How Online Crowds Influence the Way Individual Consumers Answer Health Questions

An Online Prospective Study

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Summary

Objective: To investigate whether strength of social feedback, i.e. other people who concur (or do not concur) with one's own answer to a question, influences the way one answers health questions.

Methods: Online prospective study. Two hundred and twenty-seven undergraduate students were recruited to use an online search engine to answer six health questions. Subjects recorded their pre- and post-search answers to each question and their level of confidence in these answers. After answering each question post-search, subjects were presented with a summary of post-search answers provided by previous subjects and were asked to answer the question again.

Results: There was a statistically significant relationship between the absolute number of others with a different answer (the crowd's opinion volume) and the likelihood of an individual changing an answer (P<0.001). For most questions, no subjects changed their answer until the first 10–35 subjects completed the study. Subjects' likelihood of changing answer increased as the percentage of others with a different answer (the crowd's opinion density) increased (P=0.047). Overall, 98.3% of subjects did not change their answer when it concurred with the majority (i.e. >50%) of subjects, and that 25.7% of subjects changed their answer to the majority response when it did not concur with the majority. When subjects had a post-search answer that did not concur with the majority, they were 24% more likely to change answer than those with answers that concurred (P<0.001).

Conclusion: This study provides empirical evidence that crowd influence, in the form of online social feedback, affects the way consumers answer health questions.

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Background

People are one of the most important sources of information that influence consumer health decisions [1–7]. With the role of the Internet as a social network, typified by growing interest in Medicine 2.0 and Health 2.0, patients and consumers are increasingly seeking health information and advice from online peer networks. Yet, few studies have evaluated the health impact of social processes that is possible through such websites [8].

According to Berkman and Glass, five processes faciliated by social networks and relationships have been identified to affect health behaviors and outcomes. *Social influence* refers to how the presence, actions or expectations of others influence the way one behaves [9]. Demonstrated by over eighty years of experimental research, studies have examined different classes of social influence, such as allelomimetic behavior, behavioral contagion, conformity, compliance, group pressure, imitation, normative influence, observational learning, social facilitation, suggestion, and vicarious conditioning [9]. In the context of health, the norms of what is considered an acceptable health behavior is often defined by others around you (e.g. smoking), or the mechanisms others impose to achieve adherence (e.g. medication regimens). Studies have shown adolescents are more likely to adopt health-risking behaviors, such as consumption of tobacco, alcohol, marijuana and unsafe sex, when their friends are also (or perceived to be) involved in these activities [10, 11].

Social engagement and attachment refers to how network ties increase engagement and contact with other people and lessen isolation. Patients with rare conditions have shown to change their treatments plans as a result of participating in online communities and engaging with similar patients to compare health progress [12]. The contact hypothesis, which proposes social contact is more effective in achieving changes to attitudes and behaviors than information alone, may provide a theoretical basis for this phenomenon [13]. People are influenced by their close friends, as well as their peers in structurally similar positions; and influence by cohesion has shown to be stronger than influence by structural equivalence [14].

Access to social recommendations, tangible resources and material goods is faciliated by social networks. How social network structure affects one's sources of knowledge and access to recommendations on health matters, is of direct relevance [15]. The Social Information Foraging Model, which proposes interventions such as: brokerage over social structural holes, socially mediated discovery (e.g. foraging for information in groups), and increasing diversity of opinion (e.g. facilitating recommendations by peers), may facilitate better access to resources and recommendations by establishing better ties and connections in one's social network. For example, among men who sought help who sought help for psychological concerns, study has shown their decision to seek help was heavily influenced by recommmendations around them, where approximately 75% had someone recommend that they seek help and about 94% knew someone who had sought help [16].

Social contagion: not only do social networks help track infectious disease, almost a decade of research pioneered by Fowler and Christakis suggest that many non-infectious conditions (such as obesity, depression) may be "transmitted" by "person-to-person spread" across social networks [17]. In addition, consumers are likely to be a major source of early signal for outbreak detection, as demonstrated in the strong correlation reported by Google between web search terms and influenza-like outbreaks [18]. This science of distribution and determinants of electronic information (known as info-epidemiology) is gaining attention as an effective means of informing public health issues [19], where news and behaviors spread and become 'contagious' through one's network in a similar way as infectious diseases.

Social support, such as emotional, functional, and informational assistance, are well-documented to influence one's health significantly [7]. However, traditional electronic health records only model the state of the body; relationships between people that have a major impact on health decisions and management plans, such as one's close support network and clinical care team, are currently not readily accessible in patients' health records [20]. Further, consumers are influenced by online communities, where they receive advice and support from similar others on a range of topics from managing day-to-day issues related to their condition to learning about treatment choices and experiences; yet the *extent and impact* of these sources on health decisions and behavior change are rarely documented and poorly understood.

Previous research shows that when consumers search for online information, they experience cognitive biases that influence their health decisions [21] and that such biases are difficult to remove [22]. In particular, pre-existing beliefs are likely to make individuals discount information that is correct [23], where those who lack confidence are 28.5% more likely to change their decision after receiving social feedback online [24]. Yet, few studies have evaluated the impact of social influences faciated by online medium on health decision making.

Objectives

The aim of this research is to examine whether strength of social feedback, i.e. other people who concur (or do not concur) with one's answer to a question, influences the way one answers health questions after searching for online information. We use two measures *opinion volume* (the absolute number of people expressing a view) and *opinion density* (the relative percentage of a group holding a view) to assess the impact of social feedback on consumer health decisions in this study.

Methods

A convenience sample of 227 undergraduate students was recruited from the University of New South Wales (UNSW) to use an online search engine developed at UNSW to answer six consumer health questions. Subjects with Internet access who had previously used an online search engine were recruited by announcements via student email lists, posters, leaflets, weekly student magazines, and a UNSW research news website. The search engine retrieved documents from tested resources known to have high relevance in answering health questions [25], namely PubMed [26], MedlinePlus [27], and HealthInsite [28].

Study protocol

A pre/post protocol was used in this study. Subjects were advised to spend about 10 minutes for each question and to use only the provided search system to answer the questions. To prevent subjects from visiting external websites during the experiment, the navigation bar on the Web browser was hidden once the subject logged on to the study website. Upon completion of the study, subjects were entered into a draw for one of 100 cinema tickets. Ethics approval was obtained from the Human Research Ethics Advisory Panel at UNSW.

Subjects recorded their pre- and post-search answers to each question and their confidence in these answers. Order of questions was randomized for each subject, which controls for the potential order effect one may experience when answers to a question may subsequently affect answers to subsequent questions. After answering each question post-search, subjects were presented with a summary of the post-search answers provided by previous subjects and were asked to answer the question again, which we termed "post-social-feedback" (▶Fig. 1).

Scenario questions

The consumer health questions and the expected correct answers are shown in ▶Table 1. Each subject was presented with six questions, selected at random from the set of eight with no further manipulation. There were four possible answers to each question: "yes", "no", "conflicting evidence", and "don't know." Confidence was measured by a 4-point Likert scale from "very confident" to "not confident". The questions varied in difficulty and topic in order to cover a spectrum of healthcare consumer topics. They were developed in consultation with a general practitioner and two academics from the School of Public Health and Community Medicine at UNSW.

Agreement was reached on the "correct" answer and the location of the best evidence sources for each question. A pilot test with three members of the general public was used to assess the questions for interest and readability. Two additional pilots, each with five subjects, were conducted to confirm that it was possible to locate documentary evidence required to answer the questions correctly.

Data analysis

Subjects' pre-search/post-search/post-social-feedback answers and confidence for each question were recorded during the experiment. Responses to questions were coded "correct", "do not know", or "incorrect" according to the pre-determined answers for each question. Cases were excluded from data analysis when subjects did not conduct a search before providing answers, did not answer post-search, or answered "don't know" post-search.

Categorical data were reported in counts and percentages. Chi-square test and Fisher's exact test were used to examine whether subjects were significantly more likely to change their answer post-social-feedback when

1. their post-search answer concurred (or did not concur) with majority of subjects (i.e. >50%);
2. a greater *number* of subjects had a different answer;
3. ia greater *percentage* of subjects had a different answer (i.e. >60%); and
4. they changed (vs. did not change) their answer post-search.

Statistical significance was defined a priori as a P value of less than 0.05 (determined using a 2-tailed test). Data were analysed using PASW Statistics 18.

Results

Subjects' pre-/post-search answers and confidence for each question were reported in our earlier study [24]. They were equally likely to change their answer post-social-feedback regardless of whether they changed their answer post-search ($\chi^2 = 0.49$, $df = 1$, P = 0.486) (►Table 5). Of the 1362 answers from 227 subjects each answering six questions, 338 were excluded from analysis because an answer was not selected, the subject selected "don't know" as the answer, or the subject did not perform a search prior to selecting an answer. The first answer received for each of the eight scenarios was also excluded, since the first subject to attempt each question could not be given any feedback about other subjects' answers; this left 920 answers for analysis.

Opinion volume

►Figures 2 and 3 show that as the number of subjects who have already answered the question increases, the likelihood of subjects changing a post-search answer after reviewing social feedback also increases for each question (except Q 7, 8), and for all questions combined. For most questions (Q 1–6), no subjects changed their answer until the first 10–35 subjects completed the study (►Fig. 2).

Subjects were more likely to change their answer when a greater absolute number of subjects did not concur with their answer – the opinion volume (►Fig. 4). There was a statistically significant relationship between the number of subjects with a different answer and the likelihood of one changing an answer (P<0.001, Fisher's exact test; ►Table 2).

Opinion density

►Table 3 shows that 98.3% of subjects did not change their answer when it concurred with the majority (>50%) of subjects, and that 25.7% of subjects changed their answer to the majority response when it did not concur with the majority. In addition, ►Table 6 shows that 99.3% of the majority responses presented to subjects at social feedback are correct answers. Chi-square analysis conducted on data in ►Table 3 shows that subjects with a post-search answer that did not concur with the majority of subjects were 24% more likely to change their answer than those with answers that concurred (did not concur: 25.7% [95% CI: 19.76–32.77]; concurred: 1.7%, [95% CI: 1.02–2.95]; $\chi^2 = 133.82$, $df = 1$, P<0.001).

Subjects were more likely to change their answer when a greater percentage of subjects did not concur with their answer – the opinion density (►Fig. 5). Chi-square analysis conducted on data in ►Table 4 showed that amongst subjects whose answer differed to that of >60% of subjects, their likelihood of changing answer increased as the percentage of subjects with a different answer increased ($\chi^2 = 6.10$, $df = 2$, P = 0.047).

Discussion

This study provides empirical evidence that healthcare consumers are more likely to change their answer when a greater number of others do not concur with their answer (opinion volume) (P<0.001), even when directing participants to high-quality health websites. It also shows that the likelihood of one changing an answer increases as the percentage of others not concurring with one's answer increases (opinion density) (P = 0.047). Further, almost all consumers (98.3%) do not change their answer when it concurs with the majority (>50%) of the group, and consumers are 24% more likely to change their answer when it does not concur with the majority (P<0.001).

Comparison with prior work

From an empirical perspective, few to no studies have studied the impact of majority influences on how consumers make health decisions. Previous research showed for the first time that online social interventions can lead consumers to make unsafe decisions about their health. Consumers who are least confident in their decisions are most likely to be swayed by social feedback into making incorrect decisions, i.e. those who lack confidence in their answer to a question are shown to be 28.5% more likely to change their decision after receiving social feedback online [24]. In addition, the concepts of "opinion volume" and "opinion density" may be applicable in the continuing debate over the validity of Wikipedia entries [29–31].

From a theoretical perspective, research on how the majority/minority of a group influences the way individuals process information and alter their attitudes may offer explanations for our findings. One of the earliest and most influential contributions in this area, Moscovici's conversion theory [32, 33], proposes that when information is received from the majority, individuals conform to the majority and do not scrutinise the information because they concentrate their attention on "... what others say, so as to fit in with their opinions or judgements" [32]. Whereas, when information is received from the minority, individuals may interpret the information more closely but not as likely to agree with it openly because they fear being publicly associated with the minority.

Another piece of prominent work in this area, objective consensus approach [34], offers several possibilities on why individuals are more likely to systematically process information received from the majority than from the minority. One possibility is that individuals believe their attitudes are similar to those of the majority, and hence are more likely to agree with the majority than the minority [35]. Another possibility is that individuals believe it is more important to process information received from the majority because attitudes held by a majority are more likely to become adopted than those held by a minority [36]. A further possibility is that individuals assume that the majority views reflect reality because "several pairs of eyes are better than one" [34].

Limitations

There are several potential limitations in this study

- *Same participant completing the study more than once*: It is possible that the same participant could have registered more than once, or that a participant used multiple identities to complete the study. However, no suspicions of multiple attempts or logins from the same participant were identified in similar online studies administered previously [24, 40]. Also, other studies have shown that the rate of repeated online participation is less than 3% [41].
- *Knowing other subjects' answers discourages information searching*: It was only during data analysis and in hindsight that we realised the component that invites subjects to view other subjects' post-search answers may actually discourage subjects to search for information. To address this issue, all cases where searching was not conducted have been excluded from data analysis.
- *Use of external material to answer questions*: Even though subjects were asked to only use the provided search system and not to use any external resources to answer the questions, there was no monitoring to check whether subjects used external resources other than the provided search engine to answer questions. However, the navigational bar on the browser was disabled throughout the experiment to prevent subjects visiting other websites or going back to completed questions to alter their answers. In addition, subjects were asked to complete each question in a ten-minute

time limit, which would likely minimise the possible use of printed material. Further, to ensure subjects had a proper attempt at searching for information to answer questions, they were informed before commencing the study that their answers would be checked and verified against the information they accessed during searching in order to be eligible for remuneration [41].

- *Second decision effect*: May occur when subjects make a mistake while inputting their pre-feedback answer and use the post-feedback attempt to correct their answer; in this case, the difference in pre- and post- answers may not actually be a result of social feedback.
- *University population may not be representative of general healthcare consumers*: The study may be more appealing to consumers who are interested or literate in computers, the Internet, or health topics. These participants may be more enthusiastic about health and the Internet than the general healthcare consumer population. In addition, participants from a university setting could be more open and positive to new research ideas.

Conclusion

The Internet has delivered a glut of information, much of it neither timely nor correct, thus increasing the chances that consumers using the Internet to obtain health information may make a misinformed health decision, or experience anxiety about what to do [42]. As consumers play an increasingly active role in managing their health, it is important not to underestimate the extent to which online peer networks can influence the way people make decisions about their health. While the rise of the Social and Semantic Web has facilitated ready access to information about the masses and aggregated behaviors [43], the quality or correctness of aggregated behaviors is often measured by popularity, which does not necessarily relate to accuracy. More investigation should be undertaken to examine whether aggregated behaviors made possible via the Web is a new form of social influence that impacts significantly on consumers' health decisions.
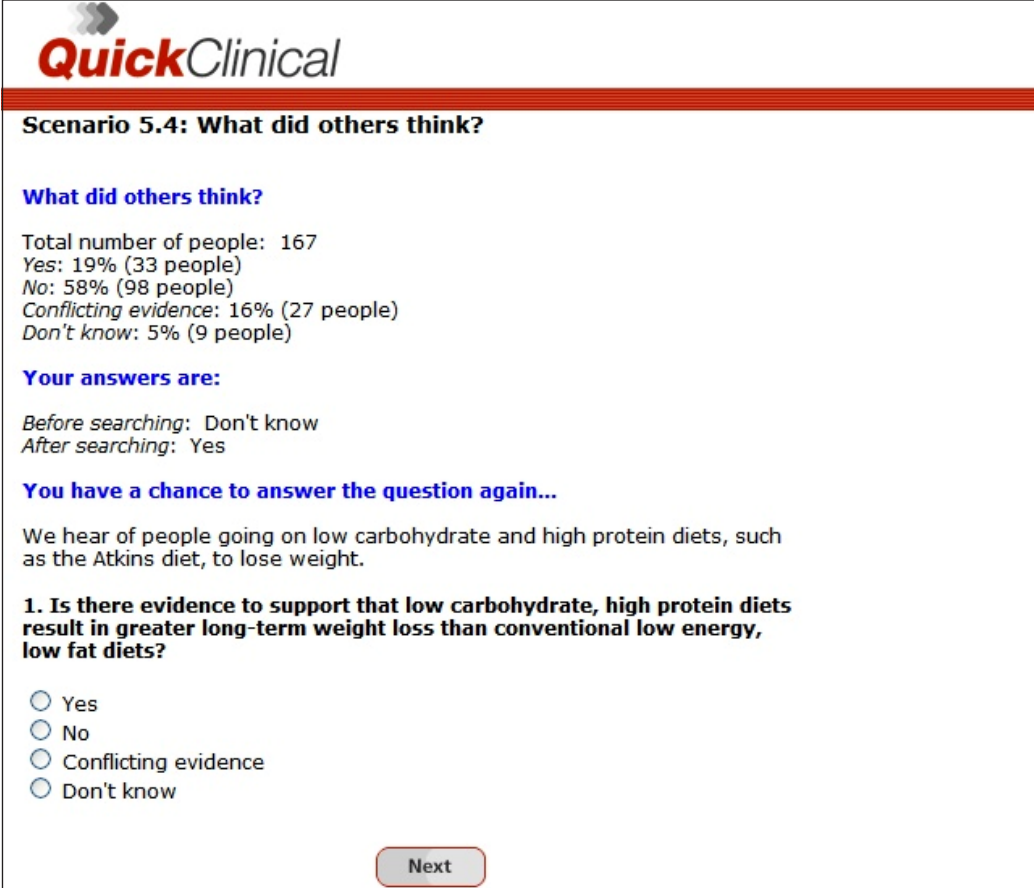
Human Subjects Protections
The study was performed in compliance with the National Health and Medical Research Council on Ethical Principles for Medical Research Involving Human Subject.

Conflict of Interest
The University of New South Wales and some of the researchers could benefit from the commercial exploitation of the Quick Clinical search engine or its technologies.

Fig. 1 Screen capture of feedback provided to subjects after answering a question post-search

Fig. 2 Likelihood of subjects changing post-search answer after social feedback, according to number of subjects who have already completed the study at the time (for each question)

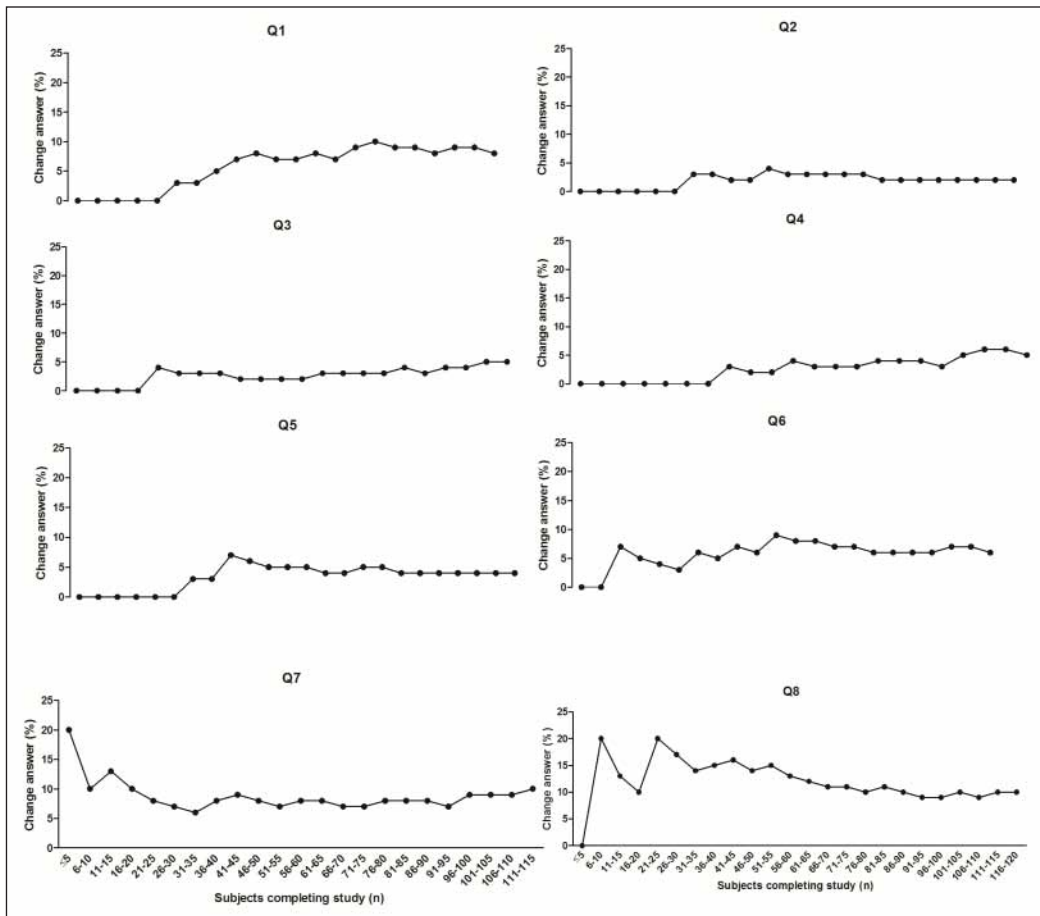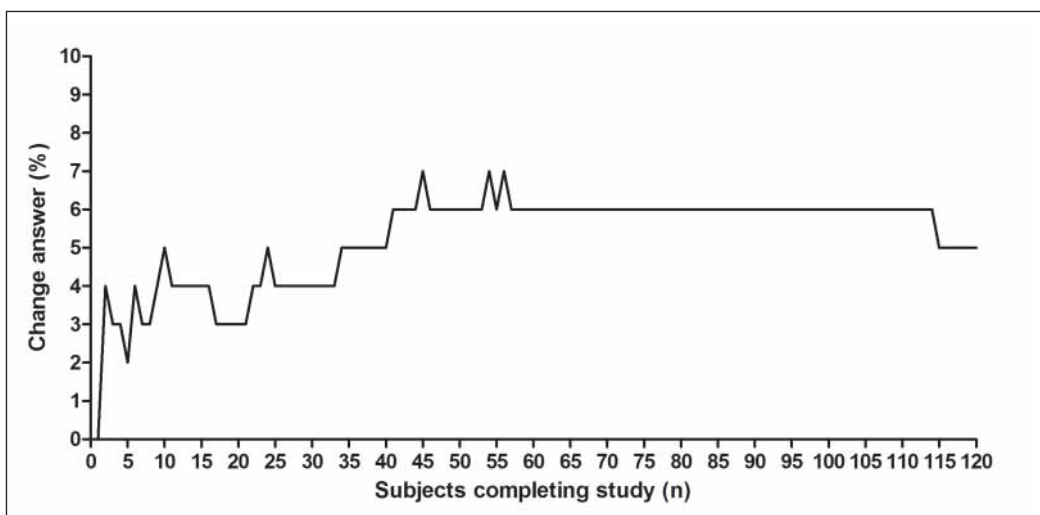**Fig. 3** Likelihood of subjects changing post-search answer after social feedback, according to number of subjects who have already completed the study at the time (all questions combined)
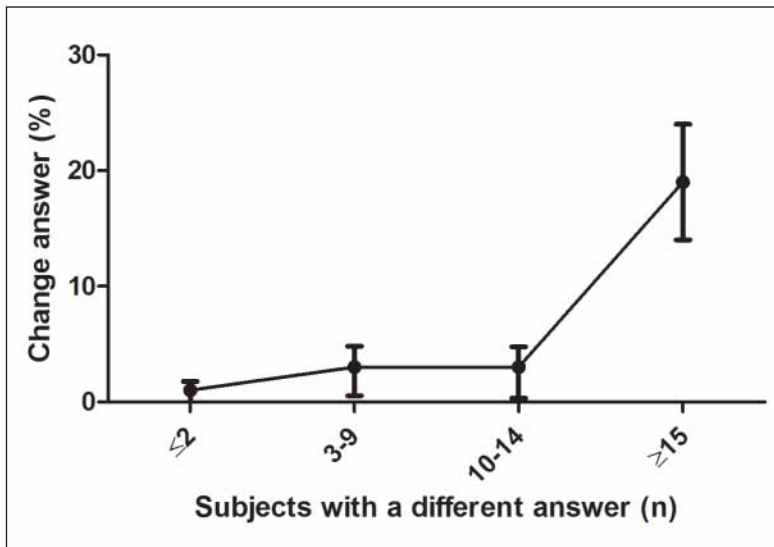
Fig. 4
Opinion volume effects – the percentage of subjects who changed their post-search answer increases with the absolute number of others who gave a different answer
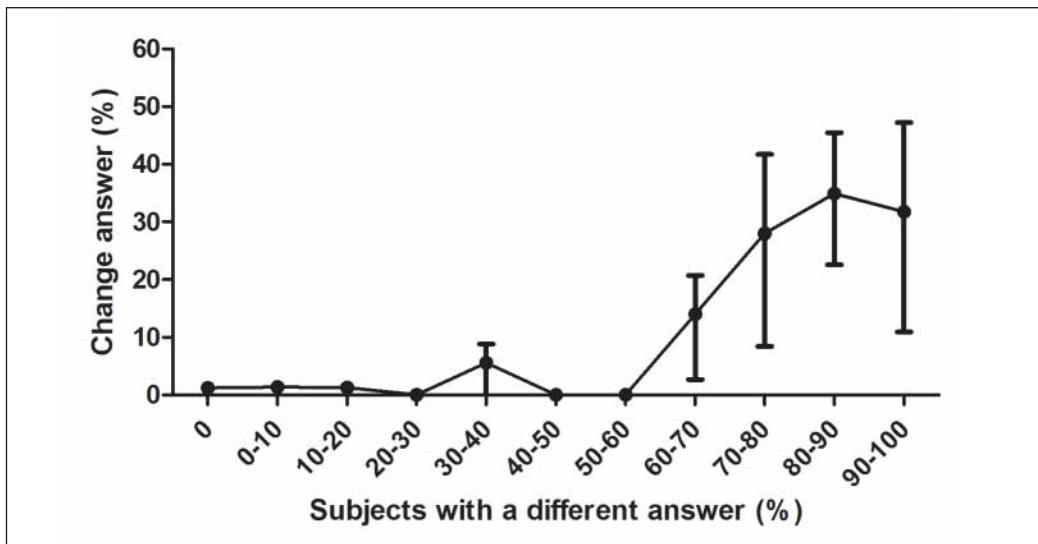
Fig. 5 Opinion density effects – the percentage of subjects who changed their post-search answer increases with the percentage of others who gave a different answer (Note: 0–10% means >0% and ≤10%)

Table 1 Case scenarios and questions presented to subjects

Scenario question	Correct answer
1. Many people use home therapies when they are sick or to keep healthy. Examples of home therapies include drinking chicken soup when sick, drinking milk before bed for a better night's sleep, and taking vitamin C to prevent the common cold. Is there evidence to support the taking of vitamin C supplements to help prevent the common cold?	No
2. We know that we can catch AIDS from bodily fluids, such as from needle sharing, having unprotected sex, and breast-feeding. We also know that some diseases can be transmitted by mosquito bites. Is it likely that we can get AIDS from a mosquito bite?	No
3. After having a few alcoholic drinks, we depend on our liver to reduce the Blood Alcohol Concentration (BAC). Drinking coffee, eating, vomiting, sleeping or having a shower will not help reduce your BAC. Are there different recommendations regarding safe alcohol consumption for males and females?	Yes
4. Sudden infant death syndrome (SIDS), also known as "cot death," is the unexpected death of a baby where there is no apparent cause of death. Studies have shown that sleeping on the stomach increases a baby's risk of SIDS. Is there an increased risk of a baby dying from SIDS if the mother smokes during pregnancy?	Yes
5. Breast cancer is one of the most common types of cancer found in women. Is there an increased chance of developing breast cancer for women who have a family history of breast cancer?	Yes
6. Men are encouraged by our culture to be tough. Unfortunately, many men tend to think that asking for help is a sign of weakness. In Australia, do more men die by committing suicide than women?	Yes
7. We hear of people going on low carbohydrate and high protein diets, such as the Atkins diet, to lose weight. Is there evidence to support that low carbohydrate, high protein diets result in greater long-term weight loss than conventional low energy, low fat diets?	No
8. You can catch infectious diseases such as the flu from inhaling the air into which others have sneezed or coughed, sharing a straw or eating off someone else's fork. The reason is because certain germs reside in saliva, as well as in other bodily fluids. Hepatitis B is an infectious disease. Can you catch Hepatitis B from kissing on the cheek?	No

Table 2 Comparison of likelihood to change answer among subjects with answers different to other subjects (N = 920)[a]

No. of subjects with a different answer	Changed answer	Did not change answer
≤ 2 (n = 229)	2 (0.9%)	227 (99.1%)
3–9 (n = 235)	6 (2.6%)	229 (97.4%)
10–14 (n = 225)	6 (2.7%)	219 (97.3%)
≥ 15 (n = 231)	43 (18.6%)	188 (81.4%)
[a]P<0.001, Fisher's exact test		

Table 3 Comparison of likelihood to change answer between subjects who concurred vs. did not concur with the majority (N = 920)[a]

Concurred with >50% of subjects?	Changed answer	Did not change answer
Yes (n=749)	13 (1.7%)	736 (98.3%)
No (n=171)	44 (25.7%)	127 (74.3%)
[a] χ^2 = 133.82, *df* = 1, P<0.001		

Table 4 Comparison of likelihood to change answer among subjects whose answer differed to that of >60% of subjects (N = 167)[a]

% of subjects with a different answer [b]	Changed answer	Did not change answer
60–70% (n = 57)	8 (14.0%)	49 (86.0%)
70–80% (n = 25)	7 (28.0%)	18 (72.0%)
>80% (n = 85)	29 (34.1%)	56 (65.9%)
[a] χ^2=6.10, df = 2, P = .047 [b] 60–70% means >60% and ≤70%		

Table 5 Comparison of likelihood to change answer post-social-feedback between subjects who changed vs. did not change answer post-search (N = 920)[a]

Post-search	Post-social-feedback	
	Changed answer	Did not change answer
Changed answer (n = 277)	20 (7.2%)	257 (92.8%)
Did not change answer (n = 643)	37 (5.8%)	606 (94.3%)
[a] χ^2= 0.49, df = 1, P = 0.486		

Table 6 Comparison of correctness of the majority answer between different scenario questions (N = 920)

Scenario question	Majority answer		
	Correct	Incorrect	Inconclusive [a]
1 (n = 110)	108 (98.2%)	2 (1.8%)	0 (0%)
2 (n = 120)	120 (100%)	0 (0%)	0 (0%)
3 (n = 112)	110 (98.2%)	1 (.9%)	1 (.9%)
4 (n = 110)	110 (100%)	0 (0%)	0 (0%)
5 (n = 120)	120 (100%)	0 (0%)	0 (0%)
6 (n = 112)	110 (98.2%)	1 (0.9%)	1 (0.9%)
7 (n = 114)	114 (100%)	0 (0%)	0 (0%)
8 (n = 122)	122 (100%)	0 (0%)	0 (0%)
Total (n = 920)	914 (99.3%)	4 (0.4%)	2 (0.2%)
[a] For these participants, there were equal number of correct and incorrect answers.			

References

1. Lieberman MA, Golant M, Giese-Davis J, Winzlenberg A, Benjamin H, Humphreys K, et al. Electronic support groups for breast carcinoma: A clinical trial of effectiveness. Cancer 2003; 97: 920–925.
2. Lorig KR, Laurent DD, Deyo RA, Marnell ME, Minor MA, Ritter PL. Can a back pain e-mail discussion group improve health status and lower health care costs?: A randomized study. Arch Intern Med 2002; 167(7): 792–796.
3. Dawes M, Sampson U. Knowledge management in clinical practice: A systematic review of information seeking behavior in physicians. Int J Med Inform 2003; 71: 9–15.
4. Coumou HCH, Meijman FJ. How do primary care physicians seek answers to clinical questions? A literature review. J Med Libr Assoc 2006; 94: 55–56.
5. Shaw BR, McTavish F, Hawkins R, Gustafson DH, Pingree S. Experiences of women with breast cancer: Exchanging social support over the chess computer network. J Health Commun 2000; 5: 135–159.
6. McGettigan P, Golden J, Fryer J, Chan R, Feely J. The sources of information used by doctors for prescribing suggest that the medium is more important than the message. Br J Clin Pharmacol 2001; 51: 184–189.
7. Berkman LF, Glass T. Social integration, social networks, social support and health. In: Berkman L, Kawachi I, editors. Social epidemiology. New York: Oxford University Press; 2000.
8. Lau AYS, Kwok TMY. Social features in online communities for healthcare consumers – a review. In: Ozok AA, Zaphiris P, editors. Online Communities, LNCS 5621. Berlin Heidelberg: Springer-Verlag; 2009. p. 682–689.
9. Latané B. The psychology of social impact. Am Psychol 1981; 36: 343–356.
10. Clark AE, Lohéac Y. „It wasn't me, it was them!" Social influence in risky behavior by adolescents. J Health Econ 2007; 26: 763–784.
11. Romer D, Black M, Ricardo I, Feigelman S, Kaljee L, Galbraith J, et al. Social influences on the sexual behavior of youth at risk for HIV exposure. Am J Public Health 1994; 84: 977–985.
12. Frost JH, Massagli MP, Wicks P, Heywood J. How the Social Web Supports patient experimentation with a new therapy: The demand for patient-controlled and patient-centered informatics. AMIA Annu Symp Proc 2008: 217–221.
13. Amichai-Hamburger Y, McKenna KYA. The contact hypothesis reconsidered: Interacting via the internet. J Comput Mediat Commun 2006; 11: 825–843.
14. Berten H. Peer influences on risk behavior: a network study of social influence among adolescents in Flemish secondary schools. Annual meeting of the American Sociological Association Annual Meeting; Sheraton Boston and the Boston Marriott Copley Place, Boston, MA 2008.
15. Pirolli P. An elementary social information foraging model. Computer human interaction conference (CHI 2009); Boston, MA2009.
16. Vogel DL, Wade NG, Wester SR, Larson L, Hackler AH. Seeking help from a mental health professional: the influence of one's social network. J Clin Psychol 2007; 63: 233–245.
17. Fowler JH, Christakis NA. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. BMJ 2008; 337: a2338.
18. Ginsberg J, Mohebbi MH, Patel R, Brammer L, Smolinski MS, Brilliant L. Detecting influenza epidemics using search engine query data. Nature 2009; 457: 1012–1014. http://dx.doi.org/10.1038/nature07634.
19. Eysenbach G. Infodemiology and Infoveillance: Framework for an emerging set of public health informatics methods to analyze search, communication and publication behavior on the internet. J Med Internet Res 2009; 11: e11.
20. Eysenbach G. Medicine 2.0: Social networking, collaboration, participation, apomediation, and openness. J Med Internet Res 2008; 10: e22.
21. Lau AYS, Coiera EW. Do people experience cognitive biases while searching for information? J Am Med Inform Assoc 2007; 14: 599–608.
22. Lau AYS, Coiera EW. Can cognitive biases during consumer health information searches be reduced to improve decision making? J Am Med Inform Assoc 2009; 16: 54–65.
23. Lau AYS, Coiera EW. A Bayesian model that predicts the impact of web searching on decision making. J Am Soc Inf Sci Technol 2006; 57: 873–880.
24. Lau AYS, Coiera EW. Impact of web searching and social feedback on consumer decision making: A prospective online experiment. J Med Internet Res 2008; 10: e2.
25. Coiera E, Walther M, Nguyen K, Lovell N. Architecture for knowledge-based and federated search of online clinical evidence. J Med Internet Res 2005; 7: e52.
26. PubMed. [2009 July 18]; Available from: http://www.pubmed.gov.

27. Eagly AH, Chaiken S. The psychology of attitudes. Orlando, FL, US: Harcourt Brace Jovanovich College Publishers; 1993.
28. Littlejohn SW, Foss KA. Theories of human communication. 9th ed: Wadsworth Publishing; 2008.
29. Encyclopædia Britannica. Britannica attacks. Nature 2006; 440(7084): 582-
30. Giles J. Internet encyclopaedias go head to head. Nature 2005; 438: 900–901.
31. Chesney T. An empirical examination of Wikipedia's credibility. First Monday 2006; 11. URL: http://first monday.org/issues/issue11_11/chesney/index.html.
32. Moscovici S. Toward a theory of conversion behavior. In: Berkowitz L, editor. Advances in experimental social psychology. New York: Academic Press; 1980. p. 209–239.
33. Moscovici S. Social influence and conformity. In: Lindzey G, Aronson E, editors. The handbook of social psychology. New York: Random House; 1985. p. 347–412.
34. Mackie DM. Systematic and nonsystematic processing of majority and minority persuasive communications. J Pers Soc Psychol 1987; 53: 41–52.
35. Ross L, Green D, House P. The „false consensus effect": An egocentric bias in social perception and attribution processes. J Exp Soc Psychol 1977; 13: 279–301.
36. Baker SM, Petty RE. Majority and minority influence: source-position imbalance as a determinant of message scrutiny. J Pers Soc Psychol 1994; 67: 5–19.
37. Knobloch S, Sharma N, Hansen D, Alter SM. Impact of popularity indications on readers' selective exposure to online news. Journal of Broadcasting Electronic Media 2009; 49(3): 296–313.
38. Westbrook JI, Coiera EW, Gosling AS. Do online information retrieval systems help experienced clinicians answer clinical questions? J Am Med Inform Assoc 2005; 12: 315–321.
39. Westbrook JI, Gosling AS, Coiera EW. The impact of an online evidence system on confidence in decision making in a controlled setting. Med Decis Making 2005; 25: 178–185.
40. Coiera E, Magrabi F, Westbrook JI, Kidd MR, Day RO. Protocol for the quick clinical study: a randomised controlled trial to assess the impact of an online evidence retrieval system on decision-making in general practice. BMC Med Inform Decis Mak 2006; 6: 33.
41. Reips UD. Standards for Internet-based experimenting. Exp Psychol 2002; 49: 243–256.
42. Coiera E. Information economics and the internet. J Am Med Inform Assoc 2000; 7: 215–221.
43. Gruber T. Collective knowledge systems: Where the social web meets the semantic web. Web Semant 2007; 6: 4–13.