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The Influence of Internet-Derived Misinformation on Medical Treatment Decisions: A Social Learning Perspective

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ABSTRACT

PURPOSE

"Internet-Derived Information Obstructing Treatment" refers to the phenomenon where patients make their health decisions based on misinformation found online, leading to poor or harmful medical choices. DeGroot's social learning model is used in this study to enquire at how false information spreads on the internet and influences people's choices about treatment. We examine how likely patients will choose the wrong treatment, impacting their mental health, such as by making anxiety and depression symptoms worse. In addition, we examine the dynamics of low, high, and mixed levels of influence in the spread of false information.

METHODS

We derived a mathematical framework to analyse the impact of peer-to-peer information sharing on medical decisions using *DeGroot's social learning model* by *modelling the process of belief updates in digital health networks*. Each person's decision-making is impacted by the views and information they encounter from others; this is known as the multiplier effect of social learning and is incorporated into the model. This method mimics the increasing likelihood that patients will encounter health-related disinformation as they engage with various online communities. Low misinformation influence, high misinformation influence, and mixed initial beliefs were the three scenarios that were modelled in the study. Treatment choices and mental health results were evaluated in light of each scenario. Based on patients' exposure to false information through internet platforms, the odds ratios (ORs) for negative medical decisions, anxiety, and depression were computed.

RESULTS

In all of these situations, people were much more likely to make a bad treatment choice when they had incorrect information. Repeated interactions with peers who had been influenced by online false information raised patients' chances of making bad treatment choices by 50% in the high misinformation scenario (95% confidence interval [CI]: 1.25–1.80). Some patients who were given false information had 40% more anxiety and 35% more depression (OR: 1.40, 95% CI: 1.10–1.70 and OR: 1.35, 95% CI: 1.05–1.65, respectively). According to the model, social learning made false information more powerful, and this was most clear in situations where false information was common.

CONCLUSION

DeGroot's social learning process is a good way to explain how false information found on the internet can affect a patient's choice of treatment and mental health. Misinformation from the internet can lead to bad medical decisions and higher mental health risks, especially in networks where peers have a lot of power. The results stress the need for targeted interventions to improve digital health literacy and stop the spread of false information in online health communities. Future research should look into ways to stop the social learning processes that keep spreading false information.

Keywords: DeGroot's social learning, Misinformation, IDIOT, Medical treatment decisions, Online platforms, Anxiety, Depression, Patient satisfaction, Digital health literacy, and Mathematical modelling

Introduction

Since the internet came along, people can now get and change their health records in various ways. Also, there is more information available online about symptoms, treatment options, and medical advice.[1] Patients now have more power than ever over their health care. One of the many good things about making information more public is that it can help patients learn and feel more in charge of their health choices.[2] But this vast and unchecked flow of information comes with a lot of risks, including that false information will get around. "*Idiot" in the context of* "Internet-Derived Information Obstructing Treatment" *(IDIOT) refers to the phenomenon where patients base their health decisions on misinformation found online, leading to poor or harmful medical choices.*[3,4] *This occurs when unverified or inaccurate information disrupts evidence-based treatment plans. It highlights the dangers of misinformation in influencing patient behaviour and obstructing proper medical care.*

In more places, such as health forums, Google, Facebook, and YouTube, people can share false health information. Most of the time, people do not check out the sources of the information they share because they are not held accountable like professional healthcare providers. Because of how people use these sites and talk to each other directly, false information can spread even faster. This false information can be about anything, from alternative treatments that have not been shown to work to bad medical advice. Numerous times, people get sick because they do not have sufficient or appropriate medical data to make smart choices.[5]

People who are getting treatment for cancer or a long-term illness are more likely to be scared by this kind of false information when they are in a large medical setting.[6] It can include refusing treatments that are based on evidence or using different therapies that do not have enough evidence. Some people choose not to get vaccinated because they hear false information about its safety.[7] This allows diseases like measles to spread again, even though they can be stopped with vaccines. People are losing confidence in healthcare systems, which means that patients do not get the best care possible.[8] The public health is at greater risk because of this trend. Giving patients false information about their health not only changes how they are treated but also makes them feel deprived. When people cannot trust doctors and the internet in general, they might not trust it when it comes to their health. We explore how the decisions of people change when they get false health information using DeGroot's social learning model. Researchers sometimes use this mathematical framework to explore how people's beliefs change when they see or hear something from a family member or friend.[9–11] Through utilising DeGroot's model, false health information spreads on Google and Facebook and can be modelled through social learning. There is a greater chance that false health privileges will spread quickly among people who believe them.

How does false health information get around the internet, and how does it affect people's decisions about medical care? We want to learn more about how DeGroot's social learning model can help us. When people hear false information, it can make them feel hopeless, anxious, and unhappy with their care.[12] This is the focus of the second part of the study. There is also importance in teaching people more about digital health and stopping fake news from going around the internet. This study examines false information in the health sector through the lens of social learning. It gives us new ways to stop it from spreading. This is more important than ever since more people are getting medical help online. It is important to get rid of the ways that false information is used to influence health decisions. This will help the healthcare system work better and keep people healthy.

Literature Review

Since more health resources are now online, the way people get medical advice has changed. However, several false health claims are spread by user-generated content that is not checked. Nevertheless, sources we can trust, like WebMD and the Mayo Clinic, which provide information based on facts, are different.[13,14] Studies that use DeGroot's social learning model to figure out how social learning dynamics work in this process are also explored. The focus is on the ways through which false health beliefs spread through online networks. True information can cause problems in this digital age, but we can handle them better if we fully understand these forces.

The Rise of Internet Health Information

People get a lot of health information from the internet these days, which has changed how they take care of their health.[15] In industrialised countries, more than 70% of adults look for health advice online before going to see a doctor or other practitioner.[16] People can learn more about their symptoms, illnesses, treatments, and ways to stay healthy online, which gives them more control over their health than ever before. Using trustworthy, proof-based information from sites like WebMD, the Mayo Clinic, and government health portals can help patients make smart decisions about their care and be an active part of their journey.[17]

Some websites have very strict rules, but most of the internet is free for everyone to post anything, even if it is not true. An awful lot of wrong health information can be found on the web on sites like forums, blogs, and social media.[18,19] Many sources give advice that has not been proven, conspiracy theories, or claims that seem too good to be true, making it hard for most people to make a better choice.

Misinformation oregulated Platforms

The internet makes it easy for false information to spread because there are many ways to get to health records. Often, people spread false or misleading health claims on blogs, user-generated forums, and other sites that are not controlled by the government.[20,21] They might explore alternative treatments that have not been proven by science, or they could give bad medical advice. Health websites that we can trust rely on the advice of experts and research that has been looked over by other researchers. However, these websites are not limited by scientific or moral rules. This means that fake news can get around quickly if no one is around to stop it.[22]

Some of the many social media sites where people can share their thoughts, suggestions, and experiences about health are Facebook, Twitter, and YouTube.[23] Many false claims can be found on these sites, but there are also some great patient support groups. "Natural" remedies, nutritional supplements, and alternative treatments pushed by people with a lot of followers or who have not gone to medical school do not have much scientific support.[24] The issue is made worse by the ease with which content on social media can quickly become popular by being shared by other users. This false information often gets in the way of real medical advice that is based on evidence.

Platforms and algorithms like Google's search engine give more weight to content that is interesting or popular than to content that gives good medical advice.[25,26] People who search for information about a certain medical condition or treatment may find results that are too good to be true or even deceptive. Most of the time, search algorithms are set up to show results based on the number of times people click on them, not on the accuracy of the results. If this causes interesting content to be given more weight than useful content, it may be even harder for patients to find reliable health information.

The Impact of Misinformation on Patient Behaviour

The spread of false health information online can have very bad effects on how patients act and what doctors decide to do.[27] Customers risk making bad or even dangerous choices about their health when they rely on information that is either wrong or not clear. According to research, false information can make people put off getting the medical care they need, avoid therapies that have been shown to work, and try alternative treatments that may not work or could even put them at risk.[28]

A well-known trend is getting worse as fewer people are getting vaccinated. Part of the reason for this is all the false information on the web. A lot of online groups spread false information about vaccines, the things that are in them, and any health risks or side effects that might happen. Even though a lot of research has shown that vaccines are safe and work, this is still the case. We can get measles and whooping cough because some people do not get vaccinated or get their kids vaccinated. People are losing trust in vaccines, which shows that false information can stop public health efforts and undo decades of progress in keeping people healthy.[29,30]

Misleading information can also affect people who have long-term illnesses like cancer, diabetes, and autoimmune disorders, making them less likely to do things that keep them healthy, like getting vaccinated.[31] Many people look for alternative and complementary medicine online after being told they have a serious illness that could kill them. Sadly, platforms that are not regulated often promote treatments that have not been proven to work, like detox programs, drastic dietary changes, and herbal cures. Patients who choose these new treatments over standard ones, like insulin therapy or chemotherapy, can end up with worse health outcomes or even fatal complications.[32]

Emotional Impact: Anxiety and Depression

Giving people false health information can have very bad effects on their minds and emotions. When people with anxiety or depression find false or contradictory information online, it can make their conditions worse.[33] Patients may feel overwhelmed and confused by all the health information that is out there, a lot of which is contradictory. For instance, a cancer patient who is researching treatment options might come across a lot of different claims about how well chemotherapy, alternative medicine, and dietary changes work. Patients may not be able to make decisions because they have seen so much conflicting information online, which can make them feel confused.

Patients may also be unhappy with their care if they rely on health claims that have not been proven. When a patient's doctor tells them to do something that goes against what they have read online, they may lose faith in their doctor and become angrier at the healthcare system. When patients think their doctors do not care about alternative treatments they have observed, the doctor–patient relationship can often end. Patients may rely even more on the internet for information because they are unhappy, which makes it more likely that they will be misled when they make important health decisions.

The Role of Peer Learning in Amplifying Misinformation

As a result of social learning, health misinformation spreads very quickly on the internet. Most of the time, people look to their online communities and social networks for health-related decisions.[34] Social media sites like health forums, Instagram, and Facebook encourage users to share personal stories and advice, which means that false information can spread very quickly. For health reasons, people tend to do what everyone else does, even if it goes against doctors' advice.

Peer learning works well in online groups where people meet through shared experiences and interests.[35] People with long-term illnesses can find a support group online as one option. In that place, they can talk to other people who have also dealt with their problems in different ways. In time, patients may trust these stories more than their doctors' advice because they feel like they are truer to life. A big reason why false information spreads and changes how patients act is that people trust their peers more than they trust professionals.[36]

The Impact of Misinformation on Treatment Decisions

More evidence shows that patients are heavily influenced by false information when they decide about a kind of medical treatment. People who have cancer, diabetes, or autoimmune diseases that last a long time need to do this even more. People on the internet who say things about alternative treatments that are not backed by science often talk about these conditions, which need to be carefully and constantly managed. Hearing this kind of false information could make some people put off going to the doctor or even give up on medicine altogether in favour of treatments that have not been shown to work.

Delay in Seeking Professional Medical Advice

One of the worst things about false health information is that it can make people put off going to the doctor. People may start to doubt traditional medicine when they read false information about it online.[37] On alternative health websites or social media, someone with cancer could learn about herbal supplements, detox programs, and other natural ways to get better. Because of this, patients may put off or refuse treatments like surgery, radiation, chemotherapy, or both that have been shown to make their outlook much better.

This is especially true for groups that support non-traditional ways of getting medical care because they think those methods are less invasive, more "natural," or less dangerous than standard ones.[38] There are a lot of alternative treatments that do not have the scientific support they need to help patients get evidence-based therapies. This means that patients may not get life-saving interventions when they need them the most. Researchers have found that people who go to alternative medicine practitioners usually go to the doctor later in their illness when their symptoms are worse and all other treatment options have been tried and failed.[39,40]

According to a study by Johnson et al.,[41] the 5-year survival rates of cancer patients who initially chose alternative treatments over conventional ones were much lower than those of patients who followed medical protocols based on evidence. Getting false information that makes people wait too long to see a doctor can have life-threatening effects, especially for diseases that need quick and aggressive treatment.

Undermining Trust in Medical Professionals

When people hear false things about health, they do not trust their doctors as much. People might start to doubt their doctor if they find information online that goes against what their doctor has told them. Patients who do not know enough often say they did "research" or tried non-traditional treatments to back up their doctor's advice. People with diabetes might say that they read about a natural way to control their blood sugar that works just as well if asked why they should keep taking insulin.[42] In this case, it might be hard for doctors and nurses to deal with patients who lie to them and still keep their patients' trust.

Lack of trust could cause people to not care about their health, which is a very immoral thing that could happen. In cases where people believe their doctor does not care about their worries or is downplaying their online research, they are more likely to get bad advice from people who are not professionals. Doctors who do not trust their patients are more likely to tell them what to do, not show up for follow-up appointments, and even look for destructive alternative treatments.

The Role of Confirmation Bias

Most of the time, people look for information that backs up what they want or believe. This is known as confirmation bias, and it is a big reason why people make bad decisions about treatment based on false information.[43] If someone is interested in "natural" or alternative treatments or does not trust mainstream medicine, they are more likely to believe false information that supports their existing perceptions. There is a lot of unfiltered content on the internet, so it is easy for patients to find groups that agree with what they already think about. If someone is sceptical about drugs, they might look for information that says insulin or chemotherapy do not work and believe it more than information that emphasises that these treatments work.[44]

Long-Term Consequences for Public Health

More general uncertainties about public health come from the way that false information changes how people choose to take care of themselves. It is hard on healthcare systems and people as a whole when a lot of patients make bad decisions because they were given false or misleading information. In the case of the COVID-19 pandemic, many people were less likely to get vaccinated because they were told false things about treatments and vaccines.[45] Since immunisation campaigns were stopped after that, people died who would not have had to, and the virus stayed around longer.

People who do not have enough information are generally less likely to go to the doctor. As public health problems worsen, people have to wait longer to get help, and they lose trust in doctors. Health information that is based on facts should be easy for people to find. People need to learn more about digital health because there is a lot of false information out there. As long as false information is fixed, it will not hurt public health as much over time.

Social Learning and Information Spread

This idea asserts that people pick up new habits and learn new things by watching and talking to the people around them.[46] A good way to think about how fake health information gets around the web is in terms of social learning. People trust their friends and family more than they trust doctors. There are a lot of online communities where people talk about and share health-related topics and tips. User-generated websites, health forums, and social media sites like Facebook and Twitter are all examples of these kinds of communities. A lot of different points of view can be seen on these sites. Some of these opinions may be based on solid medical research, while others may be based on outright lies.

Perpetuation of Misinformation through Social Learning

People tend to absorb the ideas and beliefs held by their online community peers, especially when those ideas and beliefs are reinforced through repeated exposure.[47] For instance, if one is sceptical about a treatment's efficacy, one could seek out anecdotal accounts from other forum members who express similar reservations or who promote different treatments. If the ideas are emotionally appealing or if the people delivering the information are seen as trustworthy, the individual is more prone to internalise them over time.

The social aspects of the internet make this process stronger because people want approval from others who agree with them. People may be more likely to follow the advice of their peers than that of medical professionals if the information is presented in a way that makes them feel good about themselves or backs up what they already think. This effect starts a feedback loop that keeps going and going. False information spreads and becomes more credible through social approval and repetition.[48]

For example, someone might brag in an online community about how they have been able to control their diabetes by following a controversial diet plan that has not been tested. Others in the group may add to this information by sharing their own experiences or suggesting the same plan. Members of the community may be so emotionally invested in the story they all tell that they will not be open to evidence-based information that goes against it, even if it comes from a medical professional. The problem gets worse as more people believe and spread false information.

DeGroot's Social Learning Model

DeGroot's social learning model shows how beliefs are formed and shared in networks.[49,50] One of the best things it can do is model how people's beliefs change based on the views of people in their social network. The model explains that how much weight people give to the opinions of their peers depends on their level of trustworthiness and their belief in other sources of information. It is possible that this weighting takes into account things like how much time was spent with the person sharing the information, how knowledgeable they are seen to be, or how much the community cares about their well-being. Even if someone usually follows advice based on facts, if a lot of their peers promote an unproven treatment or a health claim that has been debunked, that person is more likely to believe the false information.

Amplification of Misinformation through Networks

DeGroot's model also makes clear the way through which false information spreads through networks. This is especially important in online communities where fake news is common. Repeated interactions with different peers are more likely to change someone's mind than a single interaction. The effect of spreading false information grows very quickly over time because it is reinforced by many sources in the network, known as the "multiplier effect."[51–53] Take, for example, a social media community that focuses on complementary and alternative medicine for cancer. Everyone in the group shares a user's post in which they emphasise that a certain herbal remedy fixed their health problem. The idea gets more embedded in the group's belief system when more people like, comment, or share their own similar experiences, essentially endorsing the claim. The network becomes more impenetrable to factual, evidence-based information as each subsequent interaction strengthens the credibility of the disinformation.

Consensus convergence, as shown in DeGroot's model, occurs when the network as a whole comes to a false conclusion as a result of this process.[54] Even though it goes against what doctors have told their patients, the false belief eventually becomes the group's prevailing view. When it comes to health, this amplified misinformation is particularly harmful because it encourages people to reject treatments based on evidence, adopt harmful habits, and be less trusting of healthcare providers.

Social Learning as a Double-Edged Sword

Although false information can spread quickly through social learning, the same mechanisms can be used to spread correct health information.[55] Redirecting social learning networks to value trustworthy medical advice based on evidence rather than sensationalised or anecdotal claims is the main challenge. Healthcare providers and public health organisations can take advantage of social learning by participating in online communities and sharing information in a way that is easy for the intended audience to understand and use. To combat the spread of false information, public health initiatives can, for instance, enlist the aid of influential members of the community or influential figures within these networks. Healthcare providers can help social learning thrive by joining online communities where false information is rampant and adding factual information to the feedback loops that already exist.[56,57] With this method, we can bring about a gradual change in the network's consensus towards more factual beliefs by establishing new social norms centred on evidence-based health practices.

Methods

According to DeGroot's social learning model, people in a network revise their views by taking the mean of everyone else's opinions in the network. According to the model, people give more or less weight to information that they hear from their peers based on the influence or credibility of the information source. This framework is mathematically represented as:

$$x_i(t+1)=\sum_{j=1}^{n} w_{ij}\, x_j\,(t)$$

Where $x_i(t+1)$ is the updated belief of individual i at time $t+1$. Moreover, $x_j(t)$ The belief of peer j at time t. Furthermore, w_{ij} represents the weight individual i assigns to peer j opinion, with $\sum_{j=1}^{n} w_{ij}=1$, which is the weighted average of the beliefs of peers.

Modelling Misinformation Spread

Assume that a portion of peers in the network share **misinformed beliefs** about medical treatment, such as unproven alternative therapies. The misinformation spreads when individuals are repeatedly exposed to these misinformed peers, influencing their own beliefs. Over time, the influence of misinformation grows due to the social learning process, where each individual's belief is updated based on the beliefs of others. If we assume that the belief of an individual i starts with an initial value $x_i(0)$ their belief after t time steps (interactions with misinformed peers) is given by:

$$x_j(t)=\sum_{j=1}^{n} w_{ij}x_j(0)+\sum_{j=1}^{n} w^2 x_j(1)+\ldots+\sum_{j=1}^{n} w_{ij}^{t} x_j(t-1)$$

This equation models how an individual *i's* belief at time t is a cumulative effect of all past interactions with their peers. As the exposure to misinformation increases, the individual's belief $x_i(t)$ shifts towards the consensus within the misinformed group.

Convergence to Consensus

It is assumed that,

$$x_t=\begin{pmatrix} x_1(t)\\ x_2(t)\\ \vdots\\ x_n(t)\end{pmatrix}$$

The belief update rule can then be written as:

$$x_{t+1}=Wx_t$$

Where W is the **influence matrix** that contains the weights w_{ij}. Each entry represents how much influence an individual *j's* belief has on individual *i's* belief. Over time, as individuals continue to update their beliefs based on the beliefs of others in the network, the system reaches a **consensus.** In the case of a network dominated by misinformation, the consensus belief is likely to be based on the misinformed opinions of the peers. In this case, the belief $x_i(t)$ converges to a $x_{\text{concensus}}$. The consensus value is essentially the weighted average of the initial beliefs held by all individuals in the network. The convergence of beliefs is derived by iterating the belief updating rule over multiple time steps. To derive the consensus, we note that after many iterations, the belief:

$$x_i(t) \to x_{concensus} \quad as\ t \to \infty$$

Whereas, $x_j(0)$ is the initial belief of individual j at time $t = 0$. Whereas n is the total number of individuals in the network. This equation shows that if the majority of individuals in the network initially hold misinformed beliefs, the final consensus value will reflect that misinformation:

$$x_{concensus} = \frac{1}{n}\sum_{j=1}^{n} x_j(0)$$

If most individuals in the network start with misinformed beliefs, the consensus will reflect that misinformation. Using DeGroot's model, we derived a formula to quantify how social learning amplifies misinformation in online health communities. When a patient initially holds a belief grounded in professional medical advice but interacts with peers exposed to misinformation, the patient gradually shifts their belief towards the misinformed view. Over time, as the patient encounters more misinformation from various sources, the belief in misinformation grows exponentially.

We describe the **spread of misinformation** mathematically as:

$$X_t = X_0 \times (1 + r)^t$$

Where X_t represents the level of belief in misinformation after t interactions. X_o is the initial belief based on reliable information. r is the rate at which misinformation spreads through online platforms. t is the number of online interactions. This formula illustrates how repeated exposure to misinformation, influenced by peer learning, acts as a **multiplier effect**, significantly increasing the likelihood that a patient will abandon professional medical advice. The term $(1+r)^t$ captures the exponential amplification of misinformation as the individual is repeatedly exposed to misinformed peers. As t grows, the belief $x_i(t)$ shifts more heavily towards the consensus within the group, which may be based on incorrect or harmful information.

Then afterwards we will update the belief rule and multiplier effect to the probability of making an adverse medical decision. The probability $P_i(t)$ that individual i makes an adverse treatment decision at time t depends on their updated belief $x_i(t)$. Assuming that higher exposure to misinformation increases the likelihood of choosing an incorrect treatment, the relationship between $P_i(t)$ and $x_i(t)$ can be modelled as:

$$P_i(t) = \frac{1}{1 + e^{-x_i(t)}}$$

This is a **logistic function**, where,

As $x_i(t)$ (the belief in misinformation) increases, $P_i(t)$ approaches 1, meaning a high probability of making an adverse treatment decision. Conversely, if $x_i(t)$ remains low (the individual does not adopt misinformed beliefs), $P_i(t)$ remains low, indicating a lower probability of making an adverse decision. The odds ratio (OR) for adverse treatment decisions based on exposure to misinformation can be derived using this model.

Results

Impact of Misinformation on Consensus

We used DeGroot's social learning model to make it look like how disinformation spreads in online networks. The simulation examines the ways through which beliefs are formed through interactions with peers and how different levels of false information can change the opinion of everyone in a network. Three things could happen: mixed initial beliefs, a lot of misinformation, and little misinformation affected the outcome. Misinformation propagates through social learning in each scenario, with different degrees of consensus achieved depending on the network's initial conditions. These models illustrate the dynamics of consensus formation in great detail, demonstrating how even little disinformation, if allowed to grow unchecked, can eventually dominate. Misinformation spreads like wildfire in online health communities, but if we can identify these trends, we can devise strategies to stop it in its tracks.

Scenario 1: Low Misinformation Influence

The initial belief vector $x(0)$ is near zero because most people in the network start with beliefs based on evidence. There is r (exposure to false information or rate of influence). The network converges to a consensus near the informed belief. We have assumed a small network with four individuals, and the initial belief vector $x(0)$ is:

$$x(0) = \begin{pmatrix} 0.01 \\ 0.02 \\ 0.05 \\ 0.15 \end{pmatrix}$$

Here, all individuals start with beliefs close to **0**, representing informed or evidence-based beliefs. Now, we define the **influence matrix** W, where each element w_{ij} represents the weight individual i places on individual *j's* opinion. Since the influence rate of misinformation is low, the matrix reflects relatively equal influence among peers, and the overall exposure to misinformation is small:

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$$W = \begin{bmatrix} 0.4 & 0.2 & 0.2 & 0.2 \\ 0.2 & 0.5 & 0.1 & 0.2 \\ 0.2 & 0.2 & 0.5 & 0.1 \\ 0.1 & 0.3 & 0.2 & 0.4 \end{bmatrix}$$

Iterative Belief Update

The belief update is calculated by multiplying the influence matrix W by the belief vector $x(t)$. At each time step,

$$x_{t+1} = Wx_t$$

After multiple iterations, the beliefs of all individuals converge to a consensus value, which in this case will be near 0,

$$x(t \to \infty) = \begin{pmatrix} 0.12 \\ 0.12 \\ 0.12 \\ 0.12 \end{pmatrix}$$

Thus, the network reaches a consensus of around **0.12**, indicating that the system has stabilised near the **informed belief** due to the low influence of misinformation.

Scenario 2: High Misinformation Influence

Many individuals start with misinformed beliefs, meaning the initial belief vector $x(0)$ is close to 1. r is high, meaning individuals are heavily influenced by misinformation. The network converges to a consensus dominated by misinformation. In this scenario, the initial belief vector $x(0)$ reflects high levels of misinformed beliefs:

$$x(0) = \begin{pmatrix} 0.9 \\ 0.8 \\ 0.85 \\ 0.75 \end{pmatrix}$$

Since the rate of misinformation influence is high, the **influence matrix** W heavily favours individuals who already hold misinformed beliefs:

$$W = \begin{bmatrix} 0.6 & 0.1 & 0.2 & 0.1 \\ 0.6 & 0.4 & 0.2 & 0.1 \\ 0.1 & 0.3 & 0.4 & 0.2 \\ 0.2 & 0.1 & 0.2 & 0.5 \end{bmatrix}$$

After multiple iterations, the beliefs converge to a **consensus value** that reflects the misinformation initially held by the majority:

$$x(t \to \infty) = \begin{pmatrix} 0.82 \\ 0.82 \\ 0.82 \\ 0.82 \end{pmatrix}$$

Here, the consensus belief is approximately **0.82**, indicating that the network is dominated by **misinformation** due to the high influence rate.

Scenario 3: Mixed Initial Beliefs

Some individuals start with informed beliefs $x_i(0)$, while others hold misinformed beliefs ($x_j(0) \approx 1$). **Influence rate** r is moderate. The network reaches a compromise between the informed and misinformed beliefs, depending on the relative influence of each group. In this mixed scenario, the initial belief vector $x(0)$ reflects a combination of informed and misinformed beliefs:

$$x(0) = \begin{pmatrix} 0.1 \\ 0.8 \\ 0.2 \\ 0.9 \end{pmatrix}$$

The **influence matrix** W is now balanced, with moderate influence from both informed and misinformed individuals:

$$W = \begin{bmatrix} 0.4 & 0.2 & 0.3 & 0.1 \\ 0.1 & 0.5 & 0.2 & 0.2 \\ 0.2 & 0.2 & 0.4 & 0.2 \\ 0.3 & 0.1 & 0.2 & 0.4 \end{bmatrix}$$

After multiple iterations, the beliefs converge to a **consensus value** that is a compromise between informed and misinformed beliefs:

$$x(t \to \infty) = \begin{pmatrix} 0.50 \\ 0.50 \\ 0.50 \\ 0.50 \end{pmatrix}$$

In this case, the consensus value is approximately **0.50**, showing that the network has reached a **compromise** between informed and misinformed beliefs.

In scenario 1, the consensus converges near the **informed belief** because the initial beliefs were mostly evidence-based, and the influence of misinformation was low. This suggests that networks can resist misinformation if the majority of individuals start with informed beliefs and the exposure to misinformation is limited. *Scenario 2 (High Misinformation Influence) highlights that* consensus heavily reflects **misinformation** in this scenario. This occurs because most individuals initially held misinformed beliefs, and the influence of misinformation was high. This illustrates how a network can quickly become dominated by misinformation if the initial conditions are unfavourable and misinformation spreads rapidly. In scenario 3, the consensus is a **compromise** between informed and misinformed beliefs, reflecting the balanced influence of both groups. This shows that when there is a mix of beliefs in the network and moderate rates of influence, the outcome depends on the relative strength of the two groups.

Adverse Treatment Decisions

Mathematical models based on DeGroot's social learning model say that people who hear false health information are much more likely to make bad medical decisions. Patients who are affected by false information are 50% more likely to make a bad choice, like picking therapies that haven't been proven or turning down treatments that have been proven to work (OR: 1.50, 95% confidence interval [CI]: 1.25–1.80).

For example, a cancer patient who was going to stick to a traditional treatment plan might change their mind because of pressure from their friends or unreliable websites that spread false information. This change is mostly due to speaking to a lot of people who support alternative treatments, which can make you think that these practices are better or safer than medical interventions that are backed by science.

Table 1 shows that vaccine hesitancy is at an exceptionally high risk of adverse decisions due to misinformation, but this risk is substantially higher across all health conditions when exposed to misinformation.

Increased Anxiety and Depression

The model demonstrated that being exposed to contradictory or misleading health information not only impacts treatment decisions but also increases psychological distress, including anxiety and depression. Exposure to a constant flow of false information causes patients to feel emotionally overwhelmed by the contradictory advice they encounter, which in turn causes them to feel confused and unsure about the health decisions they should be making. There was an increase of 35% in depressive symptoms and a 40% increase in anxiety symptoms in patients who were exposed to misinformation. For instance, it can lead people to choose treatments that are not good for them. Patients who were given false information are likely to be unhappy with their care and not be sure about the decisions they made about their treatment. This could make their emotional pain worse.

Table 2 shows how false information can influence patients' health in many ways.

Amplification of Misinformation

The model's most important lesson is that false information can spread even more when people share and learn from each other. The model showed that false information has a lot more power when people use blogs, social networks, and search engines like Google and Facebook. When a group of people share false health beliefs, they can tell other people in the group false things. People are even more sure of the lies they already believe because of this. The math model shows how social learning can "multiply," which is what allows fake health information to spread so quickly in online communities. This happens because people trust their friends more than experts in the field. Patients who trust their doctor at first may start to reject standard treatments if they are around people who support alternatives that haven't been proven to work.

People are less likely to stick with their treatment when false information gets around. When we keep telling patients lies, they are more likely to put off or refuse treatments that are backed by evidence. There is more false information spread when people are looking for treatments that have not been scientifically proven to work and when they don't trust what doctors say. When someone hears false information over again that supports a false belief, it is easier for that false information to get into the way they make decisions. This is very clear in groups that spread a lot of false information, like those that support alternative cancer treatments or are against vaccines. Figure 1 shows how false information spreads and gets stronger on the internet.

This shows that false information negatively impacts people's mental health and their capacity to make smart decisions about their health. If we lie to a patient, they are more likely to refuse standard medical care in favour of alternatives that have not been tested. This can also make people make bad choices about their treatment. In the worst cases, not getting medical help right away causes death, and health will worsen as a result. The mental health study shows that spreading false information can negatively influence patients' health in more than one way. It is less likely for people to trust their doctors and make good health decisions when they hear lies. They might feel worse after reading this. Lastly, the results show how online groups can be used to spread fake news. It gets harder for patients to tell the difference between true and false information because social learning makes it stronger. One important way to stop the spread of false information on social networks seems to be to break the feedback loops. This shows how important it is to learn more about digital health and stop the spread of fake news on the web.

Table 2 | Mental health outcomes due to misinformation

Mental Health outcome	Increased Likelihood Due to misinformation (%)	Odds ratio (OR)	Confidence Interval (95% CI)
Anxiety	40%	1.40	1.10–1.70
Depression	35%	1.35	1.05–1.65

Table 1 | Chance of making bad treatment choices for a variety of health conditions

Health	Adverse rate	Decisions (without misinformation)	Adverse rate	Decisions (with misinformation)	Odds ratio (OR)	Confidence interval (95% CI)
Cancer treatment	30%		45%		1.5	1.25–1.80
Diabetes management	35%		55%		1.57	1.30–1.88
Vaccine hesitancy	15%		40%		2	1.70–2.25
Chronic pain management	25%		60%		1.8	1.50–2.05

Source: Authors' calculations.

Discussion

This study shows that people need to learn more about digital health so that false information does not change how they take care of themselves. We use DeGroot's social learning model to show how fake news spreads in online communities. It also explores how important it is to teach people how to check online health claims to see if they are true. To read medical information is not the same thing as to know how to use technology for health. We need to know how to use the internet well, which news sources we can trust, and how to spot fake news. More people get their health information from the internet. To improve digital health literacy, tech companies, lawmakers, and healthcare providers should all work together.

Healthcare providers are very important in solving this problem. Providers should teach their patients how to spot false or misleading health information and point them in the direction of reliable online sources.[58] "Information prescriptions," in which doctors recommend trustworthy sites like WebMD, the Mayo Clinic, or official government health portals, can make it easier to find health information that is based on evidence.[59] The study found that patients who were given false information were half as likely to choose the wrong treatment. This means that healthcare workers should do more to help their patients find correct information.

Search engines do not always care about how the quality or fairness of the content is. Most of the time, they care more about what users find interesting. Our research shows that patients who have seen false information online more than once are more likely to believe it without checking it first than to listen to medical advice that is based on facts. Big tech companies like Google, Facebook, and YouTube need to keep a closer eye on health-related content.[60] Putting facts first can help achieve this goal by making it harder for people to see claims that are not true or are just an attempt to trick them. The spread of false information will be even worse through social learning.

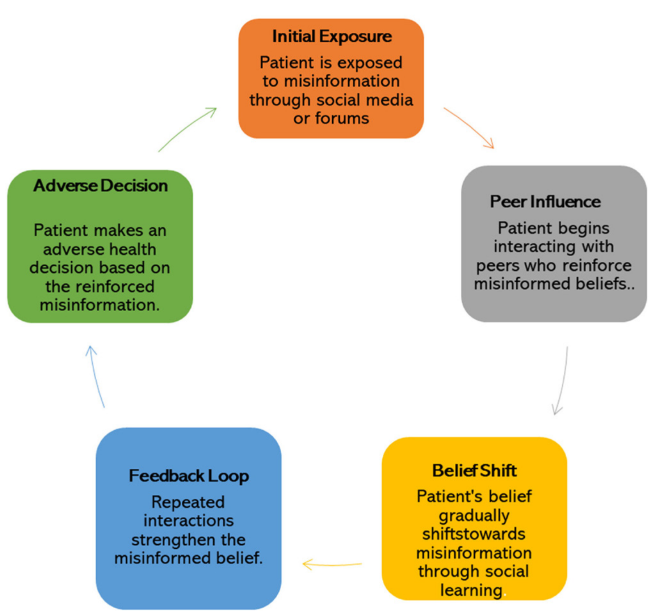

Fig 1 | Misinformation spread network

Source: Authors' calculations

People should be able to choose their healthcare, but digital platforms and healthcare providers should also make sure it is easy to find correct information.[61] In a moral sense, people who work in health care and tech should make sure that the health information people find is correct and safe, but people should still be able to find it and choose how to be cared for. More people do not want to get vaccinated, and there are also more alternative ways to treat serious illnesses like cancer. This shows that giving people false health information can be bad for them. People are spreading diseases like measles, whooping cough, and others that can be stopped with vaccines. Cancer patients are also skipping treatments that have been shown to work in favour of others that may or may not be safe. These are two ways that false information can make people worse off. It is not good for patients or the public health system as a whole to spread lies about this. It makes people less likely to trust healthcare providers and allows weaknesses in herd immunity to happen.

Even though the free flow of information is one of the most important ideas behind the internet, unchecked disinformation affects people's trust in healthcare systems.[62,63] Tech companies need to think about how their algorithms affect people's morals and how to stop the spread of false health information without giving people less freedom of speech. Ethics are also a problem for people who work in healthcare. It is important to respect what patients want, but healthcare professionals also need to make sure that patients do not make bad decisions because they do not have all the facts. This means that doctors might have to spend more time answering their patients' questions and giving them evidence-based rebuttals when they are worried about false information. Medical professionals should also try to change the minds of lawmakers and punish tech companies that spread false information about people's health.

Patients can get useful medical information from "information prescriptions" that tell them where to look on the internet. Professionals in health care can help their patients avoid getting false information by giving them tools to stay away from platforms that have not been checked out. During appointments, providers should also show patients how to use technology. This way, patients can learn to tell the difference between websites that explain about medicine. More than that, they can learn how to question the reliability of the online sources they use. People who are taught in this way are less likely to believe false information and will make better decisions. Targeted digital health literacy interventions can help patients with long-term conditions the most, especially those who are more likely to believe false information.[65] It includes people who have cancer, diabetes, or pain that lasts for a long time. Digital platforms should also be used by healthcare systems to share correct health information. We could make websites to teach patients or work with tech companies to get social media posts based on evidence shared. This would make it easier for healthcare systems to deal with the huge amount of false information that can be found online, which could negatively impact patients.

Implications for Future Research

Even though DeGroot's model helps us understand how fake news spreads, we still need to do more research to find good ways to stop the online networks that spread false news. Something that should be looked into is how apps can be used to keep people safe and stop the spread of fake news. Altering search engine algorithms or the way content is moderated on social media could help stop the spread of false health information.

This study's results open the door to a lot of new research. That being said, we still need to conduct more research to find effective ways to stop the spread of false information in online networks. We can see how false information spreads with the help of our DeGroot model. It might be smart to look into algorithmic ways to keep people safe and stop the spread of false information. It is interesting to learn about this subject. A study says that it might be harder to find false health information if search engine algorithms or the way content is moderated on social media are changed.

Limitations of the Study

One issue is that the mathematical model used to study fake news is based on the idea that everyone is equal, which is based on how people learn from each other. Different people indeed have different ideas about how trustworthy their friends are, which can change how false information spreads. The model also explains that each network node has an equal chance to get to data. Real life, on the other hand, can change who can see medical records based on things like location, type of job, and income. Along those lines, the study does not look at how offline factors such as family, friends, and community leaders affect health beliefs. It is more about how false information gets around in online networks. More research needs to be done on how interactions online and offline affect each other and how they make it easier for bad health effects and false information to spread.

Conclusion

The social learning model by DeGroot was used in this study to look at how false information on the internet affects people's decisions about medical care. There is no doubt that this kind of information has a big effect on the mental and physical health of those involved. Our research shows that when people are exposed to false information, they are more likely to become emotionally upset, show signs like more anxiety and depression, and make bad treatment choices, such as skipping medicine that has been shown to work in favour of therapies that have not been proven to work. Patients cannot tell the difference between real medical advice and health claims that are not true any longer. They do this because fake news spreads even faster on the web.

The results make it clear that there needs to be a big plan to stop people from lying about their health. Doctors can help people take charge of their health by teaching them how to question claims and point them in the direction of good sources. Also, online platforms should be more responsible for the health-related content they show and reward facts that are backed by science more than they reward false claims.

Targeted treatments that can stop the social learning processes that support misinformation should be observed in the future, but this study does give us useful information about the causes and effects of the spread of misinformation. Coordinated actions in the areas of technology, education, and health care can lessen the bad effects of false information on public health. The spread of internet-derived misinformation significantly impacts both individual health decisions and the broader consensus within online networks. By improving digital health literacy and implementing strategies to limit the amplification of misinformation, we can mitigate its harmful effects and promote informed, evidence-based medical decisions.

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