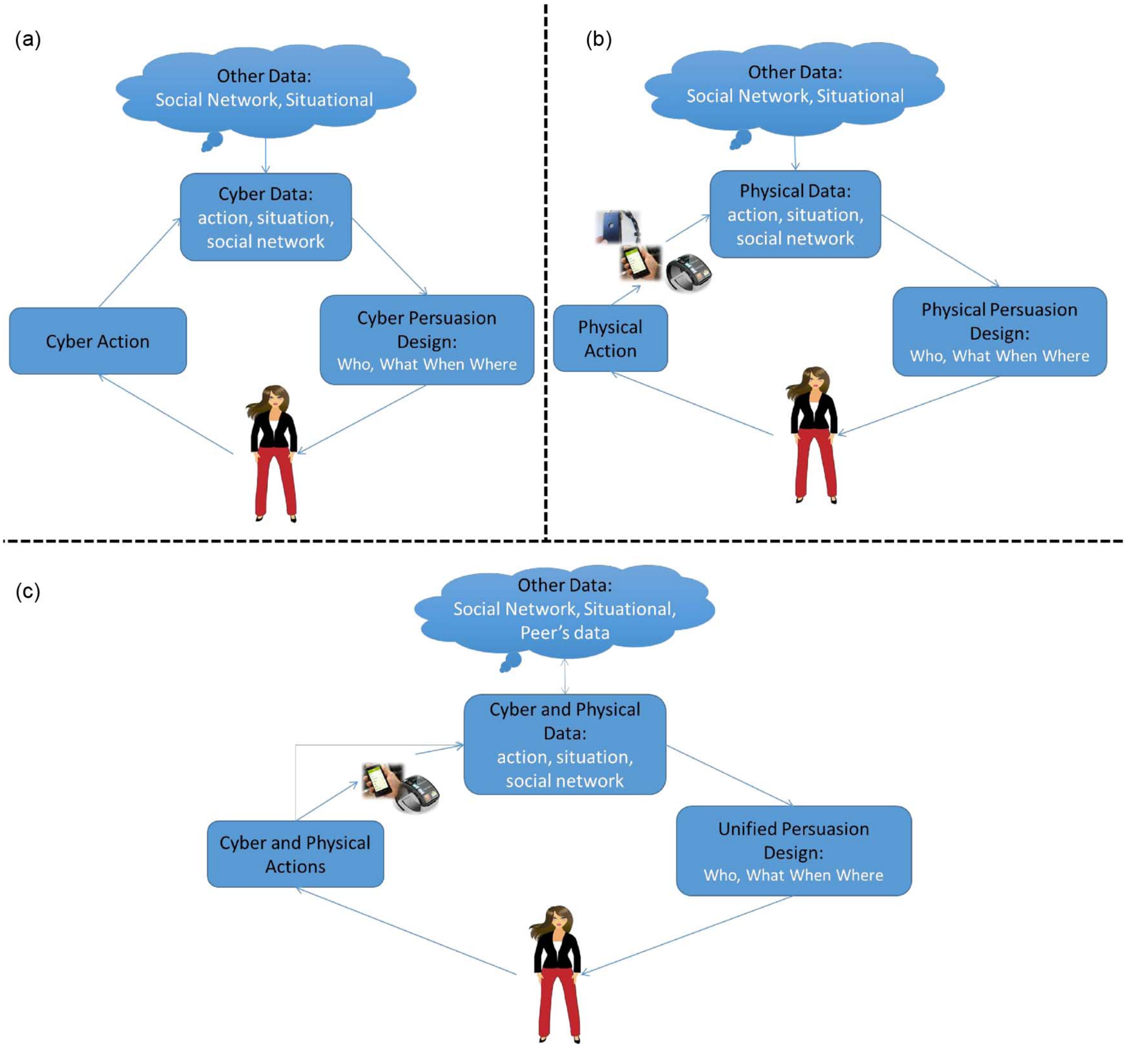

Fig. 2. ***Conventionally, the persuasion scenarios involving user actions, generated data, and persuasion design have focused only on one realm: (a) cyber, or (b) physical. Emerging persuasion scenarios (c) will be able to combine and move seamlessly across the cyber and physical worlds for understanding the actions, capturing the data, and intervening.***

results highlighting the value of word of mouth for marketing campaigns. In the last decade, multiple government and nongovernment agencies have been providing comparison metrics to other users to convince users to regulate their consumption of electricity, water, food, and other sustainability-driven choices. For example, in a study involving more that 80 000 households, Alcott [3] found that social comparison was an effective method for reducing the energy consumption of households.

In cyber social networks (e.g., Twitter and Facebook), users' comments and views on products, brands, and issues are already being viewed as electronic words of mouth [15]. These word-of-mouth impressions can persuade others to adopt or reject certain products or services [13]. Multiple advertising campaigns highlight the users in one's online social network (e.g., Facebook and Google+) who have also bought the same product, consumed the same media content, or taken similar ideological positions. Taken together, the data relating to every "like," "poke," tweets, search history, articles read, media consumed, and messages shared are being analyzed by online firms using data-driven techniques (network analysis, user profiling, influence analysis, contagion and homophily effects, associative rule mining) to recommend products and services to users based on the behavior of other users. For example, the collaborative filtering [21] approach, which recommends products to users based on the ratings provided by "similar" users has been widely adopted by online firms to recommend products and services to users.

Traditionally, while the offline networks have involved a much stronger sense of trust, human intelligence, and real-world context, the online settings have had a richer access to data, algorithms, and analytics. The emergence of "big data," Internet of Things, and similar advancements is changing this scenario. Computing technologies are now able to understand detailed human behavior in physical-world settings. With the right permissions, it is now possible to capture every gaze, interest, and heartbeat of any given user. With mobile phones becoming the key enablers, it is possible to use computational mechanisms and data-driven approaches originally defined for "cyber" networks to now work with physical behavioral data.

III. TECHNOLOGY CHANGES

The Internet of Things has been a huge driver for the merging of the cyber and physical webs. According to Acatec, the German Academy of Technical Sciences, over 98% of microprocessors today are embedded in everyday objects and devices [1]. Similarly, it is estimated that today there are more than 12 billion Internet-enabled devices [8], and more active phone connections than the population of the world. According to Walker Sands (Chicago, IL, USA), over 28% of the Internet traffic requests come from mobile devices [26]. A unique property of these mobile phones is that any data coming from them are inherently spatio–temporal [exact Global Positioning System (GPS) or coarse cell tower and timestamps]. All of these are part of a growing trend. The International Data Corporation (IDC) reported that the number of smartphones sold was already more than the number of "nonsmart" phones in 2013 [14]. This means that devices, which can capture human movements (GPS), face-to-face interactions (via Bluetooth, infra-red, GPS), and call/SMS social networks as they occur in the physical world are soon going to be ubiquitous.

These trends impact the technology in multiple important ways.

1) *Merging silos of data:* While the traditional methods for data-driven persuasion focused on only one type of data (either cyber or physical) in a single format, multiple emerging technologies are enabling combination of these data for a more holistic understanding of the user situation. These technologies include the semantic web, information fusion, federated databases, and mashups, and are being applied for applications ranging from healthcare, to travel, and politics. For example, Pongpaichet *et al.* [25] describe a method for integration of user's personal context with distributed spatio–temporal data to create the right interventions for allergy patients.
2) *Always on, just in time:* While traditional persuasion strategies were employed in limited spatial and temporal bounds, today's computational systems are always on. Apps running on the mobile phone are with the person 24/7, wherever he/she goes. This allows the intervention mechanisms to respond just in time to undertake preventive measures and allow for *ex-post* optimized persuasion.
3) *Scale and resolution:* The emerging trends on "big data" imply that computational systems have access to information at scales and resolution levels that were never captured before. For example, today every gaze, glance, heartbeat, emotion, movement, financial activity, and social activity of a person can be digitally captured and shared with the community if the person chooses so. This implies that systems can be personalized in ways not possible before. Similarly, satellite imagery, Internet-of-Things-based devices, sensor networks, and projects such as the Planetary Pulse are channeling data coming from more parts of planet Earth in more detail than ever before to users and their mobile applications. This, in effect, allows user applications to have access to the pulse of the planet and the actions of the society [11] while taking every action.
4) *Closed-loop systems:* Siloed persuasion strategies were often open loop. For example, it was very hard for online smoking cessation campaigns to follow through and observe the physical actions of the users. Even within the physical realm it was impractical for persuaders (e.g., smoking awareness volunteers) to observe the actions of their subjects. The newer technologies are allowing for the impact of persuasion strategies to be observed in a closed loop. Over time these systems will identify which strategies work best in different scenarios.

These technology changes are also allowing scientists to study social persuasion at newer scales and granularity, and cause *in situ* interventions by combining multiple layers of data. Multiple early initiatives have already started building tools, algorithms, and techniques that employ smart devices to understand and influence cyber–physical social networks.

For example, the "Friends and Family" study conducted at the Media Lab, Massachusetts Institute of Technology (MIT, Cambridge, MA, USA), studied a community of 100+ users living in a residential dorm for a period of over a year [2]. They obtained face-to-face interaction data, Facebook interaction data, as well as self-reported social ties via surveys. In multiple studies, they have shown how face-to-face and other types of networks can be combined to predict flu spread, spending patterns, mobile app adoption, and to encourage users to undertake certain actions such as jogging [2], [22], [28]. A related effort is combining layers of data ranging from Twitter streams and air quality levels to personal GPS coordinates and accelerometer readings to cause just-in-time interventions [25].

Similar effort is being conducted by the University of Trento (Trento, Italy) under the umbrella of "Mobile Territorial Lab" where multiple studies are being conducted to understand user behavior in "work" as well as "personal" social environments. For example, the "Socio-Metric Badges" study analyzed social interaction data for six weeks in a research institution monitoring the interaction activity of 53 people [20]. The generated corpus allows researchers and practitioners with a digital trace data of people's physical as well as online (e-mail) social interaction behavior. With supporting information about participants' individual characteristics (e.g., personality traits) and the interaction context (e.g., participants' current situation), this study is being expanded onto a broader program where a community of 100+ users is being studied in terms of their spending habits and affect levels.

The Copenhagen Networks Study at the Technical University of Denmark (Lyngby, Denmark) [30] has been using smartphones and the associated sensors (GPS, WiFi access points, calls) as well as Facebook messages to understand a community of freshmen at the university. The NetSense project at the University of Notre Dame (Notre Dame, IN, USA) also analyzes the social interaction patterns in a community of 200 freshmen as measured through text, voice call, e-mail, Facebook posts, and the proximity between the devices. Such initiatives point to a growing interest in studying physical social networks at scale: 100+ users and multiple months, and complement it with online networks and contextual data. The "Phone lab" initiative (http://www.phone-lab.org/) at the State University of New York at Buffalo (SUNY Buffalo, Buffalo, NY, USA) provides a public Android testbed designed to simplify large-scale social experiments that can be undertaken via smartphones. Initiatives like these may soon make experimentation and analyses in physical social networks accessible to a much larger pool of researchers and practitioners.

IV. IMPACT ON PERSUASION

These technology changes are blurring the boundaries between online and offline (or cyber and physical) social networks. We expect many of the computationally rigorous methods that were originally designed for the cyber data to evolve to consider the rich contextual data provided by the physical sensors. Specifically looking back at the four key aspects identified in Section I, we expect the systems to be able to understand the who, how, when, and where aspects in much greater detail than possible before.

A. Who

Multiple studies have suggested that identifying the right node for conveying a message is extremely important for successful persuasion [6], [32]. People respond to persuasion by close friends and family as opposed to strangers, and persuasion by people with authority [6], [24]. Our earlier work has also shown that close friends could be very persuasive [2], [22]. Segmentation-based approaches are used to spread messages to a group of similar people, for example, those who share a common passion for rock music or certain sports, or political ideologies. Induction tries to activate newer connections between users where certain thought leaders, celebrities, or early adopters are encouraged to communicate the message and persuade people. This effect is seen also in social media: celebrities are often paid to tweet about products and multiple firms try to make their campaigns go "viral." Last, alteration of networks to change the underlying interconnections is an emerging but extremely powerful mechanism for behavior change. For example, Aharony *et al.* [2] experimented with a social mechanism, described in [23], where the peers of the target users were rewarded rather than the target users themselves. This strategy was found to be more effective at persuading users to exercise than the traditional approach of paying the users themselves. Our previous work has also shown that emerging technologies (smartphones with physical proximity sensors) and computational approaches can also be used to automatically recognize close and trusted ties. In fact, these trusted ties were found to be even more effective at causing behavior change than the close ties [27].

Peer influence for persuasion is more pronounced for products and services with network externalities like phone communication plans and adoption of online social networks such as Facebook. However, the earlier choice of choosing peers and celebrities was *ex-ante* optimized for an assumed distribution about the population without detailed information about peer relationships and individual likings for celebrities.

We have also presented the theoretical underpinnings of this phenomenon. Our results on the joint model of externalities and peer pressure show that even after considering the (positive and negative) changes in the relationship between the two agents in a persuasion scenario, using right peers to persuade can help control global externalities much more efficiently than direct persuasion through subsidies [23]. For example, in the described smoking scenario, there is a cost associated with Jane's persuasion, and it may impact the relationship between the two both positively or negatively. Our model in [23] indicates that using right peers to persuade is more efficient than direct persuasion through subsidies.

Going forward, the systems with an ability to merge data across silos at high scale and resolution in real time will be able to identify the right person to initiate the intervention. Further, the information about these interventions and the success/failure of them in terms of actual user actions could be tracked to refine the social ties as well as strategy scores. Over time, these may allow systems to adapt and also point out relevant trends on the success and failure of various persuasion strategies.

B. How

An important change that technology brings is that there is increased and accurate information about intent and preferences of the individuals needed to be persuaded. In the example, Alice was actually lonely and was going to smoke. The standard pricing mechanisms that would pay Alice a little money to not smoke would not have had a big impact. However, a company to watch her favorite movie was a big incentive for her, worth a lot more than a little amount of money. Persuasion theories have utilized several ways to persuade, such as using force, appealing to reason, appealing to emotion, coercion, and deception [6]. The use of force is considered the failure of persuasion [33]. Public policies such as taxation and subsidies are often designed to appeal to reason, while advertising is often appealing to emotion, coercion, and sometimes deception.

Our earlier work has argued a case for the leveraging the difference between "incurred cost" and "perceived value," especially in nonmonetary transactions [29]. For example, better game armor, "mayor" status, and higher download bandwidth typically cost much less to the enabling platform than their perceived value by the user. Similarly, social incentives can be a lot more effective than purely monetary incentives. In our previous work [23], we found that peer persuasion via payments to friends was 3.5 times more effective at causing behavior change than direct payment to users. In fact, we have also found that passive social persuasion can already be effective in multiple application settings. For example, a previous study in the group on Meeting Mediator—a mobile system that detects social interactions and provides real-time feedback to enhance group collaboration and performance—showed that visualizing the social interaction pattern data in real time on the mobile phone of each user could induce changes in group collaboration patterns [17]. In particular, the results show greater productivity and trust within geographically separated groups that are using the Meeting Mediator. A different study conducted by Balaam *et al.* [4] used a multiuser public display to enhance the interactional synchrony by visualizing subtle feedback about users' behavior. Their results suggest that social dynamics can be used by machines to support group behavior without requiring a direct and exclusive interaction with the users.

Since one technique often does not fit all people, the emerging trends of fine-grained information about individual preferences can help not just identify the optimal method but also what will appeal to the individual the most and how to persuade can be *ex-post* optimized as well. The merging of online and offline worlds also creates possibilities to provide incentives to people in the physical world for actions in online worlds. Often people are given discount coupons to restaurants for taking an online survey. Several such possibilities are being increasingly made possible by the virtual currencies such as bitcoin.

C. When and Where

An understanding of the user situation allows the system to intervene at the most opportune time and place. For example, the intervention by Jane in the example in Section I at the "right" time and place was critical to its success. The relationship between time and place gives a good estimate of point of action, and persuasion is very effective at the point of taking action. The timing of the intervention has been identified to be a critical determinant of success in Fogg's behavioral persuasion model [9], and similar results have been reported in practical intervention studies in interpersonal settings [34]. The timing and the location are important aspects for the success of geofencing-based approaches for marketing and advertisements. Users are more likely to be interested in discount coupons or physically be able to attend shows and concerts when they are in the vicinity to these establishments. Pushing upgrades, up-sells, and checkout-counter purchases have been well documented in terms of their effect on purchase behavior. These approaches also connect very well with the "bait-and-switch" or the "commitment-and-consistency" principle proposed by Cialdini [6].

Some of our recent work has focused on providing users the right situational interventions just when and where they need them. For example, Pongpaichet *et al.* [25] define a generic approach for users to receive allergy/asthma related alerts just as the combination of their personal and spatio–temporal parameters matches certain criteria. The approach of intervening at the right time and place has also been adopted by multiple other efforts. For example, multiple studies have shown that the placement and display of water meters right when one is taking the shower can be a lot more effective than posteffect awareness [16], [31].

The emerging always-on technologies that are able to cause the right "situational intervention" at the right time will allow future systems to monitor and maybe even predict the right time to initiate an intervention. In fact, Google "Now" is providing anticipatory methods to send alerts to users about things that maybe of interest to them in the near future. For example, if a person has already booked and paid for a hunting trip, it will be difficult to convince her to not go for the trip as she is leaving her home. However, if the peer of a person was available to persuade the person (online or in person) at the time of purchase of the trip, then the persuasion will be more effective. The technological changes will also help identify such persuasion opportunities and make such persuasions possible.

V. RESEARCH OPPORTUNITIES

The intersection of the online and offline social networks creates multiple novel opportunities to devise tools, techniques, and algorithms that connect varied information and persuasion channels across these networks. While many of the existing research directions will need to be reexamined and refined to support for this intersection, certain newer challenges will become exceedingly relevant.

1) *Privacy and ethics:* While privacy and ethics of persuasion were already important concerns in the online networks, the emergence of technology that captures rich personal behavioral (every heartbeat, gaze, interest, mobility pattern) and social interaction (face-to-face interaction, calls, sms, colocation) data and uses them for *in situ* persuasion opens doors to a very different level of ethical and privacy concerns. While users are presumably able to adopt newer cyber identities, physical identities and health parameters once compromised cannot be restored. Hence, the recording and analysis of physical data at the same level of discourse as online data poses multiple privacy risks and hence research challenges. One possible approach to tackle this might lie in creating trusted "personal data stores" [7] that allow for question-and-answer approaches that support such persuasion frameworks without giving away raw data to third parties. Further, a technological ability to persuade does not imply that persuasion should actually be carried out. For example, while many people might support sharing of such information for well-accepted societal goals (e.g., to eradicate behavioral diseases like diabetes, or trigger early interventions to avoid traffic accidents), a much more nuanced discussion is required on the right policies for recommending newer products and commercial services. Clearly, newer research efforts are needed to define the right norms and policies that govern the use of persuasion in cyber–physical social settings. In fact, we anticipate that the same kind of computational mechanisms that have been employed for better "product" recommendations will be adapted to provide "privacy" recommendations to a large number of users.
2) *Orchestration and tradeoffs between cyber and physical persuasion:* So far, the persuasion approaches have stayed within their respective realms (online or physical). Soon the merging of the realms will open up interesting tradeoff and coordination challenges. For example, how many online signatures on an issue at Change.org are as effective as ten people physically protesting about the same issue? Similarly, if both online and physical methods are available for persuasion, which method should be used for which tasks? For example, certain sensitive or health-related campaigns might work best in semianonymized settings, while others will benefit from the trusted ties between users. Further, if certain campaigns require a combination of online and physical intervention, what should be their count and order? While early studies such as [10] have started exploring these issues, many more such efforts are needed.
3) *Living labs for social science:* The emergence of platforms for cyber–physical mining of social behavior and interventions opens the doors to an exciting opportunity to test, validate, and refine multiple social science theories. Multiple social science theories have been based on experiments conducted in limited laboratory settings and self-reported surveys. These approaches were costly, piecemeal, retrospective, and often suffered from perception bias. Hence, an ability to conduct longitudinal studies on social behavior as human beings live their natural lives is emerging as a vital tool for computational social scientists [19]. Further, the opportunity to cause interventions and make changes in these longitudinal studies may allow social scientists to differentiate between correlations and causations and develop normative social science that can potentially improve the quality of human life. ■

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