Human social sensing is an untapped resource for computational social science

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The ability to 'sense' the social environment and thereby to understand the thoughts and actions of others allows humans to fit into their social worlds, communicate and cooperate, and learn from others' experiences. Here we argue that, through the lens of computational social science, this ability can be used to advance research into human sociality. When strategically selected to represent a specific population of interest, human social sensors can help to describe and predict societal trends. In addition, their reports of how they experience their social worlds can help to build models of social dynamics that are constrained by the empirical reality of human social systems.

Much of human sociality depends on people's ability to perceive and make inferences about what others think and do[1]. Human social sensing has been studied in separate strands of research within psychology and sociology. However, its potential to advance social science has not been fully realized. In this Perspective, we show that human social sensors—individuals who are strategically selected and asked about subjective representations of their immediate social environments—can help to describe and predict political and health-related societal trends[2–10] as well as to advance theoretical and practical understanding of human sociality[11–13].

Psychologists have long studied how individuals represent and are influenced by their social environments[14]. However, they have rarely used people's knowledge about their social environments as a measurement device to learn more about beliefs and behaviours in society. A primary reason for this reluctance is the notion that human social cognition is fraught with biases[15]. Examples are false consensus, when individuals who support a particular view believe that this view is more common than non-supporters believe[16], and self-enhancement, in which people overestimate their performance relative to others'[17]. By contrast, sociologists have developed sociometric techniques to collect people's subjective reports about the structure of their social networks[18] and have used them to learn more about society through better sampling of different populations[19,20], deriving better estimates of their size[21], and investigating how networks affect the spread of beliefs and behaviours[22,23]. However, sociologists have typically not collected people's subjective representations of what their social contacts believe or do, or data on the cognitive processes that underlie social influence (but see ref. [24]).

Two key developments pioneered by computational social science can bridge this gap between psychology and sociology. The first is the continuously increasing amount of data about human social networks, derived from the multitude of digital and other traces of people's connections on social media, by phone, or in person[25–28]. Such data enable a better understanding of how human social cognition interacts with social environments and how apparent cognitive biases can be a product of an unbiased mind accurately perceiving biased samples from its social environment[29–31]. The second is the development of computational models of human social dynamics that aim to recreate different patterns of belief and behavioural change and to better understand social systems[32–37]. These models produce quantitative predictions of societal trends and provide important insights about events and interventions that could steer social systems in different directions[38–40]. These models can be fruitfully combined with information from human social sensors to enable better understanding of the cognitive mechanisms that underlie social dynamics[11,41,42] (Fig. 1).

As we describe next, these developments in computational social science open doors to the use of human social sensing for better description and prediction, as well as to models of social dynamics that are empirically grounded in human social cognition.

Describing and predicting social dynamics

Even though social scientists have never had access to as much data as today, many social phenomena are still hard to understand, including voting behaviour, civil unrest, vaccine hesitancy and epidemic spread. How can we capture early signals of emerging trends within standard research budgets and time frames? And how can we collect data while respecting the privacy of individuals who may not want to reveal their own beliefs? Social phenomena can be difficult to anticipate not only in light of the inherent limits of predicting complex societal systems, but also because important parts of the society are hard to reach or are intentionally hidden[43,44] (Fig. 1a). Some important social phenomena happen so fast and unexpectedly that researchers do not have enough time to collect data from sufficiently large samples. Indirect measures of social worlds, such as traces of people's activity on various social media platforms, are valuable[45] but cannot fully compensate for these information deficits. The relevant traces are often unavailable to researchers or are prohibitively costly[46]. Many people do not use these

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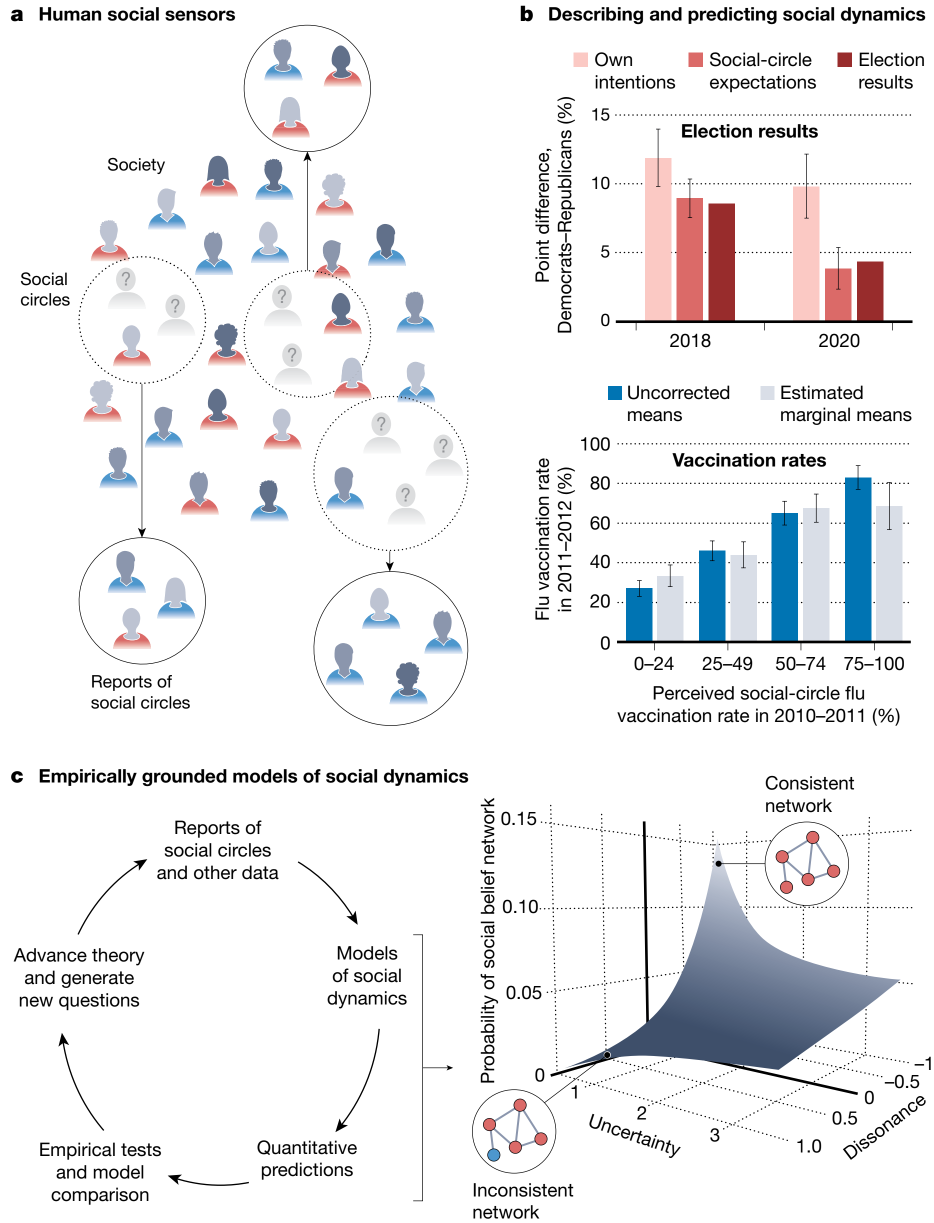

Fig. 1 | Human social sensing as a resource for computational social science. **a**, Human social sensors can provide useful information when asked directly about beliefs and behaviours in their immediate social circles. They can provide information about parts of the society that can be otherwise difficult to reach (question marks). **b**, When human social sensors are selected to be representative of a population of interest, their subjective reports about their immediate social environments (social circles) can help to describe and predict real-world social phenomena. Top, the 2018 and 2020 US elections were predicted better by social-circle expectations than by traditional polling questions about own intentions[3]. Bottom, flu vaccination behaviour is related to perceived vaccination in social circles as reported in the year before (blue bars) even after accounting for own vaccination behaviour reported in the year before and sociodemographic characteristics (grey bars show the estimated marginal means)[5]. Error bars are standard errors. **c**, Reports from human social sensors and other empirical data can inform models of social dynamics, which can be used to make quantitative predictions. For example, computational models inspired by statistical physics can be used to predict belief change[12,13]. As shown on the right, social beliefs reported by human social sensors can be represented as networks. Consistent networks (here shown as networks in which all nodes agree) are associated with lower levels of cognitive dissonance (or energy in statistical physics' terms) and therefore have a higher probability than less consistent networks, especially when their overall uncertainty (temperature) is low. By testing and comparing different models, we can generate theoretical insights about social systems and derive new, empirically testable research questions.

technologies, and those who do might intentionally modify their digital traces for fear of social costs[47].

As we describe next, human social sensors can provide useful reports about the beliefs and behaviours of other people around them, despite apparent cognitive biases in human social cognition and social network biases. Studies that rely on human social sensors can resolve some ethical concerns with collecting social data, and can be conducted economically using standard research tools such as surveys.

In one line of studies with human social sensors, people have been asked to report about properties of their immediate social environments—their social circles. For example, participants in election polls were asked what percentage of their family, friends, and

Box 1

Accuracy of social sensing

People have a plethora of neurocognitive capacities that facilitate perception of and inferences about the observable properties of their social worlds and the mental states of others[178,179]. These capacities are based on cognitive and affective processes that have been identified in research on theory of mind and empathy[178,180] as well as on more general processes of memory, categorization, and learning[181]. These capacities allow people to make quick inferences about the personality traits[182] and behavioural tendencies of others[183], and to predict and reason about other people's choices[184]. People can encode frequencies of distinct events with ease[185] and can report back these frequencies using different cognitive strategies[186]. They are also able to learn complex network structures of relationships, both nonsocial and social[187].

There are several distinct lines of research on the accuracy of human social judgements, scattered among cognitive science, social psychology, sociology, and anthropology. One line investigates the accuracy of judgements about individual social contacts. This line of research shows that friends can accurately judge one another's characteristics, although there is also evidence for projection of one's own characteristics to others[188,189]. This 'ego projection' can be rational, as in many social environments one is right to assume that most others are similar to oneself[190] and this assumption can produce accurate estimates about other individuals[159].

Another line of research investigates the accuracy of judgements of group properties; in particular, the relative frequencies of different characteristics in a group. Conclusions about accuracy depend on the population about which people are asked. Some studies ask about the percentage of individuals with particular characteristics in people's immediate social circles, with which they have direct experience. The averages of estimated frequency distributions in people's social circles tend to follow closely the actual population distributions[191] and are predictive of independently measured population trends[4,5]. On the other hand, when people are asked to estimate distributions in broader populations, with which they do not have direct experience, they show some systematic biases[192]. These biases are likely to occur because people must make inferences about these broader populations based on their own limited social circles and sometimes on inaccurate information from the media and other public sources[3,9].

A third line of research studies the accuracy of people's judgements about the frequency of interaction and the resulting structure of their social networks. In a prominent series of papers, Bernard and Killworth[193,194] voiced strong concerns about people's ability to report who they interacted with in a specific time period. However, while such reports are less accurate about interactions at specific time periods, they correspond to long-term patterns of interactions[195]. In other words, people appear to have a correct overall impression about the average frequency of interaction with others. This echoes results from studies of how people answer frequency questions in surveys[196], showing that estimates of 'typical frequencies' are more valid than estimates of frequencies in a specific time period. Further research suggests that the number of friends one has might be more accurately estimated by aggregating nominations one gets from others, rather than asking oneself directly[197]. This line of research also shows that people have a reasonably good idea of the overall structure of their social networks and know who in their network could spread a piece of information quickly[198].

In summary, people seem to have a good grasp of the relative frequency distributions of different properties of their immediate social circles, and they have a good overall impression of how often they interact with different social contacts in the long run. They are less accurate when asked about a specific individual or time period, or about populations with which they do not have direct experience. These findings can inform studies that rely on human social sensors to obtain valid social information.

acquaintances would vote for different candidates. These social-circle questions improved predictions compared to traditional polling questions about participants' own voting intentions in three recent US elections[2,3] (Fig. 1b) as well as in three recent elections in European countries with larger numbers of political options (France[2], the Netherlands and Sweden[4]). Social-circle questions were also useful in predicting participant's own behaviours. For example, people's reports about the flu vaccination behaviour of their social contacts predicted their own vaccination likelihood a year later, beyond their own past vaccination behaviour and sociodemographics[5] (Fig. 1b). These results suggest that human social sensors can help to derive more accurate descriptions and predictions of current and emerging societal trends. One likely reason for this gain in accuracy is that reports about people's friends indirectly improve the representativeness of the survey sample, allowing researchers to gain more information about the overall population[3,48]. People also might be more willing to report socially undesirable characteristics of their social contacts than of themselves[49]. In addition, people's estimates of their social circles today can provide hints about how they themselves will change in the future due to social contagion, which improves predictions[2,5,6].

Another line of studies has shown that people can also provide useful reports about broader populations[50–53]. In election polls, these judgements can anticipate election results[7,54,55], and prediction markets have been successful in predicting future events across a variety of fields, including business[56], medicine[57], politics[8], and sports[58]. People's reports about broader populations might be largely based on what they know about their immediate social environments[3,9], but they also include information from other sources such as the media, experts, and general education. Human social sensing of both immediate and broader populations can therefore be usefully combined. The theoretical challenge here is to determine how much weight to give to each of these types of social sensing data. A recent method called Bayesian bootstrapping[3] offers a theoretical solution to the integration problem, and has been used for US election polls in 2018 and 2020 to produce forecasts that combine participants' own voting intentions, their social-circle reports and their predictions of the overall election outcome. The accuracy of these election forecasts surpassed those based on any one type of question alone.

These demonstrations of the usefulness of human social sensors are in line with studies showing the well-developed human capacities for social sensing (Box 1), but appear to contradict decades of research in social psychology that produced a long list of cognitive biases in social judgment[15,59]. However, these seemingly contradictory findings can be reconciled by considering the statistical properties of social environments in which human cognition operates[60–67], which are often ignored in the studies that show cognitive biases. For instance, the

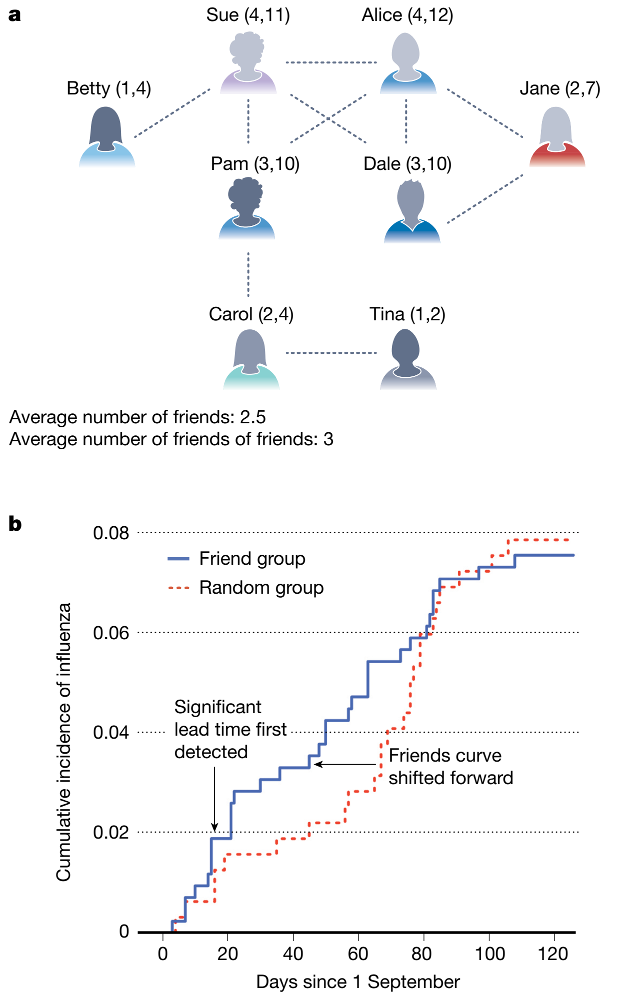

Fig. 2 | Friendship paradox. a, This example from Feld[74] shows a friendship network among a group of high-school students. The number of friends and the number of friends of friends for each student are shown in parentheses. The eight students in the figure have a total of 20 friends. Adding up each student's friends yields 60 friends of friends. This means that the students have an average of 2.5 friends each and that their 20 friends have an average of 3.0 friends each. This occurs because the students with many friends (for example, Sue and Alice) are the friends of many of the other students. That people's friends on average have more friends than people themselves have is inevitable in any network where there is any variation in the number of friends (their degree). **b**, This network bias can be useful for describing and predicting social phenomena. For example, surveying the friends of initially selected participants helped to identify an early outbreak of an epidemic. Reproduced with permission from ref. [6].

degree to which people are surrounded by similar others (homophily)[68], together with basic memory processes, can explain[30,69] whether people's judgements of broader populations show false consensus[16] or its opposite, a well-documented false uniqueness bias[70]. And, depending on the shape of the true frequency distribution of a particular belief or behaviour, people's estimates of the overall population will appear to be biased towards self-enhancement[17] (when the true distribution is skewed left so most people perform well), towards the opposite bias of self-depreciation[71] (when the true distribution is skewed right so most people perform poorly), or in both directions (when the true distribution is symmetrical)[69]. A parsimonious explanation for these effects is that the apparent biases result from an unbiased mind that accurately perceives a biased social world. By contrast, relying on the assumption of a biased mind while ignoring the social world requires a different explanation for each observed bias. For example, self-enhancement bias has been explained by inadequate metacognitive skills but self-depreciation bias observed in the same studies by false consensus bias[72], although both biases can be explained by the same basic memory process operating in a social environment characterized by some homophily and a symmetric distribution of the target characteristic[69]. The fact that apparent cognitive biases might stem from biased samples rather than faulty social cognition means that people's reports about their social environments can contain useful information about the social reality.

When using human social sensing methods, one still needs to be aware of some persistent social network biases that are likely to occur even in the absence of cognitive biases. One such social network bias is homophily bias—people tend to have social circles that are similar to them[68], so their reports about the beliefs and behaviours of their social contacts will often resemble their own. This does not mean that these reports do not contain useful information beyond individuals' own beliefs and behaviours. People frequently report that many of their social contacts are not like them[69], and their reports include useful information about diverse segments of the population[3]. The homophily bias, however, has an important implication for studies with human social sensors: if the goal is to use their reports to describe a broader population, then sensors need to be a representative sample from that population, allowing homophily biases in social-circle reports to cancel out on average. That said, the homophily bias can also be useful to researchers interested in specific (sub)populations: some sampling techniques[19,20] rely on homophily to reach samples of small, geographically dispersed, and/or stigmatized populations, such as unhoused people or undocumented immigrants[73].

Another social network bias that is important to consider when using human social sensing is the friendship paradox—the phenomenon that one's friends, on average, always have more friends than oneself[74] (Fig. 2). This occurs because people with more friends will be more likely to occur in one's friend group, and consequently people's reports about their social circles will inevitably over-represent individuals with many friends[29]. Depending on the correlation of the characteristic of interest with the number of friends one has, as well as the number of friends one's friends have, asking people about their social circles can yield biased population estimates. Characteristics that have a positive correlation with the degree in the social network are likely to be overestimated, while those that have a negative correlation with the degree are likely to be underestimated.

However, the friendship paradox is not necessarily detrimental to the usefulness of human social sensors. For many societal trends, from the spread of disease to the spread of misinformation, individuals with more social connections might be a more useful early indicator than an average individual in the population. They might be driving the trends in beliefs, fashions or voting intentions and can therefore serve as 'early warning signals' for later trends. Furthermore, better connected people are often more likely to be 'infected' with a characteristic of interest, such as a contagious disease or misinformation. Identifying those people can help with managing the spread of epidemics and choosing the best-positioned human social sensors[6,48,75,76], as well as in implementing public health interventions[77].

Using human social sensors to describe and predict social phenomena can alleviate some ethical concerns related to asking about sensitive issues. Human social sensors know that they are participating in a research study, unlike in some applications of 'mechanical social sensors' where people might not be aware that their data are used for research purposes[78]. In addition, human social sensors do not need to reveal the identity of their specific social contacts. They can provide useful information about the relative frequency of a particular characteristic in their social circles (for example, defined as adults they were in contact with within a specified time period) without revealing information about any particular individual. This gives researchers the opportunity to obtain some indication of the characteristics of hidden populations, while protecting their privacy.

Empirically grounded models

To understand why in certain societies new beliefs—such as opinions on climate change or vaccines—spread more quickly or polarization rather than consensus emerges, and to turn these insights into predictions, researchers have developed a number of analytic and computational models of social dynamics, in particular of belief dynamics and collective behaviour[11,30,32–42,79–85].

Most models assume that these processes occur on a social network, reflecting the fact that much of human thought and action happens in the context of interaction with other people[86]. Computational social science has contributed a large amount of data on the structure of social environments[25–28], but most models of social dynamics still do not incorporate plausible psychological components, such as how people actually experience and interact with their social networks. This can reduce the ability of these models to help with understanding and predicting real-world patterns of belief dynamics and collective behaviour[87,88]. It has long been recognized that human ability to adapt to an ever-changing social world is shaped by both the structure of social environments and cognitive processes[89]. What eventually matters for explaining how social environments affect beliefs and behaviours is how these environments are subjectively represented in individual minds. The nature of subjective representation has been a subject of great interest to sociologists from classical works[90,91] to recent times[92,93].

Subjective representations of social networks, as reported by human social sensors, can be used to enhance the descriptive validity and predictive power of models of social dynamics. This grounding in knowledge about human social cognition is important because these representations, unlike indirect 'objective' measures of social environments[94], depend on what people attend to at the moment, their past experiences, and their overall social context[95]. Different people can experience the same social network structures differently, depending on how much they like their social contacts[96], how interdependent they are[97], and whether they perceive others as members of their group or as outsiders[98].

In turn, researchers can use these empirically grounded computational models to understand how the same subjective representations of social networks can influence people's beliefs and behaviours in different ways, depending on the strategies people use to integrate their social considerations. Models that combine human social sensing with behavioural data from experiments and the real world can implement and compare different plausible integration strategies[99–104], from heuristics such as random choice and averaging[88,105,106], majority rule[107,108], and non-compensatory strategies such as following an 'expert'[109,110], to more general normative mechanisms that provide explanations at a different level[111,112], such as Bayesian learning[113–115] and logic[116]. Such computational implementations and comparison of plausible integration strategies would enable researchers to compare different models and establish minimal models that can still reproduce main empirical patterns.

One useful framework for developing and comparing computational models that can incorporate plausible psychological mechanisms is statistical physics[11,36,41,79,87,88,110,117–123]. Statistical physics models of social dynamics can reproduce a variety of empirically observed patterns of belief spread using only a few components, showing that models of complex systems do not by themselves need to be complicated. Traditionally, the field of statistical physics studies the collective behaviour of interacting building blocks of a system, typically atoms or their components, by introducing a function that maps a microstate of the system (that is, a description of the state of every microscopic constituent) onto a single number (for example, the energy in a physical system). That is, statistical physics analyses directly connect microscopic and macroscopic descriptions of the same system by using a function that maps many microscopic variables onto a single macroscopic variable that characterizes an important (and in physics, directly measurable) feature of the current state of the system. Using this collective variable, the statistical physics analyses then assign probabilities to each of these microstates that can be updated according to dynamical rules in an evolving system.

While people are far more complex, dynamically evolving social behaviours in large populations tend to obey statistical patterns that are amenable to mathematical modelling of their micro- and macrostates. With advances in computational social science and human social sensing, models of social dynamics inspired by statistical physics can be empirically grounded in people's social cognition and networks as measured in surveys and experiments, through analysis of social media, or from other digital footprints[124]. While the details of any social system certainly do not show one-to-one mapping to analogous physical systems[110], the main premise of minimizing energy in physics corresponds to the idea prevalent in social sciences that many choices can be modelled as minimization of dissonance or maximization of utility[125]. Statistical physics models can incorporate psychological concepts such as cognitive dissonance[126] (energy), uncertainty or lack of attention (temperature), subjective representations of networks (linkages), and belief integration strategies (updating rules)[110,121,127]. The statistical physics framework can be used to implement and compare many different models that have so far been studied independently and without empirical testing[11].

In a recent example, van der Does et al.[12] used a computational model developed within a statistical physics framework and grounded in human social sensor data to investigate how different educational interventions affect the cognitive dissonance that stems from inconsistent social and moral beliefs. This analysis helped to uncover how people integrate these considerations, as well as conditions under which changes in dissonance due to interventions lead to belief change. In another example, Dalege and van der Does[13] used a network theory of individual attitudes inspired by statistical physics[121] (Fig. 1c) to investigate how dissonance in subjective social belief networks can predict changes in science-related beliefs. They asked participants in a longitudinal national survey to estimate the percentage of groups such as their family and friends, scientists, or medical doctors that believe in the relative safety of products such as genetically modified food and childhood vaccines. These quantitative reports from several survey waves were used to reconstruct participants' changing subjective social representations as networks[85]. Changes in these networks were shown to depend on their inherent dissonance.

The statistical physics framework is just one of many possible analogies that can be useful when attempting to understand and model complex social systems. Beyond the Ising and Potts models that gave rise to the examples mentioned above[119], other analogies from physics have been used to understand complex social systems, including percolation[128], diffusion[101], Monte Carlo methods[120], and quantum physics[129]. Analogies from other disciplines, including epidemiology[130,131] and evolution[105,132], have been used as well. As one of the basic tools of human thought, analogies can be very useful when trying to better understand a complex phenomenon[133]. However, it remains important to recognize the worldview, assumptions, and methodologies that are transferred along with the analogy from one system to the other, and to avoid introducing unnecessary baggage by overusing any particular analogy[134]. Empirical grounding of models based on analogies with other systems, using data from human social sensors among others, provides an important way to constrain these models and check their usefulness for describing complex social systems.

Outlook

Further research on human social sensing could investigate ways to increase its informational value, explicitly include it in models of social dynamics, and combine it with machine learning. One important research direction is further development of theoretically grounded strategies for sampling human social sensors[135], for example by taking advantage of the friendship paradox[10,48,76,136]. Research is also needed on statistical methods for deriving proper population inferences based on human social sensing data, by, for instance, building on the methodology for deriving point estimates and associations[137] from samples recruited via methods such as respondent-driven sampling[138], successive sample size estimation[139] and methods based on recruitment timing[140,141], as well as on the methodology for correction of underreporting biases[142]. It is also important to better understand to what extent the reports of human social sensors are affected by different measurement errors[143], to explore psychometric models to estimate their accuracy[144,145], and to study their reliability and performance bounds[45].

The accuracy of human social sensing can be further increased by providing truth-telling incentives with algorithms such as the Bayesian truth serum[146], peer-prediction[147], Bayesian markets[148] or choice-matching[149]. These game-theoretic algorithms do not assume that honesty can be independently checked. Instead, they leverage the fact that people with different characteristics should make different predictions of the prevalence of these characteristics in the population. For example, Bayesian truth serum incentives have been used to estimate the prevalence of questionable research practices by academic psychologists[150]. Apart from increasing informational value at the individual level, truth serum scores can also be used to assess which sensors are more accurate detectors of true population distributions[151].

Data from human social sensors can be usefully combined with existing administrative records and various digital trace data. Governments across the world are opening up administrative data sources for social science research[152,153]. The value of such data sources can be enhanced by asking human social sensors to provide the necessary context for people not covered by the records or to provide evaluations of relevant social interactions at a specific point and location in time[154]. Human social sensing can also be used to overcome frequent problems related to digital trace data, such as unknown populations of inference, missing covariates, and overall unclear measurement properties[155–158].

Computational models of belief dynamics can be further improved by explicitly incorporating social sensing processes. Rather than assuming that everyone has the same representation of the social world, different people might be more or less likely to detect others' beliefs, and beliefs about different issues might be more or less socially visible[3,159,160]. Without taking social sensing processes into account, one might inaccurately conclude that differences in the spread of beliefs stem from differences in objective social network structures, whereas in fact the differences might stem from what people perceive subjectively. While we show that social sensing is generally accurate, research on individual differences in this accuracy and differences in accuracy between topics is an important avenue for future research.

Human social sensing provides exciting opportunities for interactive machine learning, where it could inform the training data, predictions, and algorithms[161–163]. Human social sensors can detect early language signals of emerging societal trends, contained in words and phrases the meaning of which can be understood only by some parts of social networks. For example, while many algorithms exist to detect overt hate speech online[164], more subtle covert signals (including metaphors, humour and memes) can be difficult to detect. Human social sensors who can interpret these covert signals can be selected using theory-driven predictions[47]. These subgroups of human social sensors could also help to illuminate the motivations of groups using hate speech, and help to detect, understand, and counter such 'dangerous speech'[165,166].

The ability of human social sensors to pick up on societal trends could be used in hybrid human–machine forecasting systems[167–170] that combine machine forecasts with forecasts based on human social sensor data. Human social sensors can also contribute to the development of better machines and algorithms that affect all aspects of our lives[171,172]. Examples include news ranking algorithms, self-driving vehicles, algorithmic trading and pricing, online dating, and crime assessment[173].

Summary

Developments within computational social science can help to integrate research in psychology and sociology in order to enable wider use of human social sensing across all social sciences. In turn, human social sensors can help social scientists to come closer to the next frontier in the study of human social systems[174,175] and to achieve more rigorous theoretical understanding and predictions of real-world complex social phenomena.

As described above, human social sensors are likely to be particularly useful when asked about beliefs and behaviours in their immediate social environments, and when they are sampled to represent the population of interest and provide early indicators of emerging trends. While we have focused on reports collected in surveys, researchers can also use social media, apps, or wearables to prompt participants to report about their social environments at particular time points and places. Such data can serve as an important bridge between data on offline networks traditionally collected in sociometric surveys and online networks studied through data available from the social media.

Apart from its scientific interest, data from human social sensors can also be useful for policy interventions that are most likely to succeed given a current state of public needs and opinions. Especially after sudden incidents that require quick interventions (for example, mass shootings, environmental catastrophes, or public unrest), a smaller number of well selected human social sensors could quickly provide estimates about many other members of the same population. Human social sensors can be engaged through citizen science platforms, which were so far almost exclusively targeted towards the natural sciences[176]. Developing these platforms to collect data from human social sensors (for example, to report symptoms of contagious disease in their social circles[177]), possibly combined with machine learning algorithms, could be an effective way of forecasting societal trends and engaging the public in social science research.

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