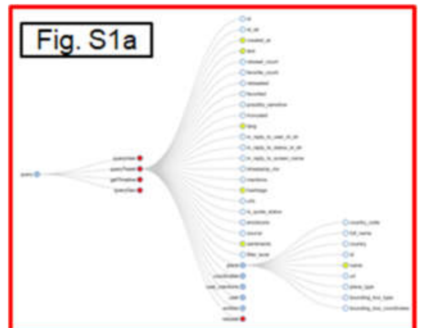
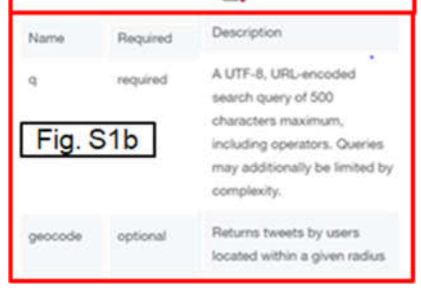
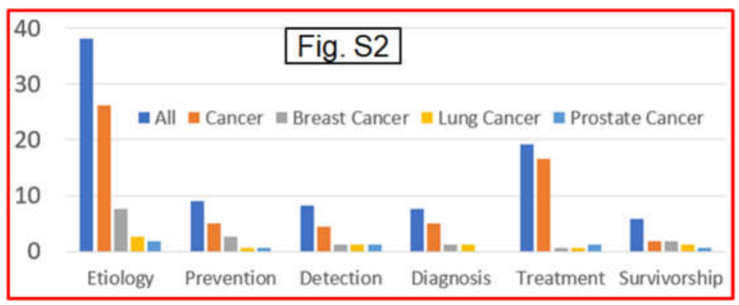
Pilot Studies. We conducted preliminary studies, supported by seed grants from UIUC's Cancer Center at Illinois and Center of Social and Behavioral Science, aiming to understand and motivate the problems and assess their feasibility. We focused on online data collection in four studies (S1 to S4) to answer a set of hypotheses (H1 to H10) that are crucial for planning and organizing our project.

Study S1: Social Observatory. For building a social observatory, we implemented a prototype at http://listen.online. The system supports users to create and execute an observation task, e.g., "*listen to hashtags mentioned with breast cancer on Twitter and get the comments of videos related to these hashtags on YouTube*." A user can (manually) select one or multiple social channels, as the screenshot of Fig. S1a shows, and build a "listener", which is a *query* that specifies input (e.g., keyword = "breast cancer") and output attributes (e.g., hashtag, comment), in an intuitive tree-like, level-by-level GUI. Note that, unlike web browsers which rely on standardized HTTP protocol, different social channels employ different APIs, e.g., Fig. S1c shows the "search" API specification of Twitter. To realize a web-like architecture for weaving social channels uniformly, we built a "wrapper" [cite]—an adapter software—to convert the APIs of a source to *the GraphQL protocol* (https://graphql.org/). GraphQL satisfies two important requirements, for connecting channels and users: 1) Unification of channels in a standard protocol, 2) Interaction with users in a graphical representation of APIs, allowing building queries in a graph-like GUI.





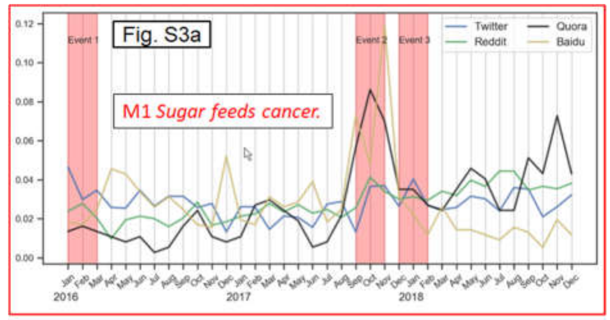
Study S2: Misinformation Watchlist. We surveyed the compilation of identified cancer misinformation by various organizations at their websites, via exhaustive web searches on Google, extracted the misinformation statements listed, merged duplicates by manual inspection, and categorized them by the six stages in the cancer control continuum. Results: We found **32 organizations** including well-known authoritative sources such as the National Cancer Institute (NCI), the World Health Organization (WHO), and American Cancer Society (ACS),totally **157 misinformation statements** (from originally 330 unmerged). We categorized the misbeliefs in terms of the cancer continuum with the distributions, as Fig. S2 shows, in the order of *Etiology* (38% for all cancers), *Treatment (19%)*, *Diagnosis*, *Prevention*, *Detection*, *Survivorship* (6%) and in terms of cancer type with the distributions of *Cancer*, *Breast Cancer*, *Lung Cancer*, *Prostate Cancer*.

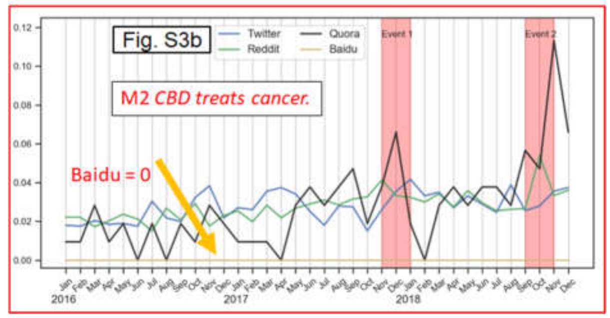


- **Hypothesis H1:** *Cancer misinformation is inconsequential in seeking and choosing treatments.* **Finding:** *False*. While some misinformation statements, such as "*sugar feeds cancer*" may not be a priority for intervention since reducing or eliminating sugar is not considered harmful, other statements could affect treatment decisions and conventional therapies (e.g., CBD cures cancer [pmid30931189]). As Fig. S2 shows, Treatment-related misinformation is the second largest category, accounting for 19%, after only etiology.
- **Hypothesis H2:** *It is not necessary to automatically watch cancer misinformation*, since authorities such as NCI and WHO already listed cancer misinformation comprehensively and timely. **Finding:** *False*. We found that no individual authorities are comprehensive—they all cover only **2.5 to 17.2% of the total list**. Worse, none were

up to date; they were updated between **29 to 3994 days** ago (from the survey date of May 29, 2019); e.g., **none listed** a current trending myth "*measles prevents cancer*".

Study S3: Misinformation Prevalence. We surveyed the prevalence of three sample misinformation statements—M1 *Sugar feeds cancer*; M2: *CBD treats cancer*; M3: *Cell phones cause cancer*, which represented the most frequent Etiology (M1, M3) and Treatment (M2) categories, as reported above. For each statement, we collected the monthly *numbers* of relevant posts from 2016 to 2018, in four different social media that are popular in different countries (US and China): *Twitter* (US), *Reddit* (US), *Quora* (US), and *Baidu Knows* (China), to compare their behaviors. Note that our objective was the popularity of misinformation, which could be indicated by any posts that are relevant to such a statement, advocating or refuting, which we thus did not distinguish. Fig. S3a and b show the 3-year monthly distributions for M1 and M2 respectively. We also categorized the types of accounts that generated misinformation and their frequencies of generation.

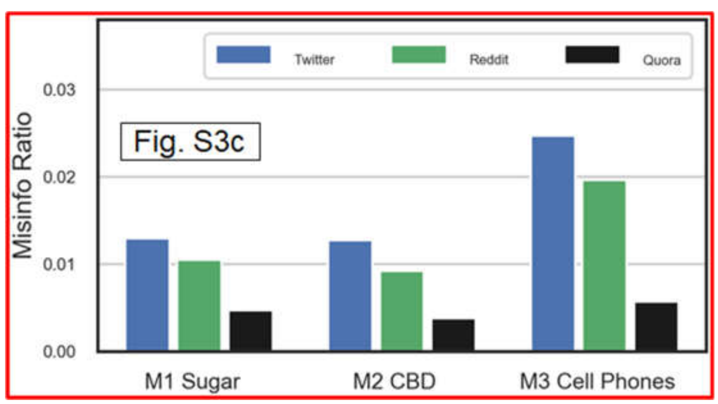




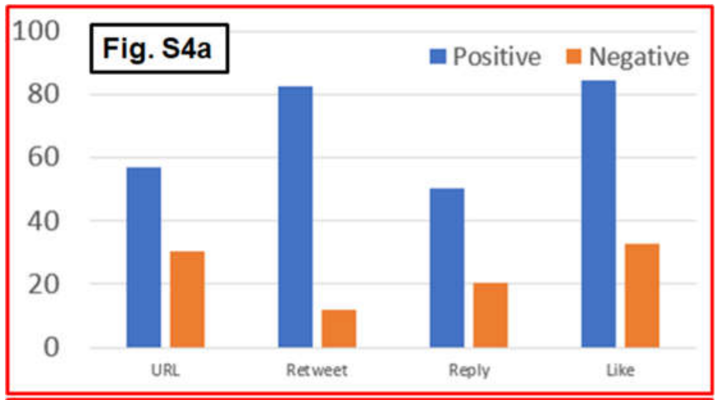
● **Hypothesis H3:** *Misinformation, once debunked, is dead for good.*
Finding: *False*. We found that misinformation, as Fig. S3a and b shows, reemerged with repeated spikes, despite already debunked (by NCI and WHO).

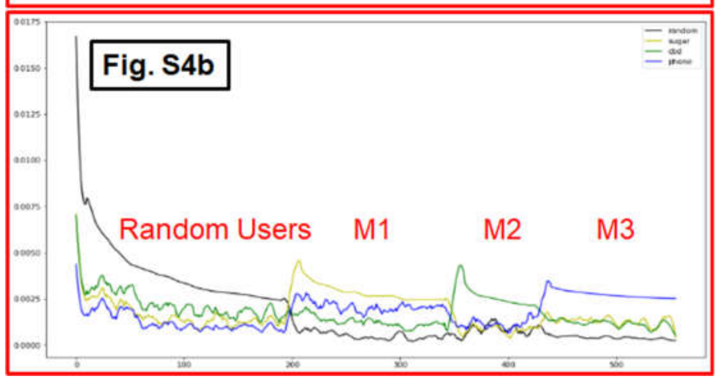
● **Hypothesis H4:** *The emergence of misinformation is quite random and cannot be predicted.* **Finding:** *False*. First, H3 indicates high chances that an existing misinformation statement can be anticipated to reemerge. Second, We found that the spikes in Fig. S3a and b (shaded in red), which indicated major outbreaks of misinformation, were consistently preceded by relevant events (news or research publications); e.g., the second spike in M1 was triggered by a news "[KU Leuven] *Scientists reveal the relationship between sugar, cancer*" from *ScienceDaily.com*, and the first spike in M2 by the news of FDA sending warning letters to CBD companies. We note that the originating sources (KU Leuven, FDA) might contain evidence-based information, but its interpretation by secondary sources led to related misinformation.

● **Hypothesis H5:** *Misinformation is produced by random people.* **Finding:** *False*. We found that, first, misinformation was often generated from certain types of accounts, such as pharma merchants or health-related organizations. Second, such producers of misinformation were highly likely to repeat the same behavior; in particular, the **top-50 most frequent** producers posted, on average, **4.8 tweets** in each year.



● **Hypothesis H6:** *Misinformation appears similarly in different social media.* **Finding:** *False*. While the behaviors are similar, as the temporal trends in Fig. S3a and b show, we also observed some major differences. For amounts, as Fig. S3c shows, Twitter has more misinformation posts than Reddit, and both have much more than Quora. For M2 (Fig. S3a), we observed **zero** presence in Baidu. For timing, we saw that the US social media often led a spike before the Chinese Baidu (Fig. S3b), suggesting the triggering primary events often took place in the US (or the western world). This finding confirms a recent conjecture [pmid28721645] and related observations [pmid26156568] that social media channels disseminated education messages differently-- but systematic comparative studies across various channels remain lacking.





● **Hypothesis H7:** *Moderation of a social network can reduce the prevalence of misinformation in it.* **Finding:** *True*. As H6 found, different social media with different degrees of moderation resulted in quite different levels of misinformation—Twitter is non-moderated, Reddit is loosely moderated by subreddit moderators, and Quora is self-moderated with a strong author reputation mechanism.

● **Hypothesis H8:** *Moderation of potential misinformation is always helpful.* **Finding:** *Probably not*. We also found some extreme measures of moderation: Baidu has a strong nation-wide censorship which removed all "CBD" posts, resulting in zero M2 (Fig. S3b). Such extreme moderation-- or censorship-- removed misinformation and useful information all together. Is an absence better than conflicting information? We were thus motivated, in this proposal, to study effective moderation.

Study S4: Misinformation Characteristics. We surveyed misinformation more specifically on Twitter, for tweets about M1, M2, and M3 during 2016 - 2018 as well as their *producers*, i.e., users who produced these tweets. We compared several characteristics of these "positive" tweets and users to the rest "negative" ones.

● **Hypothesis H9:** *Misinformation tweets look just like the rest.* **Finding:** *False*. As the research community has just started exploring automatic credibility appraisal of tweets [Shah2019], we found that positive tweets featured quite distinctive characteristics from negative ones. As Fig. S4a shows, first, for content, they were more likely to post a URL link (**57% vs. 30%**)-- mostly referring to a primary event source (as H4 found). Second, for responses, they were more likely to attract retweets (**82% vs. 11%**), replies, and likes, suggesting more engagement. Our finding is consistent with earlier observations that misinformation tended to attract more engagement [pmid30502104].

● **Hypothesis H10:** *Misinformation producers look just like the rest.* **Finding:** *False*. It turns out that producers have certain interests or motives [pmid30138075]. We surveyed the producers of misinformation and who they followed. We found that they were often distinguished by a particular set of "friends" that they followed, which indicated their interests, as Fig. S4b shows.